1. Introduction

The subseasonal to seasonal (S2S) time range (~2 weeks to ~2 months) falls at the interface of medium-range weather forecasts and seasonal climate predictions (Vitart et al., 2017). Predictions at this lead time are often considered difficult as much of the information from atmospheric initial conditions is lost, but there is insufficient time for the development of predictable ocean processes (Vitart & Robertson, 2018). Nevertheless, several studies have demonstrated that ocean-atmosphere coupling can improve forecast skill at S2S lead times (e.g., Boisséson et al., 2012; Woolnough et al., 2007).

Although coupling to a dynamic ocean model allows a more realistic representation of air-sea interaction, it also introduces the potential for systematic errors in sea-surface temperatures (SST), which can have a negative impact on forecast quality. In particular, ocean configurations that do not adequately resolve mesoscale ocean eddies in the midlatitudes cannot accurately simulate the separation of the Gulf Stream from the North American continent (Chassignet & Xu, 2017; Hewitt et al., 2020; Marzocchi et al., 2015). It has thus been suggested that increases to ocean model resolution sufficient to resolve the ocean mesoscale at midlatitudes will benefit coupled predictions across weather and climate time scales (Hewitt et al., 2017).

Roberts et al. (2020) recently investigated the sensitivity of ECMWF subseasonal forecasts to an increase of ocean model resolution. They concluded that increasing resolution from ~100 to ~25 km can drive improvements to subseasonal predictability over Europe. However, this skill originated from improvements to the Madden-Julian oscillation (MJO) and an increase in the strength of extratropical teleconnections following enhanced convective activity in the Indian Ocean rather than improvements in air-sea interaction in the North Atlantic region. However, neither ocean configuration was “eddy resolving” and thus both suffered from North Atlantic SST errors exceeding 3 K associated with an erroneously positioned Gulf Stream.
To interpret the impact of North Atlantic SST biases in a coupled forecasting system, it is useful to consider observational and idealized modeling studies that have investigated the influence of the Gulf Stream on the mean state and variability of the overlying atmosphere (e.g., Brayshaw et al., 2011; Minobe et al., 2008, 2010; Nakamura et al., 2008; Parfitt et al., 2016, 2017; Woollings et al., 2010). In particular, Minobe et al. (2008) demonstrated that the Gulf Stream is associated with a pattern of near-surface wind convergence and upward motion that anchors a band of precipitation along the warm edge of the SST front. Furthermore, Minobe et al. (2008) showed that this response extended throughout the entire troposphere and also identified a pathway through which the Gulf Stream could influence remote regions by forcing a planetary wave response.

More recent studies have emphasized that the climatological relationship between Gulf Stream SST gradients and the atmosphere above is a consequence of the aggregated impact of frontal circulations and convective instability triggered by extratropical cyclones crossing sharp SST gradients (Czaja & Blunt, 2011; O’Neill et al., 2017; Parfitt & Czaja, 2016; Parfitt & Seo, 2018). Consequently, SST biases in a coupled forecast model that modify the position of the Gulf Stream have the potential to impact the location, magnitude, and timing of upward motion and convection associated with extratropical cyclones propagating in the North Atlantic storm track (Woollings et al., 2010). The associated changes in diabatic forcing can therefore impact atmospheric forecasts in the North Atlantic and beyond.

Idealized climate model studies have also shown that large-scale atmospheric circulation errors can be attributed to biases in North Atlantic SSTs (e.g., Keeley et al., 2012; Lee et al., 2018; Scaife et al., 2011). For example, Scaife et al. (2011) found that a more realistic representation of the Gulf Stream and its extension into the North Atlantic leads to improvements in the representation of Atlantic blocking in multidecadal climate integrations. More recently, Lee et al. (2018) imposed Gulf Stream SST biases from a coupled climate simulation in an atmosphere-only configuration of the same model. They found that the resulting heating anomalies stimulated spurious vertical motions and a planetary wave response that propagated throughout the entire northern hemisphere. Based on these results, they speculated that forecasts with coupled prediction systems will be improved by reducing SST biases in western boundary currents and areas of intense air-sea interaction.

The studies described above have focused on the impact of fully developed SST errors from multidecadal climate integrations. Here, we show that North Atlantic SST biases and errors in the position of the Gulf Stream can also have a significant negative impact on atmospheric forecasts at subseasonal lead times. The impacts provide important evidence for the potential benefits of higher-resolution ocean models in initialized coupled forecast systems.

1.1. Data and Methods

To evaluate the impact of North Atlantic SST biases in subseasonal forecasts, we perform coupled reforecasts with cycle 43r1 of the ECMWF Integrated Forecasting System (IFS), which includes dynamic representations of the atmosphere, sea ice, ocean, land surface, and ocean waves. Further details on IFS cycle 43r1 can be found in Roberts et al. (2018, 2020), and Johnson et al. (2019), and in the online documentation (ECMWF, 2020c).

The atmosphere is configured with 91 vertical levels and uses the Tco399 cubic octahedral reduced Gaussian grid (i.e., grid-point resolution of ~25 km). The IFS is coupled hourly to a 75 level version of the NEMO v3.4 ocean model (Madec & team, 2008) and the LIM2 sea-ice model (Bouillon et al., 2009; Fichefet & Maqueda, 1997), both of which use the ORCA025 tripolar grid (grid-point resolution of ~0.25°). Coupling follows the implementation used in ECMWF operational forecasts. During the first 10 days of the forecast, SSTs seen by the atmosphere are derived by adding ocean model SST tendencies to observed values at initialization time that correctly represent the position of high-resolution features such as ocean fronts (Janssen et al., 2013). From day 10 onwards, the ocean and atmosphere are freely coupled and ocean SST biases develop without constraint.

Our reference reforecast experiment (CTRL; ECMWF, ) 2020a s a 15-member ensemble of coupled subseasonal integrations initialized on the first and fifteenth of each month of an extended winter period (November-March) from 1989 to 2015 (i.e., 270 start dates). Atmospheric fields are initialized from the ERA-interim
reanalysis (Dee et al., 2011) and ocean/sea-ice fields are initialized using the ORAS5 ocean (re)analysis (Zuo et al., 2019). Ensemble spread in coupled forecasts is generated through a combination of initial condition perturbations and stochastic parameterizations in the atmospheric model as described in Lock et al. (2019).

To evaluate the impact of North Atlantic SST biases, we run a second reforecast experiment (BCFC; ECMWF, 2020b) in which the ocean receives atmospheric fluxes as normal, but the SSTs seen by the atmosphere are adjusted using the model SST bias derived from CTRL, which varies as a function of location, calendar start date, and forecast lead time. Biases are computed relative to SSTs from the ERA-interim reanalysis (Dee et al., 2011), which in turn are derived from a combination of the NCEP 2D-VAR reanalysis (December 1981 to June 2001; Reynolds et al., 2002), the NCEP OIv2 reanalysis (July 2001 to December 2001; Reynolds et al., 2002), the NCEP Real-Time Global analysis (January 2002–January 2009; Thiébaux et al., 2003), and OSTIA (February 2009 onwards; Donlon et al., 2012). This bias-correction term is applied only in the North Atlantic region (see highlighted box in Figure 1c) and is smoothly reduced to zero at the edge of the domain. This method effectively reduces SST biases in the North Atlantic, particularly in the region of the Gulf Stream. Further methodological details can be found in Vitart and Balmaseda (2018).

Figure 1. (a) and (b) Climatological SSTs seen by the atmosphere (contour spacing 2 K) and biases relative to ESA CCI observations (shading; Merchant et al., 2019). (c) Difference between BCFC and CTRL SST climatologies (shading) and region of SST bias correction (yellow box). (d–f) As (a–c), but for surface latent heat fluxes (SLHF) with biases relative to the ERA5 reanalysis (Hersbach et al., 2020). Positive values indicate a heat flux out of the ocean. (g–i) Differences between BCFC and CTRL climatologies of 2 m temperature ($T_{2m}$), parameterized convective precipitation ($P_{conv}$), and vertical velocities at 850 hPa ($w_{850}$). Negative values of $w_{850}$ indicate ascent. All differences are computed using climatologies constructed from days 26 to 32 of forecasts initialized on the first and fifteenth of each month in the extended winter season (November-March) for the period 1989–2015.
The impacts on forecast quality are assessed by separately considering the mean state and the forecast skill of anomalies relative to climatology. Impacts on the mean state are assessed using a bias score (Equation 1), where $< x >_{i,m}$ represents a climatology as a function of grid-point $i$ and the month of the forecast start date $m$, and $w$ is a weight to account for variations in cell area as a function of latitude. A positive value indicates that absolute biases aggregated across all locations and start dates in BCFC are reduced compared to CTRL:

$$\text{BiasScore} = 1 - \frac{\sum_i \sum_m w_i \sum_m (BCFC)_{i,m} - (Obs)_{i,m}}{\sum_i \sum_m (CTRL)_{i,m} - (Obs)_{i,m}}$$ (1)

Impacts on deterministic and probabilistic forecast skill are evaluated using anomaly correlations and the continuous ranked probability score (CRPS; Hersbach, 2000), respectively. Forecast anomalies are defined relative to a start-date and lead-time dependent climatology that excludes the forecast start date. Regional scores are computed by summing CRPS across start dates and grid-points with weights to account for variations in cell area. The associated skill scores (CRPSS; Equation 2 are computed relative to a reference score determined from the observed climatological distribution (CRPS$_{clim}$).

$$\text{CRPSS} = 1 - \frac{\text{CRPS}}{\text{CRPS}_{clim}}$$ (2)

All scores are calculated from data that has been interpolated to a regular 2.5° × 2.5° latitude-longitude grid. Statistical significance is evaluated using a bootstrap resampling approach where scores (and associated differences) are calculated 1,000 times using randomly selected (with replacement) start dates. Values are deemed significant if the 2.5th and 97.5th percentiles of the bootstrap distribution have the same sign.

2. Results

2.1. Impact on the Mean State

The largest North Atlantic SST biases in CTRL are associated with errors in the position and structure of the Gulf Stream (Figure 1a). The resulting SST biases follow the path of the SST front and are positive to the north and negative to the south. We also note the positive SST biases along the southern tip of Greenland, which are also present in the ocean initial conditions and seasonal/climate runs with the same model (see Figure 1 of Roberts et al., 2020).

All North Atlantic SST errors are effectively reduced in BCFC (Figures 1b, 1c, and 2). The improvement is present at all lead times (Figure 2), though the magnitude of the impact increases with forecast lead time. There are also significant improvements to 2m temperatures and surface heat fluxes over the North Atlantic region, particularly over the Gulf Stream (Figures 1d–g and 2). Furthermore, the atmospheric circulation responds to the southward shift of the Gulf Stream with increased convective precipitation and upward motion over areas of increased SST and convective precipitation (Figures 1h, 1i, and 2).

As shown previously, changes to the time-mean convection and vertical motion over the Gulf Stream can be interpreted in terms of the cumulative impact of extratropical storms interacting with the SST front (e.g., Czaja & Blunt, 2011; O’Neill et al., 2017; Parfitt & Czaja, 2016; Parfitt & Seo, 2018). A southward shift in the Gulf Stream will thus directly impact the location, magnitude, and timing of upward motion and convection associated with extratropical storms, and therefore also impact the variability of diabatic forcing in the upper atmosphere. The impact on atmospheric variability in BCFC is most evident in the variance of vertical velocities at 850 hPa ($w_{850}$), which is increased by 5–10% in areas of increased SST and increased convective precipitation (Figure S1).

Figure 2 summarizes the impact of reduced North Atlantic SST biases on the mean state for a range of variables and regions in terms of the bias score described in Section 2. The improvements to near-surface fields are clear at all forecast lead times, particularly in the Gulf Stream region. However, other than the changes to $w_{850}$ and convection over the Gulf Stream, we detect very few significant improvements to the upper atmospheric mean state. Nevertheless, the changes to vertical motion and convection along the Gulf...
Stream have consequences for the predictability of weekly mean anomalies that extend far beyond the North Atlantic basin.

### 2.2. Impact on Forecast Skill

The reduction of SST biases in BCFC significantly improves forecasts of weekly mean atmospheric circulation anomalies at a lead time of 26–32 days (i.e., “week 4”; Figures 3 and 4). We see very few significant differences in weekly mean forecast skill at earlier lead times (i.e., weeks 1–3). Figure 3 shows difference maps for week 4 CRPSS and anomaly correlation skill for mean sea level pressure (mslp), zonal wind at 850 hPa (u$_{850}$), geopotential height at 500 hPa (z$_{500}$), and meridional wind at 200 hPa (v$_{200}$). Although the difference maps exhibit some noise, there is a signal for significantly increased mslp and $u_{850}$ skill over the North Atlantic that extends westward into Europe and northern Africa (Figures 3a, 3b, and 4). We also see

| Variable | GSTREAM | NATL | EUROPE | NWAVEGUIDE |
|----------|---------|------|--------|-----------|
| Lead (days) | 5-11 | 12-18 | 19-25 | 26-32 |
| SST | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| mslhfl | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| msshfl | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| t | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| cprate | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| lsprate | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| msl | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| uas | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| vas | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| t850 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| r850 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| u850 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| v850 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| w850 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| z500 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| t200 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| r200 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| u200 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| v200 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |
| w200 | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ | ▲ ▲ ▲ ▲ |

Figure 2. Score card summarizing the impact of North Atlantic SST bias correction on the mean state as diagnosed using the bias score described in Section 2. Positive (blue) values indicate an improvement in the mean state relative to ESA CCI observations (SSTs; Merchant et al., 2019) or the ERA5 reanalysis (all other variables; Hersbach et al., 2020). Note that the bias score is defined as a fractional change, and thus large signals in the bias score are not necessarily indicative of large changes in the underlying data if the bias was small to begin with. Symbol areas are proportional to the magnitude of the score and significance is determined using a bootstrap resampling procedure. The regions corresponding to GSTREAM, NATL, EUROPE, and NWAVEGUIDE are shown as yellow boxes in Figures 3a–3c. The variables shown are sea-surface temperature (SST), surface latent heat flux (mslhfl), surface sensible heat flux (msshfl), 2 m temperature (t), convective precipitation rate (cprate), large-scale precipitation rate (lsprate), mean sea level pressure (msl), zonal/meridional wind at 10 m (uas/vas), temperature (t), relative humidity (r), zonal/meridional/vertical wind (u/v/w), and geopotential height (z). Numbers in variable names correspond to a specific pressure level in hPa.
Figure 3. Impact of North Atlantic SST bias correction on the forecast skill of weekly mean anomalies at a lead time of 26–32 days (verified against ERA5; Hersbach et al., 2020). (a) Difference in CRPSS (shading) and anomaly correlation (gray contour spacing of 0.1) for mean sea level pressure (mslp). Yellow boxes indicate the GSTREAM and EUROPE regions used in Figures 2 and 4. (b) As (a), but for zonal wind at 850 hPa ($u_{850}$). The yellow box indicates the NATL region used in Figures 2 and 4. (c) As (a), but for geopotential height at 500 hPa. The yellow box indicates the NWAVEGUIDE region used in Figures 2 and 4, and is intended to envelope the northern hemisphere waveguide that is identified in the panel below. (d) As (a), but for meridional wind at 200 hPa. The yellow contours highlight the position of the northern hemisphere waveguide diagnosed as the $3 \times 10^{-11}$ m$^{-1}$ s$^{-1}$ contour of the meridional gradient of absolute vorticity computed from the November-March climatology of zonal wind at 200 hPa.
increased skill for the North Atlantic Oscillation (NAO) at lead times of 15–32 days (Figure 5). The NAO index in Figure 5 is defined using mslp (see caption for details), but we find qualitatively similar results for NAO indices defined using $z_{500}$ and other measures of forecast skill (e.g., CRPSS). However, we also note that the difference maps in Figure 3 exhibit some areas of reduced skill (e.g., over the North American continent) such that changes in week four skill aggregated over the entire Northern Hemisphere are positive but not statistically significant (Figure S4). These areas of degradation in response to reduced SST biases could be sampling noise or may be indicative of compensating errors that were previously balanced by errors originating from the North Atlantic.

Figure 4. Score card summarizing the impact of North Atlantic SST bias correction on forecast skill of weekly mean anomalies as a function of lead time and region. Variables are as described in Figure 2. Positive (blue) values indicate increased CRPSS when verified against ESA CCI observations (SSTs; Merchant et al., 2019) or the ERA5 reanalysis (all other variables; Hersbach et al., 2020). The regions corresponding to GSTREAM, NATL, EUROPE, and NWAVEGUIDE are shown as yellow boxes in Figures 3a–c. The impacts over Europe are also shown for start dates with and without an active MJO in the forecast initial conditions.
Importantly, the atmospheric response to reduced SST biases is not limited to the North Atlantic and its immediate surroundings. Both $v_{200}$ and to a lesser extent $z_{500}$ exhibit evidence for significantly increased skill that extends out of the North Atlantic and circumnavigates the globe along the northern hemisphere subtropical wave guide (Figures 3c, 3d and 4). These improvements are also visible in surface variables, including 2 m temperature, mean sea level pressure, and 10 m winds (Figure 4). This response is characteristic of the propagation of stationary wave activity along wave guides defined by meridional gradients of absolute vorticity associated with the zonal jet (Figure 3d). Crucially, once wave activity has been stimulated in the entrance to the wave guide there are no obstacles to stationary wave propagation at these latitudes (i.e., the stationary wavenumber $K_s$ is real-valued; see Figures S2 and S3). Furthermore, the theoretical group speed ($c_g$) for zonally propagating barotropic stationary wave activity is given by $c_g = \frac{2\pi}{\lambda} \cdot \frac{U}{\sin \beta}$, where $\lambda$ is the climatological zonal mean wind (Hoskins & Ambrizzi, 1993). During the November-March season considered in these experiments, $c_g = \frac{2\pi}{\lambda} \cdot \frac{U}{\sin \beta} \approx 80 \text{ m s}^{-1}$ and there is thus a clear pathway for signals initiated in the North Atlantic to propagate unimpeded around the globe within ~1 week.

The impact of reduced North Atlantic SST biases on forecast skill is summarized in Figure 4 for a range of variables as a function of lead-time and region. It is clear from this comparison that North Atlantic SSTs can have a positive and significant impact on the remote atmosphere at subseasonal lead times. Although the CRPSS differences in Figure 4 may seem small, the statistically significant differences are considerable when compared to the implementation of a new IFS cycle and thus non-negligible when considering how to improve a forecast system. The limited impact on forecast skill at lead times earlier than 25 days is likely a consequence of the partial coupling that mitigates the influence of SST biases in both CTRL and BCFC during days 1–10 (see Section 2) combined with the time taken for SST errors to establish and impact the atmosphere.

It is also worth noting that the improvements to mean SSTs as seen by the atmosphere in BCFC do not translate to improved SST anomaly forecasts. This is because the ocean model, and its underlying deficiencies in the representation of the Gulf Stream and its associated SST variability, are not impacted directly by the atmospheric model bias correction. In fact, we see a small but significant degradation of SST anomaly forecasts in the Gulf Stream region (Figure S4), which is likely a consequence of the resulting inconsistencies in air-sea interaction arising from the differences in SSTs modeled by the dynamic ocean model and those seen by the atmosphere. This degradation of SST anomaly forecasts could offset the benefits of bias correction at longer lead times. Nevertheless, at lead times of 26–32 days, the reduced North Atlantic SST biases have a significant and positive impact on skill in the North Atlantic, Europe, and along the northern hemisphere waveguide (Figure 4).
Finally, we note that the impact of SST biases on forecast skill is modulated by intraseasonal variability. In particular, forecasts with an active Madden-Julian Oscillation (MJO) in the initial conditions exhibit a stronger impact over Europe and along the northern hemisphere waveguide (Figures 4 and S5). In contrast, forecasts without an active MJO have a stronger response over the Gulf Stream and North Atlantic (Figures 4 and S6). This sensitivity is unrelated to changes in MJO forecast skill, which is insensitive to North Atlantic SST biases (Figure S7). We speculate that this sensitivity is a consequence of modulations of the background state by the MJO and its associated teleconnections that then act to steer or obstruct planetary wave activity that is initiated in the North Atlantic region.

3. Conclusions

Subseasonal forecasts with the ECMWF model suffer from North Atlantic SST biases associated with errors in the location and structure of the Gulf Stream. Correcting these errors with an online SST bias-correction scheme improves the mean state of near-surface atmospheric fields in the North Atlantic region. Furthermore, the resulting southward shift of the Gulf Stream drives changes in convective precipitation and vertical motion, which reflect changes in the location, magnitude, and timing of air-sea interaction associated with extratropical storms.

These impacts on the mean state are associated with significant improvements to forecasts of weekly mean atmospheric circulation anomalies at a lead time of 26–32 days. Though modest in magnitude, this increased skill extends beyond the North Atlantic into Europe and northern Africa and circumnavigates the globe with a spatial structure characteristic of stationary wave activity propagating along the northern hemisphere subtropical waveguide. These impacts provide important evidence for the potential benefits of higher-resolution ocean models in initialized coupled forecast systems.

Data Availability Statement

ERA5 and ERA-interim atmospheric reanalysis data can be accessed through the ECMWF website: https://www.ecmwf.int/en/forecasts/datasets/browse-reanalysis-datasets. ESA CCI SSTs are distributed by the Copernicus Marine Environmental Monitoring Service (CMEMS product SST_GLO_SST_L4_REP_OBSERVATIONS_010_024) and can be downloaded from https://marine.copernicus.eu/. The IFS reforecast experiment data used in this study (ECMWF, 2020a; ECMWF, 2020b) are available under a Creative Commons Attribution 4.0 International license (CC BY 4.0). To view a copy of this license, visit https://creativecommons.org/licenses/by/4.0/.

References

BoisRésoÉ, E., D., Balmaseda, M., Vitart, F., & Mognelsen, K. (2012). Impact of the sea surface temperature forcing on hindcasts of Madden-Julian Oscillation events using the ECMWF model. Ocean Science, 8(6), 1071.

Bouillon, S., Maqueda, M. A. M., Legat, V., & Fichefet, T. (2009). An elastic-viscous-plastic sea ice model formulated on Arakawa B and C grids. Ocean Modelling, 27, 174–184.

Brayshaw, D. J., Hoskins, B., & Blackburn, M. (2011). The basic ingredients of the North Atlantic storm track. Part II: Sea surface temperatures. Journal of the Atmospheric Sciences, 68(8), 1784–1805.

Chassignet, E. P., & Xu, X. (2017). Impact of horizontal resolution (1/12° to 1/50°) on Gulf Stream separation, penetration, and variability. Journal of Physical Oceanography, 47(8), 1999–2021.

Czaja, A., & Blunt, N. (2011). A new mechanism for ocean–atmosphere coupling in midlatitudes. Quarterly Journal of the Royal Meteorological Society, 137(657), 1095–1101.

Dee, D. P., Uppala, S., Simmons, A., Berrisford, P., Poli, P., Kobayashi, S., et al. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society, 137(656), 553–597.

Donlon, C. J., Martin, M., Stark, J., Roberts-Jones, J., Fiedler, E., & Wimmer, W. (2012). The operational sea surface temperature and sea ice analysis (OSTIA) system. Remote Sensing of Environment, 116, 140–158.

ECMWF (2020a). Extended-range reforecasts (43R1). Reading: ECMWF. Retrieved from https://apps.ecmwf.int/research-experiments/expver/gkzp/.

ECMWF (2020b). Extended-range reforecasts (43R1) with bias-corrected North Atlantic sea surface temperatures. Reading: ECMWF. Retrieved from https://apps.ecmwf.int/research-experiments/expver/gfk/.

Fichefet, T., & Maqueda, M. (1997). Sensitivity of a global sea ice model to the treatment of ice thermodynamics and dynamics. Journal of Geophysical Research, 102(C6), 12609–12646.

Hersbach, H. (2020). Decomposition of the continuous ranked probability score for ensemble prediction systems. Weather and Forecasting, 15(5), 559–570.
Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., et al. (2020). The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, 146(730), 1999–2049.

Hewitt, H. T., Bell, M. J., Chassagne, E. F., Czaja, A., Ferreira, D., Griffies, S. M., et al. (2017). Will high-resolution global ocean models benefit coupled predictions on short-range to climate timescales? Ocean Modelling, 120, 120–136.

Hewitt, H. T., Roberts, M., Malthiot, P., Blaostach, A., Blockley, E., Chassagne, E. F., et al. (2020). Resolving and parameterizing the ocean mesoscale in earth system models. Current Climate Change Reports, 6, 137–152.

Hoskins, B. J., & Ambrizzi, T. (1993). Rossby wave propagation on a realistic longitudinally varying flow. Journal of the Atmospheric Sciences, 50(12), 1661–1671.

Janssen, P. A., Breivik, Ø., Mogensen, K., Vitart, F., Balmaseda, M., Bidlot, J.-R., et al. (2013). Air-sea interaction and surface waves (Tech. Memo. 712). Reading, UK: ECMWF.

Johnson, S. J., Stockdale, T. N., Ferranti, L., Balmaseda, M. A., Molteni, F., Magnusson, L., et al. (2019). SEAS5: The new ECMWF seasonal forecast system. Geoscientific Model Development, 12(3), 1087–1117.

Keeley, S., Sutton, R., & Shaffrey, I. (2012). The impact of North Atlantic sea surface temperature errors on the simulation of North Atlantic European region climate. Quarterly Journal of the Royal Meteorological Society, 138(688), 1774–1783.

Lee, R. W., Woolings, T. J., Hoskins, B. J., Williams, K. D., O’Reilly, C. H., & Masato, G. (2018). Impact of Gulf Stream SST biases on the global atmospheric circulation. Climate Dynamics, 51, 3369–3387.

Lock, S.-J., Lang, S. T., Leutbecher, M., Hogan, R. J., & Vitart, F. (2019). Treatment of model uncertainty from radiation by the Stochastical Perturbed Parametrization Tendencies (SPPT) scheme and associated revisions in the ECMWF ensembles. Quarterly Journal of the Royal Meteorological Society, 145, 75–89.

Maced, G., & team, N. (2008). NEMO ocean engine (Tech. Rep.). France: Institut Pierre-Simon Laplace (IPSL).

Madec, G., & team, N. (2008). NEMO ocean engine (Tech. Rep.). France: Institut Pierre-Simon Laplace (IPSL).

Minobe, S., Kuwano-Yoshida, A., Komori, N., Xie, S.-P., & Small, R. J. (2008). Influence of the Gulf Stream on the troposphere. Nature, 452(7184), 206.

Minobe, S., Miyashita, M., Kuroano-Yoshida, A., Tokinaga, H., & Xie, S.-P. (2010). Atmospheric response to the Gulf Stream: Seasonal variations. Journal of Climate, 23(13), 3699–3719.

Nakamura, H., Sampe, T., Goto, A., Ohfuchi, W., & Xie, S.-P. (2008). On the importance of midlatitude oceanic frontal zones for the mean state and dominant variability in the tropospheric circulation. Geophysical Research Letters, 35, L15709. https://doi.org/10.1029/2008GL034010

O’Neill, L. W., Haack, T., Chelton, D. B., & Skillingstad, E. (2017). The Gulf Stream convergence zone in the time-mean winds. Nature, 543(7645), 2383–2412.

Parfitt, R., & Czaja, A. (2016). On the contribution of synoptic transients to the mean atmospheric state in the Gulf Stream region. Quarterly Journal of the Royal Meteorological Society, 142(696), 1554–1561.

Parfitt, R., Czaja, A., & Kwon, Y.-O. (2017). The impact of SST resolution change in the ERA-Interim reanalysis on wintertime Gulf Stream frontal air-sea interaction. Geophysical Research Letters, 44, 3246–3254. https://doi.org/10.1002/2017GL073028

Parfitt, R., Czaja, A., Minobe, S., & Kuroano-Yoshida, A. (2016). The atmospheric frontal response to SST perturbations in the Gulf Stream region. Geophysical Research Letters, 43, 2299–2306. https://doi.org/10.1002/2016GL067723

Parfitt, R., & Seo, H. (2018). A new framework for near-surface wind convergence over the Kuroshio Extension and Gulf Stream in winter-time: The role of atmospheric fronts. Geophysical Research Letters, 45, 9909–9918. https://doi.org/10.1029/2018GL080135

Reynolds, R. W., Rayner, N. A., Smith, T. M., Stokes, D. C., & Wang, W. (2002). An improved in situ and satellite SST analysis for climate. Journal of Climate, 15(13), 1609–1625.

Roberts, C. D., Senan, R., Molteni, F., Boussetta, S., Mjöen, M., & Keeley, S. P. (2018). Climate model configurations of the ECMWF Integrated Forecasting System (ECMWF-IFS cycle 43r1) for HighResMIP. Geoscientific Model Development, 11(9), 3681–3712.

Roberts, C. D., Vitart, F., Balmaseda, M., & Molteni, F. (2020). The time-scale-dependent response of the wintertime North Atlantic to increased ocean model resolution in a coupled forecast model. Journal of Climate, 33(9), 3663–3689.

Scaife, A. A., Copsey, D., Gordon, C., Harris, C., Hinton, T., Keeley, S., et al. (2011). Improved Atlantic winter blocking in a climate model. Geophysical Research Letters, 38, L25703. https://doi.org/10.1029/2011GL049573

Thiébaux, J., Rogers, E., Wang, W., & Katz, B. (2003). A new high-resolution blended real-time global sea surface temperature analysis. Bulletin of the American Meteorological Society, 84(5), 645–656.

Vitart, F., Ardilouze, C., Bonet, A., Brookshaw, A., Chen, M., Codorean, C., et al. (2017). The seasonal to seasonal (S2S) prediction project database. Bulletin of the American Meteorological Society, 98(1), 163–173.

Vitart, F., & Balmaseda, M. A. (2018). Impact of sea surface temperature biases on extended-range forecasts (Tech. Memo. 830). Reading, UK: ECMWF.

Vitart, F., & Robertson, A. W. (2018). The sub-seasonal to seasonal prediction project (S2S) and the prediction of extreme events. NJG Climate and Atmospheric Science, 3(1), 1–7.

Woolings, T., Hoskins, B., Blackburn, M., Hassan, D., & Hodges, K. (2010). Storm track sensitivity to sea surface temperature resolution in a realistic atmosphere model. Climate Dynamics, 35(2–3), 341–353.

Woolnough, S., Vitart, F., & Balmaseda, M. (2007). The role of the ocean in the Madden–Julian oscillation: Implications for MJO prediction. Quarterly Journal of the Royal Meteorological Society A, 133(622), 117–128.

Zuo, H., Balmaseda, M. A., Tietje, S., Mogensen, K., & Mayer, M. (2019). The ECMWF operational ensemble reanalysis–analysis system for ocean and sea ice: A description of the system and assessment. Ocean Science, 15(3), 779–808.