Tropical rainfall, Rossby waves and regional winter climate predictions

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Skilful climate predictions of the winter North Atlantic Oscillation and Arctic Oscillation out to a few months ahead have recently been demonstrated, but the source of this predictability remains largely unknown. Here we investigate the role of the Tropics in this predictability. We show high levels of skill in tropical rainfall predictions, particularly over the Pacific but also the Indian and Atlantic Ocean basins. Rainfall fluctuations in these regions are associated with clear signatures in tropical and extratropical atmospheric circulation that are approximately symmetric about the Equator in boreal winter. We show how these patterns can be explained as steady poleward propagating linear Rossby waves emanating from just a few key source regions. These wave source ‘hotspots’ become more or less active as tropical rainfall varies from winter to winter but they do not change position. Finally, we show that predicted tropical rainfall explains a highly significant fraction of the predicted year-to-year variation of the winter North Atlantic Oscillation.

Key Words: tropical rainfall; teleconnection; Rossby wave; North Atlantic Oscillation

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1. Introduction

Initialised climate predictions from months to years ahead are receiving increasing attention (e.g. Smith et al., 2012; Kirtman et al., 2013a, 2013b) as they account for both externally forced and internally generated climate variability and change. Given that unprecedented events are likely to occur when climate variability is exacerbated by climate change, these predictions offer great potential for early warning of impending climate extremes.

In this study we examine winter seasonal climate predictions initialised with ocean and atmosphere states estimated from historical observations. Seasonal predictions are well known to exhibit high levels of prediction skill in the Tropics, due mainly to predictability of the El Niño–Southern Oscillation (ENSO; e.g. Kumar et al., 2013). Here we aim to investigate and explain sources of extratropical prediction skill. Although even recent initialised predictions still often show limited levels of skill in the extratropics (Arribas et al., 2011; Kim et al., 2012; Kirtman et al., 2013a, 2013b), statistically significant and potentially useful levels have now been reported for the North Atlantic Oscillation (Scaife et al., 2014) and the Arctic Oscillation in single (Riddle et al., 2013; Stockdale et al., 2015; Sun and Ahn, 2015) and multi-model predictions (Athanasiadis et al., 2014; Kang et al., 2014). Various possible sources of predictability on these time-scales have been proposed (see Smith et al. (2012) for a review) and some of these originate in the extratropics (e.g. Rodwell et al., 1999; Caso et al., 2005; Folland et al., 2012; Mori et al., 2014; Gastineau and Frankignoul, 2015). Some studies have also connected predictability of the Arctic Oscillation to the Tropics (e.g. Greatbatch et al., 2003, 2012, 2015; Lin et al., 2005; Greatbatch and Jung, 2007, Sun and Ahn, 2015). Rossby wave propagation (Rossby, 1940) from the Tropics to the extratropics (e.g. Hoskins and Karoly, 1981; Simmons et al., 1983) could in principle transmit some of the well-established tropical seasonal predictability to the extratropics in seasonal forecasts. We therefore not only document prediction skill in this study, but also test the hypothesis that tropical rainfall is skilfully predicted, that this excites seasonal Rossby
wave sources, and that Rossby waves can then propagate out into the extratropics in our forecasts. Finally we show that a substantial part of the forecast signal in the winter North Atlantic Oscillation can be explained by skillful prediction of tropical rainfall.

2. Methods
We analyse ensembles of seasonal climate predictions for Northern Hemisphere winter from the GloSea5 prediction system (MacLachlan et al., 2015). Each ensemble forecast is initialised with an observational estimate of the state of the climate system made using observations that were made up until the start time of the forecasts in early November, approximately 1 month ahead of winter. The atmospheric resolution is 0.83° longitude by 0.55° latitude with 85 quasi-horizontal levels to around 85 km altitude (0.01 hPa) near the mesopause. The ocean resolution is 0.25° globally in latitude and longitude with 75 horizontal levels. This resolution is necessary to reduce key biases in the ocean and atmosphere and give a realistic winter blocking climatology in the model (Scaife et al., 2011). Further details of the forecast system are given in MacLachlan et al. (2015). An ensemble of 24 retrospective predictions were made for each of the 20 winters from 1992/1993 through to 2011/2012, a period with some extreme fluctuations in the winter North Atlantic Oscillation (Cattiaux et al., 2010; Fereday et al., 2012; Maidens et al., 2013; Hanna et al., 2014). The forecasts for each winter were initialised from lagged start dates centred on 1 November (25 October, 1 and 9 November) with eight members from each of the three start dates. Members from the same start date differ only by stochastic physics perturbations (Arribas et al., 2011).

For comparisons with observations we use the Global Precipitation Climatology Project (GPCP) v2.2 rainfall dataset throughout (Adler et al., 2003), the National Centers for Environmental Prediction (NCEP) reanalysis (Kanamitsu et al., 2002) for 200 hPa geopotential heights and winds, and the HadSLP2 dataset (Allan and Ansell, 2006) for sea-level pressure.

3. Results

3.1. Predictability of tropical rainfall
We begin with analysis of winter rainfall predictability. The tropical atmosphere is strongly coupled to the underlying ocean (Lindzen and Nigam, 1987) and large-scale ocean temperatures are slowly varying and relatively predictable. This predictability gives rise to predictable variations in tropical rainfall on seasonal

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**Figure 1.** Winter predictions of tropical rainfall. Observed winter mean rainfall anomalies for a selection of winters (a, c, e, g) compared to the corresponding predicted rainfall anomalies (b, d, f, h). Winters 1996/1997–1999/2000 are shown. Observed rainfall is from the GPCP dataset (Adler et al., 2003) and predicted rainfall values are ensemble means of 24 members. Units are mm day$^{-1}$. The resolution is 0.83° longitude by 0.55° latitude with 85 quasi-horizontal levels to around 85 km altitude (0.01 hPa) near the mesopause. The ocean resolution is 0.25° globally in latitude and longitude with 75 horizontal levels. This resolution is necessary to reduce key biases in the ocean and atmosphere and give a realistic winter blocking climatology in the model (Scaife et al., 2011). Further details of the forecast system are given in MacLachlan et al. (2015). An ensemble of 24 retrospective predictions were made for each of the 20 winters from 1992/1993 through to 2011/2012, a period with some extreme fluctuations in the winter North Atlantic Oscillation (Cattiaux et al., 2010; Fereday et al., 2012; Maidens et al., 2013; Hanna et al., 2014). The forecasts for each winter were initialised from lagged start dates centred on 1 November (25 October, 1 and 9 November) with eight members from each of the three start dates. Members from the same start date differ only by stochastic physics perturbations (Arribas et al., 2011). For comparisons with observations we use the Global Precipitation Climatology Project (GPCP) v2.2 rainfall dataset throughout (Adler et al., 2003), the National Centers for Environmental Prediction (NCEP) reanalysis (Kanamitsu et al., 2002) for 200 hPa geopotential heights and winds, and the HadSLP2 dataset (Allan and Ansell, 2006) for sea-level pressure.
time-scales (Kumar et al., 2013). Figure 1 shows examples of winter mean rainfall anomalies predicted from early November. Predictions show good agreement with observed year-to-year variations, particularly in the Pacific where large interannual variability occurs due to the El Niño–Southern Oscillation. The 1998 winter El Niño is particularly marked in Figure 1 and the dry anomalies in the central Pacific due to the extended La Niña episode in the following two winters are also well predicted. A closer look at the rest of the Tropics shows other well-predicted anomalies in the tropical Atlantic, Indian and west Pacific ocean regions in many years.

An overall summary of the skill of these seasonal global rainfall forecasts is shown in Figure 2. Positive correlations between predicted and observed winter rainfall occur in most regions and are particularly strong over the tropical Pacific, tropical Atlantic, west Pacific and Indian oceans. Even these small grid-scale averages show correlation skill in excess of 0.6 in many regions and there is a large region where correlations exceed 0.8 in the tropical Pacific as expected due to the high predictability of ENSO (Barnston et al., 2012).

We now focus on area average rainfall over the four tropical regions highlighted in Figure 2 that show skilful predictions over relatively coherent rainfall regions in Figure 1: Tropical Atlantic (5°S–5°N, 60°W–0°W), Tropical East Pacific (5°S–10°N, 160°–270°E), Tropical West Pacific (5°S–25°N, 110°–140°E) and Tropical Indian Ocean (5°S–10°N, 45°–100°E). These regions are also relevant to predictions of the extratropical flow as we will see below. The ensemble mean rainfall forecasts for each of these regions and the 20 winters considered here are shown in Figure 3. There is a wet bias of a few tens of per cent of mean rainfall in most regions, as is commonly seen in climate models (e.g. Zhang et al., 2015). Nevertheless, both observations and ensemble mean forecasts show similar sized fluctuations of around 1 mm day$^{-1}$ between winters. The similarity between ensemble means and observations also extends to individual ensemble members (not shown) and tropical rainfall in these regions is highly predictable. The rainfall predictions for these four regions are highly skilful, with almost perfect skill in the Tropical East Pacific ($r = 0.97$) and highly significant skill (all basins are significant at the 99% level here) in all other regions. We use ensemble mean rainfall to best extract predictable signals from here onwards.

### 3.2. Teleconnection patterns

Having established encouraging levels of skill in our seasonal tropical rainfall forecasts we now consider the effect on extratropical circulation. A key aim of this work is to establish
the source of seasonal forecast skill of the North Atlantic Oscillation (Scaife et al., 2014; MacLachlan et al., 2015). Figure 4 shows the correlation between North Atlantic Oscillation index (NAO, represented by the Azores – Iceland sea-level pressure difference) and rainfall across the whole globe. The rainfall leads the NAO by 1 month in this figure but very similar patterns emerge if simultaneous or winter mean rainfall and NAO are used (not shown). The four tropical rainfall regions identified earlier are marked on the correlation map. Each region contains a coherent set of grid-point correlations with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible: the Tropical East Pacific (TEP) shows a strong negative correlation with the NAO and some familiar teleconnections are visible. The negative correlation in the TEP in Figure 4 suggests that this mechanism is active in these seasonal forecasts (cf. Fereday et al., 2012). The other regions in Figure 4 also show coherent correlation with the NAO. The Tropical West Pacific (TWP) shows a strong positive correlation, implying that above-average rainfall in this region is associated with positive NAO as has been suggested for the recent extreme winter of 2013/2014 when TWP rainfall was extremely high, and the Atlantic jet stream was very strong (Huntingford et al., 2014; Davies, 2015; Watson et al., 2016). Heavy rainfall in this region is also associated with extreme winter weather over North America (Palmer, 2014) and northwest Europe (Lewis et al., 2015). Strong correlations occur with the Tropical Atlantic (TA) rainfall as seen in some other studies (Okumura et al., 2001; Manola et al., 2013). These are positive just north of the equatorial Atlantic in the model and the observations. However, despite the reasonable forecast skill for TA rainfall (Figure 2), the sign of the correlation with the NAO reverses in a narrow band on the Equator in the model compared to the observations. This could be related to model bias in this region (Zhang et al., 2015) which can in turn affect predictability of Indian Ocean (IO) rainfall on the NAO have been documented in previous studies (e.g. Yu and Lin, 2016) although there are differences between atmospheric models with prescribed sea-surface conditions (Hoerling et al., 2004) and coupled atmosphere–ocean model responses (Molteni et al., 2015) and here we find relatively weak correlations with the IO rainfall.

Correlating the interannual winter rainfall in the four regions with geopotential height in the upper troposphere yields clear teleconnections extending into both hemispheres in this season (Figure 5). Both model predictions and observations show teleconnection patterns that are approximately symmetric about the Equator – consistent with extratropical influences emanating from the Tropics. Pacific connections are particularly strong with correlations exceeding 0.5 in many places. Finally, we note an encouraging degree of agreement between the teleconnection patterns in the seasonal predictions and those in the observational analyses. We return to these patterns and the Rossby wave propagation mechanism by which they are linked to tropical rainfall below.

3.3. Rossby wave sources

To begin to construct the mechanism by which tropical rainfall drives the extratropical circulation, we start with a source of Rossby wave activity (Sardeshmukh and Hoskins, 1988; James, 1994) which can be calculated from horizontal winds. Expressing the horizontal wind in terms of its rotational ($v^\times$) and divergent ($v^\cdot$) components, the Rossby wave source ($S$) is calculated by:

$$ S = -\nabla \cdot (v^\times \, \xi) = -(\xi \nabla \cdot v^\times + v^\cdot \cdot \nabla \xi), $$

where $\xi$ is the absolute vorticity. Calculated in this way, the Rossby wave source is the rate of change of vorticity due to vortex stretching (first term) and vorticity advection by the divergent part of the wind (second term).

The Rossby wave source could in principle be calculated at high frequency but using daily rather than monthly means was found to have only a small impact on the seasonal average source. Similarly, the source could be calculated at any isobaric level in the atmosphere so we choose the level based on the vertical profile of the Rossby wave source. Figure 6 shows the vertical profile of the wave source at a typical point in the tropical Atlantic where its climatological value is large. A clear increase with height from the surface to the upper troposphere is seen in the climatological Rossby wave source from both the model and observational reanalysis. The source peaks in the upper troposphere near 200 hPa. This coincides with strong convective outflow and hence divergent horizontal flow, as well as a strong vorticity gradient near the upper tropospheric peak in the strength of the jet streams. Both factors are important for a strong wave source (Eq. (1)). Very similar profiles are obtained from other locations and wave sources peak at similar geographical locations at all levels (not shown). This is also close to the level identified in earlier calculations of the wave source (Sardeshmukh and Hoskins, 1998) and we focus on the 200 hPa level from here onwards.

We now examine the year-to-year variations in the Rossby wave sources that are associated with fluctuations in tropical rainfall in the four regions defined above. Figure 7 shows composite anomalies of the modelled wave sources for the winters in which the rainfall is higher than normal in each of the four regions. Rainfall fluctuations in all four regions produce changes in Rossby wave sources, although Pacific rainfall variations produce the strongest effects, presumably due to the intense rainfall fluctuations in Pacific basin rainfall (Figure 3) and hence divergent flow, associated with ENSO. Note how the position of these sources aligns closely with the edges of the jet streams shown in Figure 10, suggesting that the position of intense horizontal vorticity gradients (Eq. (1)) rather than the longitudinal position...
of divergence anomalies is paramount in determining the location of the anomalous Rossby wave sources (cf. Sardeshmukh and Hoskins, 1988). Figure 7 also shows a striking similarity between the location and pattern of Rossby wave sources associated with rainfall fluctuations in different regions. Similar anomalous wave sources are generated in response to rainfall in all of the regions shown here, suggesting a high degree of degeneracy in the year-to-year generation of Rossby waves. This is partly caused by the position of intense vorticity gradients as noted above, but also by the interdependency of rainfall variations in different basins, not least through ENSO (Kumar et al., 2014). The relationship between different rainfall regions is summarised in Table 1. For example, the East and West Pacific are highly anticorrelated due to ENSO, whereas the tropical Atlantic is relatively independent. Note also that these inter-basin rainfall correlations in the observations also appear to be reasonably well represented in the model, as they are within the range of ensemble member correlations in all cases (Table 1).
Whether it is due mainly to inter-basin rainfall connections or the fixed location of vorticity gradients, this simple picture, in which the same local ‘hotspots’ of Rossby wave source in the tropical Atlantic and subtropical Pacific arise irrespective of where the tropical rainfall changes occur helps to simplify the picture of year-to-year variations in Rossby wave source.

Figure 8 shows the interannual variability in the Rossby wave source and confirms that the main regions of Rossby wave source variability coincide with the active regions in the composite signals in Figure 7. Note that the hatching in Figure 8 indicates where the variability in the Rossby wave source is skilfully predicted. The strong similarity between the geographical pattern of variability and the pattern of skilful prediction confirms that the major year-to-year variations in Rossby wave source are skilfully predicted.

The similarity between the different composite wave sources in Figure 7 and the interannual variability of wave sources in Figure 8 implies that similar wave trains might be generated in association with rainfall anomalies in different regions as explained above. This helps to explain why patterns such as the Pacific–North American (PNA) pattern, while known to respond directly to nearby ENSO anomalies, may also appear to be associated with more remote fluctuations, for example in the Indian Ocean or west Pacific. This simple picture also helps to address questions about whether extratropical teleconnections are externally forced waves or internally generated modes of the circulation (Hoskins and Karoly, 1981; Simmons et al., 1983). These views are resolved by teleconnections like the PNA pattern often appearing in the flow because there are just a few ubiquitous Rossby wave source ‘hotspots’ which are stimulated in association with rainfall fluctuations in different tropical regions, as highlighted in Figures 7 and 8. Whether this occurs due to coherent rainfall variations across the Tropics (e.g. from ENSO) or due to the non-local effects of tropical rainfall variations on Rossby wave source hotspots would be an interesting topic for further work.

3.4. Rossby wave ray tracing

We now use the locations of the major Rossby wave source fluctuations in Figure 7 as the starting point for ray tracing calculations to test whether there is any similarity between
extratropical teleconnection patterns associated with tropical rainfall and steady barotropic Rossby waves. A number of similar ray tracing studies have been carried out in the past including horizontal (e.g. Hoskins and Karoly, 1981; Li et al., 2015), vertical (O’Neill and Youngblut, 1982) and three-dimensional propagation (Karoly and Hoskins, 1982). Several authors report that linear theory applies surprisingly well in many situations (e.g. Hoskins and Karoly, 1981; Webster, 1982). Meridional background flow can sometimes alter propagation in the deep Tropics (Schneider and Watterson, 1984) and we could also consider baroclinic Rossby waves with non-zero vertical wave number, but here we take the simplest, linear, barotropic Rossby wave dispersion relation with no meridional background flow (Rossby, 1940; James, 1994; Vallis, 2007) as our starting point:

\[ \omega = \frac{u}{\bar{k}} - \frac{(\beta - \pi_y)k}{(k^2 + l^2)} \]  

where \( \omega \) is the intrinsic wave frequency, \( u \) is the climatological mean zonal wind (an overbar denotes zonal average), \( \bar{k} \) is its second derivative in the meridional direction, \( k \) and \( l \) are the zonal and meridional wave numbers (\( 2\pi \) divided by wavelength) and \( \beta \) is the meridional gradient of the Coriolis parameter.

Rossby waves typically propagate from the Tropics into the extratropics in just 1 or 2 weeks (Jin and Hoskins, 1995), as we verify later. This time-scale is much shorter than the seasonal lifetime of the signals we consider here. We therefore consider only stationary waves (\( \omega = 0 \)) in this analysis to identify signals which persist on seasonal time-scales.

Taking partial derivatives of Eq. (2) with respect to \( k \) and \( l \) and using the stationary (\( \omega = 0 \)) approximation to eliminate the meridional wave number gives the group velocity in a form that just depends on \( k \), \( u \) and known constants:

\[ c_{\text{x}} = \frac{2\pi^2 k^2}{(\beta - \pi_y)} \quad c_{\text{y}} = \frac{2\pi^2 k(\beta - \pi_y)}{(\beta - \pi_y)} \]  

The zonal group velocity \( c_{\text{x}} \) is almost always positive, indicating eastward propagation, and it increases more rapidly than \( c_{\text{y}} \) with the zonal wave number \( k \), indicating that shorter waves (larger \( k \)) propagate more zonally (Hoskins and Karoly, 1981). The group velocity above could be extended to baroclinic waves with non-zero vertical wave number. In this case the zonal group velocity is actually identical to the barotropic form above, while the meridional group velocity contains an extra \( -m^2f^2/N^2 \) term in the square root. However here we consider only barotropic waves with \( m = 0 \) for simplicity, and because these waves propagate most readily and therefore dominate the remote response (Simmons et al., 1983; Sardeshmukh and Hoskins, 1988; Jin and Hoskins, 1995). Now consider the interesting square root term in \( c_{\text{y}} \) (this is in fact just the meridional wave number, \( l \)). Propagating waves require real meridional group velocity and therefore occur only when \( u \) is positive but below some threshold and only for long waves (small \( k \)). Otherwise the waves are evanescent. Are these conditions for propagation met in our seasonal hindcasts? Figure 9 shows the meridional wave number squared for zonal wave-numbers 1–4 based on the climatological zonal wind at the 200 hPa level in our seasonal predictions. A 60° zonal average is used at each point along the ray path to represent the wind on the scale of a typical wave. For wave-number 1 most of the domain supports propagation (\( l^2 > 0 \)), apart from the tropical easterlies in the south Asian and south American sectors. For wave-number 2 the picture is very similar. However, for wave-numbers 3 and 4, increasingly large regions where the meridional wave number is imaginary in the jet stream winds indicate that the zonal winds are too large for propagation of waves shorter than wave-number 3 and only a narrow waveguide in the Atlantic remains for wave-number 4. If Rossby wave teleconnections are important for extratropical seasonal forecasts it is therefore likely to be the long waves (\( k < 5 \)) that dominate.
In order to trace ray paths through the predicted wind field, we first develop a simple ray tracing algorithm and test its sensitivity to various approximations. For a given starting location (to be determined later from the Rossby wave sources above), we first calculate the group velocity \((c_g, c_g)\) and then step forwards in time by 2 h to calculate the new location of the ray in spherical coordinates and also the new local value of the group velocity. This procedure is repeated 100 times to give the ray path over the following \(\sim 10\) days. An example is shown in Figure 10(a) for two hypothetical sources of waves in the Pacific. For the west Pacific, wave-number 2 propagates out through the Asian jet while wave-number 3 undergoes total internal reflection from the strong jet before being absorbed at the zero wind (critical) line in the deep Tropics. In the east Pacific, wave-number 2 again propagates to the extratropics on a time-scale of around 10 days, while wave-number 4 undergoes reflection again. Comparison with Figure 9 suggests that the ray tracing calculations are correctly simulating the propagation, refraction, reflection and absorption expected from theory.

We now carry out sensitivity tests to assess the robustness of the ray tracing calculation. Figure 10(b) shows equivalent rays to those in Figure 10(a), but for propagation on the 500 hPa rather than 200 hPa zonal wind field. The rays follow quite different paths. For example, the refraction of higher wave numbers back into the Tropics in Figure 10(a) does not occur with the weaker winds at this lower altitude. The rays are therefore clearly sensitive to the choice of level for the background state. However, we continue with the 200 hPa wind field as the Rossby wave source was found to reach a maximum at this level. Figure 10(c) shows the same calculation as in Figure 10(a) but in this case with omission of the wind curvature term \(U_{yy}\) from the dispersion relation. This has relatively little effect on the ray paths, even for the sensitive reflective cases shown here. Finally, Figure 10(d) shows the effect of full zonal averaging compared to the 60\(^\circ\) sectoral average winds used elsewhere. This has a drastic effect on wave propagation, as many of the reflecting and absorbing regions vanish with zonal averaging. We instead use 60\(^\circ\) sectoral zonal averaging as this is close to the horizontal scale of the important waves (e.g. wave-number 3 is on this scale) and is similar to the zonal averaging used by others (e.g. Manola et al., 2013). As an
We have followed the sources of predictability in ensemble seasonal climate predictions from tropical rainfall, to the upper tropospheric source of Rossby waves and out into the extratropical winter circulation via barotropic Rossby waves.

Our seasonal predictions of tropical rainfall exhibit high levels of prediction skill in all ocean basins. The Indian Ocean is the least skillful \( r = 0.59 \) and the Pacific is the most skillful with a near perfect \( r = 0.96 \) correlation score. This skill arises despite significant mean biases in tropical rainfall, suggesting that any nonlinearity in the variability of tropical rainfall is insufficient to destroy prediction skill on these time-scales. Note also that the amplitude of ensemble mean signals is similar to the amplitude of observed year-to-year variability, suggesting that much of the observed tropical rainfall variability is predictable.

As an aside, these large predictable signals in tropical rainfall also suggest that the recently identified discrepancy between skill scores and signal-to-noise ratio in winter NAO predictions (Eade et al., 2014; Scaife et al., 2014; Siegert et al., 2016) is unlikely to originate directly from an error in the amplitude of predicted tropical rainfall, at least in the regions considered here.

Although they were not investigated explicitly here, inter-basin connections warrant future study, especially as some models may misrepresent them (Molteni et al., 2015), and the extratropical effects emanating from different ocean basins show wave interference (Fletcher and Cassou, 2015).

Given the encouraging levels of predictability of tropical rainfall, we showed large associated extratropical signals in the upper tropospheric flow. The high degree of symmetry of these patterns about the Equator is consistent with a tropical source. Furthermore, the correlations between tropical rainfall and extratropical flow in our predictions suggest that the Tropics are acting as an important source of predictability for the extratropics.

Rossby wave dynamics go a long way to explaining the extratropical signatures that originate from year-to-year tropical rainfall variations. We showed that Rossby wave sources from gradients of vorticity and divergent flow are strongly peaked in the upper troposphere at around 200 hPa and are skilfully predicted on the seasonal time-scales considered here. Interestingly, the Rossby wave source shows highly localised ‘hotspots’ that are relatively few in number. This is partly because they are anchored to regions of large vorticity gradient on the edge of the subtropical and extratropical jet streams rather than being in the very deep Tropics and partly because of significant inter-basin rainfall connections. The same ‘hotspots’ for Rossby wave generation are therefore active during quite different episodes of tropical rainfall and the same forced linear wave trains appear to be associated with a variety of different rainfall anomalies.

Given the location of wave sources, we then used linear Rossby wave theory to calculate ray paths. From sensitivity tests we concluded that:

- Zonal winds should be sector averages on the scale of the waves: typically 60°.
- Wind curvature \( u_\varphi \) can be neglected for most purposes.
- Upper tropospheric zonal winds at 200 hPa are the most appropriate mean flow.
- Time-stepping every 2 h is adequate for most purposes.

Transient and year-to-year fluctuations in the zonal winds could in principle alter the seasonal mean propagation characteristics and these would be interesting further aspects to examine in future studies. However, if the mean wind climatology in our predictions is replaced with the observed climatology then tropical rainfall was configured to drive the correct signal, again supporting the idea that tropical rainfall plays an important role in the predictability of the NAO.

4. Conclusions

Aside, we also note that exchanging model and observed wind fields makes little difference to these Rossby wave rays, suggesting that errors in the simulation of mean zonal winds is not a significant source of error in climate model teleconnections in this model.

We now start from the major centres of anomalous Rossby wave source shown in Figure 7, and calculate the ray paths according to the method described above. Results for wave-number 3 are shown superimposed on the modelled 200 hPa geopotential height anomaly in Figure 11. The importance of symmetry about the Equator and the northeastward orientation of the alternating anomaly patterns is now clear, as these features often lie along the Rossby rays and propagating wave rays pass through many of the extratropical centres of action. Although it is important not to over-interpret these simple linear ray paths, the northeastward alignment between anomalies and ray paths in Figure 11 suggests that the extratropical teleconnections to tropical rainfall in our seasonal forecasts can be at least qualitatively interpreted as stationary, linear, barotropic Rossby waves.

3.5. Explanation of climate prediction skill

If we really are to explain the winter NAO predictions in terms of linear stationary Rossby waves generated by interannual fluctuations in tropical rainfall, then it should be possible to explain the predicted NAO in terms of tropical rainfall itself. We therefore revisit the predicted NAO values over the 20 hindcast winters (Figure 12, solid line). Using just the four regional rainfall series from above, in the Indian, West Pacific, East Pacific and Atlantic regions as explanatory variables in a multiple linear regression model we are able to reconstruct the predicted NAO time series with a correlation coefficient of 0.65. This value is significant at the 99% confidence level and implies that approximately 40% of the variance in the seasonal forecast of the NAO can be explained by tropical rainfall in these few regions.

One final piece of evidence for the importance of tropical rainfall in these winter climate predictions comes from a year in which the forecast signal was opposite to the observed anomaly. The hindcast for the winter of 2004/2005 suggested that a negative NAO anomaly was more likely than a positive anomaly (Figure 12) and yet the regression to tropical rainfall suggested the opposite; that a positive NAO was most likely. In the event, a negative NAO anomaly was more likely than a positive anomaly particular winter (e.g. Santee 2016 Crown Copyright, Met Office. Published by John Wiley & Sons Ltd on behalf of the Royal Meteorological Society.

Figure 12. Tropical rainfall explains a substantial fraction of predicted NAO variability. Predicted ensemble mean winter NAO (solid) and a multiple linear regression of December rainfall using ensemble mean predicted rainfall from the four regions in the tropical Atlantic, East Pacific, West Pacific and Indian Ocean, for 1993–2012. The correlation between the two series is inset and is significant at the 99% level.

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very little change results to the rays paths, suggesting the surprising result that any errors in teleconnections may not be due primarily to the sensitivity of wave propagation to errors in the background winds, at least in the seasonal forecasts analysed here. This is important as it implies that improvements in regional seasonal forecast skill may come from improved Rossby wave sources or local feedbacks rather than improved wave propagation. With our refined methodology we were finally able to show rays that intersect many of the modelled circulation anomalies and that northeastswards propagation of stationary long waves can dominate the seasonal response to tropical rainfall variability in many situations.

Extratropical seasonal forecast skill has recently been mainly reported in winter and there may be good reasons for this. For example, ENSO tends to peak in winter, and the stratosphere, which is related to extratropical winter NAO predictability (Sigmoid et al., 2013; Scaife et al., 2016), is only dynamically active in winter (e.g. Kidston et al., 2015). In fact these two factors are also related because ENSO teleconnections have a pathway through the stratosphere (Manzini et al., 2006; Bell et al., 2009) and this again locks the response to winter and amplifies the NAO signature in the extratropics (Ineson and Scaife, 2009). Similarly, the mechanism investigated here adds a third explanation for the preference for winter skill, because it preferentially operates in winter, when the winds are westerly and wave propagation is supported over a broad domain.

The investigation of tropical rainfall teleconnections presented here helps to explain the source of predictability in seasonal forecasts of the NAO. Although other sources have been identified elsewhere, we showed here that using just four simple regional rainfall indices we were able to explain a highly significant proportion of forecast NAO variability.

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