Potential Predictability of the North Atlantic Heat Transport Based on an Oceanic State Estimate

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ABSTRACT

This paper investigates the potential predictability of the meridional heat transport (MHT) in the North Atlantic on interannual time scales using hindcast ensembles based on an oceanic data assimilation product. The work analyzes the prognostic potential predictability (PPP), using the ocean synthesis of the German partner of the consortium for Estimating the Circulation and Climate of the Ocean (GECCO) as initial conditions and as boundary conditions. The PPP of the MHT varies with latitude: local maxima are apparent within the subpolar and the subtropical gyres, and a minimum is apparent at the boundary between the gyres. This PPP minimum can also be seen in the PPP structure of the Atlantic meridional overturning circulation (AMOC), although it is considerably less pronounced. The decomposition of the MHT shows that within the subpolar gyre, the gyre component of the MHT influences the PPP structure of the MHT. Within the subtropical gyre, the overturning component of the MHT characterizes the PPP structure of the MHT. At the boundary between the subpolar and the subtropical gyres, the dynamics of the Ekman heat transport limit the predictable lead times of the MHT. At most latitudes, variations in the velocity field control the PPP structure of the MHT. The PPP structure of the AMOC can also be classified into gyre and gyre-boundary regimes, but the predictable lead times within the gyres are only similar to those of the overturning component of the MHT. Overall, the analysis provides a reference point for the latitude dependence of the MHT’s PPP structure and relates it to the latitude dependence of the AMOC’s PPP structure.

1. Introduction

The transport of heat through the oceanic circulation has a profound influence on latitudinal variations in climate, since the ocean contributes to the time-mean meridional heat transport at approximately the same order of magnitude as the atmosphere (von der Haar and Oort 1973). Fluctuations of the oceanic component of the meridional heat transport (MHT) originate from processes that are internal to the ocean, or in response to atmospheric fluctuations (Dong and Sutton 2002). On short time scales, the variability of the MHT is dominated by Ekman processes. On interannual time scales, variability of the MHT arises primarily from the variability in the ocean circulation over most latitudes (Jayne and Marotzke 2001; Dong and Sutton 2002). More specifically, the variability of the velocity field acting on the time-mean temperature field is predominantly responsible for the MHT variability. The variability of the temperature field (i.e., temperature fluctuations advected by the time-mean velocity field) plays a lesser role in the MHT variability. Jayne and Marotzke (2001) and Dong and Sutton (2002) both find that the influence of temperature variations increases at higher latitudes (i.e., the subpolar gyre), whereas Dong and Sutton (2002) also specify that the temperature variations particularly affect the decadal variability of the MHT at these latitudes.

At midlatitudes, most of the MHT in the Atlantic is conducted through the Atlantic meridional overturning circulation (AMOC; Hall and Bryden 1982), and repeated studies have shown that the fluctuations within both quantities are coherent (e.g., Pohlmann et al. 2006). Bingham et al. (2007) and Lozier et al. (2010) suggest that changes in the AMOC variability are latitude specific. At subpolar latitudes (north of 40°N), the AMOC variability has a strong decadal component, whereas at subtropical latitudes (south of 40°N), it is dominated by higher frequencies (Bingham et al. 2007). AMOC fluctuations on longer time scales than a decade are thought
to be influenced by the North Atlantic Oscillation (NAO; e.g., Dong and Sutton 2002; Eden and Willebrand 2001).

The AMOC’s latitude dependent variability is also thought to have an impact on its predictability at a specific latitude. AMOC predictability has mostly been studied in a perfect model framework (without direct comparison to observations), resulting in an estimate of potential predictability. The potential predictability of the AMOC has been analyzed at several individual latitudes (e.g., Collins and Sinha 2003; Collins et al. 2006; Hermanson and Sutton 2009; Pohlmann et al. 2009; Msadek et al. 2012). Although the variability of the AMOC and the MHT appear to be closely linked, the underlying mechanisms are not yet fully understood (e.g., Msadek et al. 2012, manuscript submitted to J. Climate). Further, different model formulations result in different AMOC states (Hurrell et al. 2010), and a long-term decrease in the AMOC’s strength does not necessarily have to be followed by a decrease in MHT (Drijfhout and Hazeleger 2006). Therefore, we focus here on the potential predictability of the MHT itself, rather than inferring the potential predictability of the MHT from the potential predictability of the AMOC. In the present study, we analyze the latitude dependencies of the potential predictability of the MHT, its components, and its relationship to the potential predictability of the AMOC on interannual time scales.

To analyze potential predictability on interannual time scales, both the initial and boundary conditions are important (Collins 2002; Collins et al. 2006). Several studies indicate that on such time scales the predictive skill of an initialized system improves over predictions without knowledge of the ocean state (e.g., Troccoli and Palmer 2007; Smith et al. 2007; Keenlyside et al. 2008; Pohlmann et al. 2009; Zhang 2011). Further improvements are expected by using the same model environment to derive the initial conditions and the forecast simulations (e.g., Pohlmann et al. 2009). Here, we use the initial conditions from an oceanic state estimate and conduct hindcast simulations in the same model environment as that used to generate the state estimate.

We use the oceanic state estimate from the German partner of the consortium for Estimating the Circulation and Climate of the Ocean (GECCO; Köhl and Stammer 2008). Since the GECCO state estimate is an ocean-only product, we use GECCO’s past atmospheric forcing to force the hindcast simulations. The feedback from the atmosphere in such an ocean-only setup is missing, and thus we expect reduced predictive skill in comparison with a coupled climate model. However, since the forcing scenarios are prescribed and because they result from only a few decades, the full range of possible evolutions may not be explored. Nonetheless, the present study does benefit from the improved representation of oceanic variability in an oceanic state estimate. This is important, because such a dynamically consistent framework is crucial when studying an integrated quantity such as the MHT.

Ideally, hindcast predictions would be compared to the observational record over the hindcast period. In the ocean, however, and particularly for integrated quantities such as the MHT and the AMOC, observations are limited both in time and space. At a specific latitude, the MHT and AMOC can be estimated from a zonal transect at the particular time of observation (e.g., Lumpkin and Speer 2007). Recently, also time series of the MHT and the AMOC have become available at individual latitudes (Cunningham et al. 2007; Willis 2010; Johns et al. 2011; Hobbs and Willis 2012). As the observations are too few to study the latitude dependent predictability of the MHT in the Atlantic, we investigate its potential predictability here by comparing hindcast ensembles initialized from an oceanic state estimate to the same oceanic state estimate.

2. Model and method

a. Model setup and reference run

We base our potential predictability analysis of the MHT on the currently available German ECCO ocean synthesis. The ECCO framework aims to bring the global 1° Massachusetts Institute of Technology general circulation model (MIT GCM; Marshall et al. 1997) into agreement with as many observations as possible. Several ECCO products exist (http://www.ecco-group.org/products.htm) covering different periods from 1992 onward, where GECCO provides an estimate of the oceanic state back to 1952. The currently available GECCO synthesis uses in situ and satellite observations that were collected over the period from 1952 through 2001 (Köhl and Stammer 2008). During the optimization process, initial temperature and salinity conditions as well as time-dependent surface fluxes of momentum, heat, and freshwater were adjusted by the adjoint method (Talagrand and Courtier 1987).

Since the exact GECCO model setup used in Köhl and Stammer (2008) is no longer available because of technical problems, we have modified the optimized forcing of GECCO so that a very similar model setup produces results similar to the original GECCO output. The original GECCO forcing is corrected with the effect of sea surface salinity (SSS) and SST relaxation to compensate for changes in the code. With this corrected optimized forcing, a 50-yr integration is generated from 1952 to 2001 (covering the same period as the original
GECCO run). This integration represents our reference run, although we focus on the period from 1959 to 2001 for our study.

**b. Rationale of the experimental setup and ensemble generation**

The reference run provides the initial conditions for the hindcast ensembles, which we construct to resemble a real forecast scenario such that no information is used in them that would not theoretically be available from observations at the time of ensemble generation. We initialize the ensembles from the second part of the reference run and force those ensembles with the optimized forcing from the first part of the reference run. This allows us to leave the option open to apply different methods to quantify predictability in the setup. We focus on the later part of the reference run when initializing the hindcast ensembles, since considerably more observations were available to constrain the GECCO state estimate during that period. By using the forcing from the earlier part of the reference run, we make the assumption that the forcing of the last decades is not significantly different from the future decades.

We initialize 10 ensembles from the reference run starting 1 yr apart (1983, . . . , 1992) to ensure continuous sampling of the initial conditions. In each ensemble, the ensemble members are generated using different 10-yr periods from the corrected optimized atmospheric forcing. These 10-yr forcing periods start 1 yr apart (1959, . . . , 1983) and end on the date of the initial conditions (1983, . . . , 1992). This setup results in 15–24 members per ensemble with a simulation period of 10 yr each (Fig. 1). The monthly mean model output is averaged to annual means for the potential predictability analysis.

The spreads of the ensembles and their latitudinal variations are similar among different ensembles. The small differences present are mostly due to varying initial conditions, although they are to some small extent also due to the number of forcing periods, or respectively to additional ensemble members. To illustrate the latitudinal variations of the ensemble spreads, we arbitrarily select two MHT ensembles (starting in 1986 and 1991; Figs. 2a,b). In both ensembles, we find increased spread between about 0° and 20°N, and about 50° and 60°N, which is also visible in the averaged variances for the forcing periods (1959 to 1983, . . . , 1992) of the reference run (Fig. 2c). The variances of the reference run are also similar over the forcing periods and the (entire) reference period (1959–2001). We show the variances and spreads for the MHT here as an example, but the abovementioned statements apply to all investigated quantities.

c. **Potential predictability method**

We estimate potential predictability by calculating the prognostic potential predictability (PPP; Pohlmann et al. 2004). The PPP of a quantity is determined using the ratio of the ensemble spread as a function of time to the variance of a reference simulation:

\[
PPP(t) = 1 - \frac{1}{\sigma^2} \frac{\sum_{j=1}^{N} \sum_{i=1}^{M} (X_{ij}(t) - \bar{X}_j(t))^2}{N \sum_{j=1}^{M} (M - 1) \sum_{i=1}^{N} X_{ij}(t) - \bar{X}_j(t)}
\]

where \(X_{ij}\) is the \(i\)th member of the \(j\)th ensemble, \(\bar{X}(t)\) is the ensemble mean, \(M\) is the number of ensemble members (here, \(M\) ranges between 15 and 24), and \(N\) is the number of ensembles (here, \(N = 10\)). Also, \(\sigma^2\) represents the variance of a reference simulation, for which we use the reference run from 1959 to 2001. Note that the subtraction of the ensemble mean (as a function of time) effectively detrends the hindcasts in computing PPP\((t)\). To avoid artificial predictability we detrend the reference run by removing the best straight-line fit from the monthly mean model output at every latitude before averaging to annual means. Turning to the results for \(PPP(t)\), a value of 1 indicates perfect potential predictability, whereas a value below 0 indicates no potential predictability.

To test whether there is any predictability inherent to the experimental setup, we first conducted a short predictability analysis similar in procedure to that described above, but which uses only the reference run. As the spread of the ensembles generally represent the variances of the forcing periods (Figs. 2a–c), we calculate 1 minus the ratio between the variances of the forcing periods and the reference period (Fig. 2d). The resulting values are quite small (<0.4), and are concentrated around 0, indicating that there is little to no predictability resulting from the experimental setup itself.

The significance of PPP is estimated using an \(F\) test. Following Pohlmann et al. (2004), we denote a quantity as being potentially predictable as long as its PPP is greater than the critical significance limit:

\[
F = \frac{M - 1}{N - M} \frac{\sigma^2}{\sigma^2_{eq}}
\]

where \(\sigma^2_{eq}\) is the equivalent variance of the ensemble spread and \(\sigma^2\) is the actual variance of the reference simulation.
Since the forcing periods overlap, the ensemble members are not strictly independent. For the sake of simplicity, we assume the ensembles’ degrees of freedom (dof) are the total sum of the varying number of ensemble members minus 1 \(\sum (M - 1)\). Varying the degrees of freedom of the ensemble does not significantly change the resulting critical significance limit. The degrees of freedom for the reference run are calculated from the decorrelation time of the first-order autoregressive process (e.g., von Storch and Zwiers 1999):

\[
dof = \frac{n}{(1 + \alpha)(1 - \alpha)} - 1,
\]

where \(n\) denotes the sample size of the reference period and \(\alpha\) denotes its lag-1 autocorrelation coefficient. For all investigated quantities the critical significance limit varies with latitude. Since the variations are small, however, we take the average of the critical significance limit over the latitudes, preserving the latitude dependence of the respective quantity’s PPP. In the following, “PPP structure” stands for the spatial and temporal extent of the significant PPP values across the North Atlantic, and “predictable lead time” stands for the time period over which the PPP values are significant.

3. Results

a. Potential predictability of the total MHT

We find that the MHT is potentially predictable within the subtropical gyre (\(\sim 15^\circ-35^\circ\)N) and within the subpolar gyre (\(\sim 45^\circ-60^\circ\)N) with a gap around 40\(^\circ\)N at the boundary between the gyres (Fig. 3). At subtropical latitudes, we find predictable lead times of 3–4 yr. At subpolar latitudes, we
find slightly higher PPP values than at subtropical latitudes and predictable lead times of 3–5 yr.

To facilitate a better understanding of the predictable lead times of the MHT, we decompose the heat transport into three dynamic components (following Bryden and Imawaki 2001): the barotropic component, the overturning component, and the gyre component. The three components are calculated as follows:

\[
H(y) = \rho c_p \int_0^D \int_0^L (u(y,\theta)(y) \, dx \, dz \\
+ \rho c_p \int_0^D \int_0^L [v(y, z)](\theta)(y, z) \, dx \, dz \\
+ \rho c_p \int_0^D \int_0^L v'(x, y, z)\theta'(x, y, z) \, dx \, dz, \tag{4}
\]

where \(u\) and \(\theta\) denote the meridional velocity and the potential temperature, \(\rho\) is the reference density, \(c_p\) is the heat capacity per unit mass of water at constant pressure, and \(D\) and \(L\) represent the depth and the width of the zonal transoceanic section. The angle brackets denote the section average, the square brackets denote the zonal average minus the section average, and the primes denote the deviations from the respective zonal average. Hence, the first term is the net transport across the section at the section-averaged temperature. The second term represents the contribution of the zonally averaged meridional circulation, and the third term is the contribution of the large-scale gyre circulation. The decomposition of the MHT is calculated for monthly mean model data, while for the following analysis annually averaged values are used (cf. section 2).

Consistent with other modeling studies (e.g., Dong and Sutton 2002), the barotropic component appears to be negligible, and the total MHT is dominated by the overturning component, apart from the subpolar latitudes (Fig. 4a). At the latter latitudes, the influence of the gyre component on the total MHT exceeds the influence of the overturning component, since the zonal temperature difference is as large as the vertical temperature difference. The spatial divide between the influence of the gyre and the overturning component on the total MHT becomes clearer in the variances (Fig. 4b). South of about 45°N most of the total variance of the MHT can be explained by the high variance of the overturning component. Yet, the increased variance at subpolar latitudes is only evident in the gyre component.

b. Potential predictability of the MHT components

At subtropical latitudes, the predictable lead times of the overturning component indicate about 6 yr of potential predictability (Fig. 5a). At subpolar latitudes, the predictable lead times indicate about 2 yr of potential predictability. Around 40°N, we find a gap between the subpolar and subtropical gyres, just as exists in the total MHT’s PPP structure (Fig. 3). Compared to the PPP structure of the total MHT, the overturning component shows longer predictable lead times at the subtropical latitudes, which also extend over a larger range of latitudes, and at subpolar latitudes slightly shorter predictable lead times and lower PPP values.

To analyze the overturning component’s influence on the predictable lead times of the total MHT, we replace \(\sigma^2\) in Eq. (1). That is, we divide the spread of the overturning component by the variance of the total MHT, instead of the variance of the overturning component. For latitudes south of about 40°N, the resulting PPP structure is similar to the PPP structure of the overturning component (cf. Figs. 5a and 5b). For latitudes north of about 40°N, the resulting predictable lead times are considerably longer than the predictable lead times using the variance of the overturning component. These high values imply that predictable lead times of the total MHT are not limited by the influence of the overturning component at latitudes north of about 40°N.

The predictable lead times of the gyre component indicate potential predictability of 5–10 yr at subpolar latitudes (Fig. 5c). Between about 30° and 40°N, we find predictable lead times of about 2 yr. South of about 30°N, essentially no potential predictability is evident. Apart from the decrease of potential predictability at the gyre boundary and the higher PPP values at subpolar than at subtropical latitudes, the PPP structure of the gyre component shows no similarities to the PPP structure of the total MHT (Fig. 3).
As in the analysis of the overturning component, we divide the spread of the gyre component by the variance of the total MHT, instead of the variance of the gyre component in the PPP calculation. This analysis shows that the spread of the gyre component is large enough to influence the predictable lead times at the subpolar latitudes and between about 30° and 40°N (Fig. 5d). At the subpolar latitudes, this indicates that the predictable lead times of the total MHT are more heavily influenced by the spread of the gyre component than by the spread of the overturning component (Fig. 5b). Although we find longer predictable lead times for the gyre component (Fig. 5c) than for the total MHT (Fig. 3) at these latitudes, the influence of the gyre component can be seen in the enhanced potential predictability of the total MHT compared to the potential predictability of the overturning component. Between about 30° and 40°N the influence of the gyre component can be seen in shorter (and spatially less extended) predictable lead times of the total MHT compared to predictable lead times of the overturning component. Overall, the PPP structure of the total MHT (Fig. 3) can be reconstructed from the analysis of the overturning and gyre component’s PPP structures (Figs. 5a,c) together with the relative influence of the component spreads on the total MHT (Figs. 5b,d).

c. Influence of velocity and temperature field variations

Jayne and Marotzke (2001) and Dong and Sutton (2002) have shown that the influence of the variability of the velocity field on the variability of the MHT clearly dominates over the variability of the temperature field, with the exception of the higher latitudes where temperature variations gain influence. To estimate the influence of the velocity (temperature) variations on the variability of the MHT, we calculate the MHT with a time mean temperature (velocity) field in the reference run from 1959 to 2001. South of about 30°N the variance of the MHT is controlled by the velocity field variations (Fig. 6a). North of about 30°N, the variance of the MHT and the variance of the MHT with a constant temperature field show significantly smaller values than the variance of the MHT with a constant velocity field. Hence, we suggest that north of about 30°N temperature field variations covary with velocity field variations, such that the net MHT variability remains relatively low.

We now turn to the assessment of whether this spatial separation between the influence of the velocity field and the influence of the temperature field on the variability of the MHT is also visible in the potential predictability of the MHT. To estimate the influence of the velocity (temperature) variations on the potential predictability of the MHT, we calculate the MHT of each ensemble member with a constant temperature (velocity) field (time mean of the respective ensemble member), but in the reference run we keep the full signal of the temperature (velocity) field.

The PPP structure of the MHT using a constant temperature field and a varying velocity field (Fig. 6b) is in general similar to the PPP structure of the total MHT with both fields varying (Fig. 3). The PPP structure in
both gyres is narrower for the MHT using a constant temperature field and a varying velocity field than for the total MHT with both fields varying, resulting in a wider band in which potential predictability is non-existent ($\sim$35°–45°N).

At every latitude, the predictable lead times of the MHT using a constant velocity field and a varying temperature field are longer than the predictable lead times of the total MHT with both fields varying (Fig. 6c). This shows that the spread created by the temperature field variations alone is too small to restrict the potential predictability to resemble the PPP structure of the MHT with both fields varying (Fig. 3).

At most latitudes, the variations of the velocity field are more important than the variations of the temperature field for the PPP structure of the total MHT, except for the latitudes in the vicinity of the gyre boundary ($\sim$30°–35°N and $\sim$40°–45°N). At these latitudes the velocity field variations alone are too large to represent the PPP structure of the total MHT. North of about 30°N the influence of the temperature field variations on the total MHT variance increases (Fig. 6a). In the PPP structure, this increased influence becomes obvious in the vicinity of the gyre boundary, where temperature field variations reduce the total ensemble spread and lengthen the predictable time scales of the total MHT to narrow the boundary gap.

d. Influence of the Ekman heat transport

Ekman dynamics contribute significantly to the MHT variability on interannual time scales (Jayne and Marotzke 2001; Dong and Sutton 2002). To analyze the influence of the atmospheric wind field on the predictable lead times of the MHT, we now subtract the Ekman heat transport from the total MHT prior to the PPP analysis. Across a zonal section, the Ekman heat transport is defined as the integral of the meridional Ekman layer mass flux, multiplied by the difference between the Ekman layer temperature $T_{Ek}$ and the section-averaged potential temperature $\langle \theta \rangle$ (Jayne and Marotzke 2001).
This assumes that, for any given section, the mass transport in the Ekman layer is compensated by a section and depth uniform return flow, and thus the Ekman heat transport can be calculated as follows:

\[ H_{Ek} = -\int \rho c_f f \tau_x (T_{Ek} - \langle \theta \rangle) \, dx, \]  

where \( f \) is the Coriolis parameter, \( \rho \) is the reference density, and \( \tau_x \) is the zonal wind stress. Here, we define \( T_{Ek} \) as the sea surface temperature since the actual depth of \( T_{Ek} \) appears to be insignificant.

To test the influence of the Ekman heat transport on the potential predictability of the MHT, we calculate the MHT minus the Ekman heat transport for the ensembles, but we keep the full MHT signal in the reference run for the PPP analysis (Fig. 7). The resulting predictable lead times are longer than the predictable lead times of the total MHT at all latitudes (Fig. 3). Within the gyres, the influence of the Ekman heat transport on the predictable lead times is not as strong, although it appears stronger at subtropical latitudes than at subpolar latitudes. Particularly at the gyre boundary and at the southern boundary of the subtropical gyre (between about 5° and 20°N), the influence of the Ekman heat transport variability is so strong that it prevents potential predictability of the total MHT at these latitudes entirely.

e. Potential predictability of the AMOC

Having analyzed the PPP structure of the total MHT, we now turn to the question of whether the predictable lead times of the total MHT are directly related to the predictable lead times of the AMOC. The predictable lead times of the AMOC increase continuously from 2 yr in the subpolar gyre to about 6–7 yr in the subtropical gyre (Fig. 8). Especially for lead times of 1 yr, the PPP values are higher in the gyres than at the boundary. Although there is no gap of potential predictability at the boundary between the subpolar and subtropical gyre, we can still distinguish between the gyres and the gyre boundary. The PPP structures of the AMOC and the total MHT (Fig. 3) are generally different. The predictable lead times of the AMOC are longer at subtropical latitudes than at subpolar latitudes, as seen in the overturning component of the MHT (Fig. 5a), but not the MHT as a whole. The potential predictability of the AMOC is...
slightly shorter than the MHT’s at subpolar latitudes. At these latitudes MHT’s PPP structure is influenced by an increased contribution from the gyre component, induced by changes in the temperature field distribution (cf. sections 3a and 3b).

At the gyre boundary, the influence of the Ekman variability on MHT’s PPP is so strong that it prevents any potential predictability, while the influence of the Ekman variability on the AMOC PPP merely decreases the PPP values, but the predictability lead times are nearly as long as in the subtropical gyre. Thus, Ekman variability appears to play a more important role in determining the potential predictability of the MHT than it does in determining that of the AMOC, since most of the heat transport occurs in the upper layers of the ocean.

4. Discussion

The PPP of the total MHT is different in the subtropical gyre, the subpolar gyre, and the area forming the boundary between the gyres. Although a gyre dependence of the potential predictability can also be seen for the AMOC, its PPP structure is only similar to the overturning component of the MHT.

For the AMOC, our predictable lead times fall within the wide range of previous findings. This wide range is due to a considerable diversity in the models employed, their setups, and the variety of initial conditions, as well as the applied methods used to quantify predictability: The AMOC’s (potential) predictability lead times range from 3 to 6 yr (Hermanson and Sutton 2009; Pohlmann et al. 2009; Matei et al. 2012; Kröger et al. 2012; Pohlmann et al. 2012, manuscript submitted to Climate Dyn.) to a decade or even longer (Griffies and Bryan 1997; Collins and Sinha 2003; Pohlmann et al. 2004; Collins et al. 2006; Keenlyside et al. 2008; Msadek et al. 2010). With the exception of Kröger et al. (2012), these AMOC (potential) predictability studies were conducted at a single (mostly subtropical) latitude or a basinwide maximum AMOC index, and not over a range of latitudes across the North Atlantic.

In contrast to the diverse findings for the AMOC’s potential predictability time scales, there are to the authors’ best knowledge no published studies on the potential predictability of the MHT. Particularly the minimum in the MHT’s potential predictability at the gyre boundary is a surprising result. However, an indication of latitudinal variations in the potential predictability, and an area of decreased potential predictability at midlatitudes in the North Atlantic can also be seen in previous predictability studies on the SST (Pohlmann et al. 2004; Boer 2009; Matei et al. 2012), the upper ocean heat content (Matei et al. 2012), and the AMOC (Kröger et al. 2012). Since no estimate thus far exist for the MHT’s predictable lead time, our results serve as a reference point for the discussion of meridional variability in MHT PPP structures, and their relation to AMOC PPP structures.

Our PPP structures of the AMOC and the overturning component of the MHT contradict the widely accepted view that the AMOC’s potential predictability is higher at subpolar latitudes than at subtropical latitudes. This view is based on the close relationship between the potential predictability of the thermohaline circulation and the North Atlantic SST (e.g., Pohlmann et al. 2004; Latif et al. 2004) and the notion that SST anomalies are more predictable in the subpolar than in the subtropical North Atlantic (e.g., Msadek et al. 2010). Pohlmann et al. (2009) anticipated that the AMOC’s predictive skill might be limited to high latitudes because of the close connection between the NAO and the AMOC strength. On the other hand, propagating AMOC signals (e.g., Köhl and Stammer 2008; Getzlaff et al. 2005) could also provide longer predictable time scales in the subtropics. While we maintain that the gyre dependence of the PPP is a robust result, our analysis cannot fully explain why the predictable lead times are shorter or longer at specific latitudes within our analysis. Thus, the actual distribution of the predictable lead time lengths remains a matter of discussion and should be subjected to further investigation.

Limitations of our analysis primarily arise from the setup employed. For example, hindcast ensembles are not generated in a coupled model but rather by using predefined atmospheric forcing (historical forcings from

![Fig. 8. Hovmöller diagram of the PPP of the AMOC (at about 1000 m) as a function of lead time (Atlantic: 0°–60°N). The white dashed line indicates values significant at the 90% level.](http://journals.ametsoc.org/jcli/article-pdf/25/24/8475/3988584/jcli-d-11-00606_1.pdf)
1959 to 1992). Assuming that the forcing in the next decade is not unlike the forcing in previous decades, the present results cover a range of expected forcings. The forcing comes from both NAO+ and NAO− periods, but the initial conditions are restricted to mostly NAO+ states. This is a consequence of limiting the initialization of the ocean to the last two decades of the GECCO state estimate, which is done to ensure the use of independent forcing data from the previous decades. Unfortunately, the present setup does not allow us to clearly distinguish between different NAO states in order to analyze the sensitivity of potential predictability within the context of the NAO’s state of the initial and boundary conditions. Since changes in the NAO are thought to influence the time scales of AMOC variability at subpolar latitudes (Eden and Willebrand 2001; Lozier et al. 2010), and GECCO furthermore shows an AMOC that is sensitive to the state of the NAO (Köhl and Stammer 2008), an influence by these conditions on our results cannot be excluded.

The actual lengths of the calculated predictable time scales depend on a number of parameters selected in the analysis to derive the predictable lead times (section 2c). For example, using a different reference period (e.g., the forcing or the hindcast period) or not detrending the reference run could increase or decrease the predictable lead times by a couple of years. Another example is the parameters entering the calculation of the significance level, and the actual method chosen to calculate the significance level. None of the choices changes the general latitudinal PPP structure for the analyzed quantities. We therefore refrain from insisting on a specific number of predictable years at a certain latitude, but emphasize the relation of potential predictability between different latitudes.

While we cannot initialize the atmosphere, our setup represents a self-consistent framework with respect to both initialization and consistency with observations. Previous studies have shown that the initialization procedure can impact resulting predictions, as is visible in the comparison between the SST predictions of Keenlyside et al. (2008) and Pohlmann et al. (2009), who use the same model but a different initialization method. The model formulation also has a considerable impact on the model state [see, e.g., the AMOC in Hurrell et al. (2010)]. Here, we use the same model framework for the synthesis with the observations, the hindcast simulations, and the verification of the ensemble spread. Further studies using initialized hindcast ensembles from coupled models, and potentially also verifying the ensemble spread against observations, are therefore essential in establishing the robustness of the conclusions.

We have restricted the current analysis to potential predictability as it is currently not possible to analyze the latitude dependence of the MHT and the AMOC against real observations. But the present experimental setup allows us to evaluate possible oceanic states (ensemble hindcasts) against an oceanic state estimate instead. In the present study we evaluate the theoretical limit of the predictable lead times by means of the PPP method, but the yearly start dates of the initial conditions (to continuously sample variability) together with the independent hindcast reference periods also allow us to quantify the potential predictability by means of the anomaly correlation (following Pohlmann et al. 2009). Given the different informative value of both methods, it is not a trivial result that the general conclusions of the PPP analysis can be confirmed with the anomaly correlation. In the chosen model environment, regardless of the chosen method, our conclusions represent an indication of latitude-dependent potential predictability of both the MHT and the AMOC, which are in agreement with previous studies of both the variances of the MHT and the AMOC (Jayne and Marotzke 2001; Lozier et al. 2010).

5. Conclusions

Based on our analysis of the prognostic potential predictability (PPP) of the MHT in the North Atlantic in hindcast ensembles initialized from the GECCO oceanic state estimate, we draw the following conclusions:

- The PPP of the MHT varies with latitude, changing between the subtropical and subpolar gyre, and at the gyre boundary.
- Within the subtropical gyre, the PPP structure of the MHT is characterized by the overturning component. Within the subpolar gyre, the PPP structure of the MHT is characterized by the gyre component.
- At most latitudes, variations in the velocity field play a determining role on the PPP structure of the MHT. The influence of temperature field variations on the PPP structure of the MHT can so far only be confirmed in the vicinity of the gyre boundary.
- On the investigated interannual time scales, Ekman dynamics influence the PPP structure of the MHT at all latitudes and limit the predictable lead times of the MHT particularly at the gyre boundary and at the southern extent of the subtropical gyre.
- We confirm earlier results that the PPP of the AMOC varies with latitude. Here, we find that Ekman dynamics decrease the PPP of the AMOC at the gyre boundary although, in contrast to the MHT, no distinctive minimum is apparent at the gyre boundary.
• The PPP structure of the AMOC cannot be directly related to the PPP structure of the MHT. But the predictable lead times of the AMOC are similar to the predictable lead times of the MHT’s overturning component.
• The suggested gyre-dependent predictable lead times of both MHT and AMOC indicate that caution should be exercised when interpreting the potential predictability of the MHT or AMOC at a single latitude.

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