Assessing the chance of unprecedented dry conditions over North Brazil during El Niño events

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Abstract
The strongest El Niño events of the past four decades were associated with large rainfall deficits in North Brazil during the December to February mature phase, leading to substantial societal and ecological impacts and influencing the global carbon cycle. While the teleconnection between El Niño and northern South America is well studied, the small number of El Niño events—and especially high magnitude ‘major’ El Niños—in the recent observational record make a robust characterisation of the response over North Brazil in today’s climate difficult. Here we use a large, initialised ensemble of global climate simulations to provide a much greater sample of North Brazil rainfall responses to recent El Niño events than is available from observations, and use this to form an assessment of the chance of unprecedented dry conditions during El Niño. We find that record low rainfall totals are possible during El Niño events in the current climate, and that as the magnitude of El Niño increases, so too does the chance of unprecedented low rainfall, reaching close to 60% for major El Niños. However, during even the largest El Niños, when the observed North Brazil response has been similar and very dry, we find rainfall rates close to normal are still possible due to internal atmospheric variability. In addition to the predictable influence of the tropical Pacific, an unpredictable influence from the extratropics appears to play a role in modulating the North Brazil rainfall response via an equatorward wave-train that propagates down the western coast of North America and across to the Caribbean. Combining forecasts of El Niño with this improved information on the underlying chance of extremely low rainfall could feed into improved assessments of risk and preparedness for upcoming droughts in Brazil.

1. Introduction
El Niño has been implicated in many of the severe droughts in Amazonia over the past century (Marengo and Espinoza 2016). The El Niño peak in December–January–February (DJF) falls within the rainy portion of the year in much of Amazonia, and it exerts strong influence during this season principally via changes in the Walker circulation, whereby convection is suppressed over the Amazon basin (Grimm and Ambrizzi 2009, Yoon and Zeng 2010, Andreoli et al 2012, Cai et al 2020). Rainfall deficits in the region are linked to wide-ranging socioeconomic and ecological impacts (Marengo and Espinoza 2016) that act on different timescales according to how they interact with local basin hydrology and ecology (Tomasella et al 2011, 2013). As a basic component of elevated fire risk (Abram et al 2021) dry conditions bring about increases in fire incidence (Aragão et al 2018, Silva Junior et al 2019) and the lack of rain leads to reductions in river and flood plain water levels (Marengo et al 2008, Tomasella et al 2011). Associated impacts follow, such as on water quality and aquatic biota (Tomasella et al 2011, Castello and Macedo 2016), food security (Marengo et al 2013) and on human health (Poveda et al 2001, Smith et al 2014, Machado-Silva et al 2020), combined with disruption to access to services including healthcare and...
education (Tomasella et al., 2011). El Niño–connected low wet season rainfall can play a role in pre-conditioning the region to enhanced effects of rainfall deficits later in the year, as occurred in the extreme drought of 2010 (Marengo et al., 2011). Through Amazonia’s regional and global water cycling functions, variations in moisture can have downstream effects on rainfall in other parts of the South American continent (Marengo and Espinoza, 2016), and beyond (Marengo and Nobre, 2001, Knight et al., 2017). Likewise, effects of dry conditions in Amazonia have global reach via its important role in the earth’s carbon budget. During the major El Niño in the DJF of 2015/16, 13% of the area of the Amazon forest was under extreme drought severity, the highest proportion recorded (Jiménez-Muñoz et al., 2016). This led to a very large release of carbon from the Amazon and Northeast Brazil into the atmosphere (Rödenbeck et al., 2018), some of which came from fire, especially in December 2015 (Aragão et al., 2018). There was a record rise in atmospheric carbon dioxide in 2015/16 (Betts et al., 2016), around 25% of which is estimated to have come from the response of the global terrestrial ecosystem, dominated by the tropics (Betts et al., 2018).

The three most significant El Niño events of the last four decades, 1982/83, 1997/98 and 2015/16, were associated with severely reduced rainfall totals across northern South America. The North Brazil region (figure 1(a) inset), which forms the subject of this study, is composed almost entirely of the Amazonia biome (IBGE, 2019). There are variations in rainfall regime across the region: DJF falls outside the rainy season in the northernmost portion (Barni et al., 2020), but in common with the wider region it is subject to El Niño-related rainfall deficits and enhanced fire incidence during DJF (Fonseca et al., 2017). As an area mean, North Brazil DJF season rainfall during each of the major El Niño events was between 1.5 and 2 mm d−1 below the mean: a reduction of approximately 20%. Within the recent climate period there are relatively few El Niño events, and fewer still major El Niños, from which to build a picture of the possible range of responses over Brazil. As the atmospheric circulation is a chaotic system, small changes could have led to different outcomes being observed during these events.

Following the UNPrecedented Simulated Extremes using ENsembles (UNSEEN) approach (Thompson et al., 2017), we use a large ensemble of initialised climate model simulations to provide a DJF event set much larger than that available from the observations. This set samples more instances of the teleconnection between El Niño and North Brazil and a wider range of plausible climate outcomes, including those outside the range that has been experienced in recent years. This enables an assessment of the chance of unprecedented extremes that is more robust than that based upon observations alone, as well as providing insight into the dynamics of extremes (Thompson et al., 2019, Kay et al., 2020, Kelder et al., 2020, Squire et al., 2021).

UNSEEN has been used to produce improved estimates of the likelihood of unprecedented extremes for any given year (Thompson et al., 2017, 2019, Jain et al., 2020, Kay et al., 2020). However, in cases where regional interannual climate variability is strongly dependent on a climate driver—and the El Niño-Southern Oscillation (ENSO) is pre-eminent in the tropics—the distribution of climate outcomes shifts in response to the state of that driver (Goddard and Gershunov, 2021). This opens the possibility of using UNSEEN to quantify how the driver modifies the likelihood of extremes (Squire et al., 2021). Here we take the case of DJF North Brazil rainfall and describe the steps taken to make a conditional assessment of the chance of dry extremes during El Niño events. Through this the following questions are addressed: Are the low North Brazil rainfall rates that have been observed typical of major El Niños in today’s climate? What are the chances of even lower, unprecedented, rainfall totals during El Niño events? In addition, UNSEEN enables an exploration of the dynamics of extremes during multiple realizations of El Niño events, allowing another question to be added to the list: What mechanisms could be behind the range in North Brazil rainfall response, given by the ensemble, to major El Niños?

2. Model and data

The Met Office decadal prediction system, version 4 (DePreSys4), uses Hadley Centre global coupled model HadGEM3-GC3 (Williams et al., 2018), which has an atmospheric grid resolution of ~60 km in the midlatitudes, and an ocean resolution of 0.25°. In the initialisation, the ocean is relaxed to full-depth analyses of ocean temperature and salinity, and the atmosphere to analyses of winds, temperature and surface pressure. DePreSys4 has a hindcast ensemble of ten members initialised in November each year. The DJF season therefore represents the forecast period of 2–4 months. This means that in a timeseries of DJF seasonal means, for a single nominal ensemble member, the DJF in one year is not part of the same simulation as the DJF in the following year. For 1982–2016, the ensemble provides a total count of 350 DJF seasons, an order of magnitude greater than the pool of DJFs available from the observed record for the same period.

The data source, observational network density and interpolation method, combined with the spatial discontinuity of rainfall, are among the sources of uncertainty in gridded rainfall products (Sun et al., 2018, Herrera et al., 2019, Peng et al., 2021). Direct observations of rainfall across North Brazil are very sparse, and to take account of some of the uncertainty in available gridded products, we use seven different
Table 1. Reference datasets used in this study. For the rainfall datasets, North Brazil area-mean DJF rainfall mean, minimum and standard deviation are listed.

| Variable       | Name               | North Brazil DJF rainfall mean (min.) & std. dev. (mm day$^{-1}$) | Type                              | Resolution | Reference                      |
|---------------|--------------------|------------------------------------------------------------------|-----------------------------------|------------|--------------------------------|
| Precipitation | WFDE5 v2.0         | 8.49 (6.57) 0.89                                                  | ERA5 reanalysis corrected to gauge based (GPCC v2020) | 0.5° × 0.5° | Cucchi et al (2020)            |
| Precipitation | GPCC v2020         | 8.18 (6.34) 0.84                                                  | Gauge-based                       | 0.5° × 0.5° | Becker et al (2013), Schneider et al (2016, 2020) |
| Precipitation | University of Delaware (UDel) | 8.32 (6.42) 0.88                                                  | Gauge-based                       | 0.5° × 0.5° | Willmott and Matsuura (2001)   |
| Precipitation | ERA5               | 8.70 (6.81) 0.88                                                  | Reanalysis                        | 0.25° × 0.25° | Hersbach et al (2020)          |
| Precipitation | CMAP               | 7.88 (5.90) 0.90                                                  | Satellite and gauge               | 2.5° × 2.5° | Xie and Arkin (1997)           |
| Precipitation | GPCP               | 8.65 (6.44) 1.00                                                  | Satellite and gauge               | 2.5° × 2.5° | Adler et al (2003)             |
| Precipitation | CHIRPS             | 8.40 (6.22) 0.90                                                  | Satellite and gauge               | 0.05° × 0.05° | Funk et al (2015)              |
| Sea surface temperature | HadISST         |                                                                  | In-situ and satellite post-1982 | 1° × 1° | Rayner et al (2003)           |
| Mean sea level pressure; Vertical velocity; u and v winds on pressure levels | ERA5               |                                                                  | Reanalysis                        | 0.25° × 0.25° | Hersbach et al (2020)          |

datasets (table 1) for the common 1982–2016 period. In recognition of the diverse nature of the rainfall products, and the likelihood that errors remain, here we use the term reference datasets rather than observations. There are discrepancies between the datasets in mean and minimum North Brazil DJF rainfall rates and in variability (table 1), which presents a challenge in evaluating the model, a fundamental step in UNSEEN (section 3). To obtain ‘best estimate’ properties of the set of DJF observations, including the mean, standard deviation, skewness and kurtosis, we calculate those properties of the individual datasets and take a mean to compare against the model. The datasets are first regridded to the model grid. A multi-reference dataset mean timeseries (figure 1) is also created to find the minimum value, which is used to represent the lowest recorded DJF rainfall rate, providing the threshold for unprecedented simulated events.

DJF mean sea surface temperatures (SSTs) are taken from the HadISST dataset (Rayner et al 2003), and variables describing the atmospheric circulation from the ECMWF Reanalysis version 5 (ERA5) product (Hersbach et al 2020).

3. Fidelity testing of the model

The use of UNSEEN hinges on the premise that the reference data and ensemble members can be treated interchangeably, i.e. that they can be regarded as part of the same statistical population so that the model provides many more samples of internal variability than the single realisation available from observations. Following the approach of previous UNSEEN studies (Thompson et al 2017, 2019, Jain et al 2020, Kelder et al 2020), to establish that the model is suitable for use in this application we conduct fidelity testing to compare the properties (mean, standard deviation, skewness and kurtosis) of the distribution of reference rainfall rates against the model (figures 1(a)–(e)). Bootstrap resampling methods provide confidence intervals on the model statistics (Thompson et al 2017, Huang et al 2021). The model ensemble is randomly resampled with replacement across its members, i.e. for each year, the value from one of the ten ensemble members is randomly selected, to generate a pseudo timeseries of the same length as the reference timeseries, 35 years, and repeated 10 000 times. As the ensemble simulations...
Figure 1. Comparison of model against reference DJF rainfall over North Brazil. Panel (a) displays distributions of North Brazil (inset) area-mean DJF rainfall rate for 1982–2016 in the mean of the reference timeseries and bias adjusted model (pink). The red dashed line indicates the model ensemble mean rate prior to bias adjustment. Fidelity testing is shown in panels (b)–(e): the model distribution of statistics of 10,000 35 year bootstrapped series, and the best estimate reference data value, vertical black line. The title contains the position (%) of the reference value within the model distribution. Dashed black lines mark the central 95% of the model distribution. (f) Timeseries of North Brazil rainfall in the reference data (mean timeseries, black dots) and bias adjusted model ensemble mean (red line) and members (grey dots). The horizontal line marks the reference minimum of 6.5 mm day\(^{-1}\) in DJF 2015/16. Correlation between the reference and ensemble mean timeseries is displayed in the bottom right. Also indicated, by orange circles, are cases where DJF Niño 3.4 SST anomalies \(\geq 2\) K. 

are initialised each year such that the DJF timeseries are not continuous, sampling across the members in this way explores the broadest range of possible timeseries from the available data. For each of the bootstrap timeseries, statistics are calculated and distributions of these created. Where the reference value lies within the central 95% of the distribution, the model is regarded as statistically indistinguishable from the reference data (Thompson et al. 2017, 2019, Kelder et al. 2020) and accepted for use. Against the reference data, the model passes all tests apart from the mean (figures 1(b)–(e)). The reference data standard deviation, skewness and kurtosis are all within the central 95% of the model distribution. The mean rainfall rate in the model is 7.9 mm day\(^{-1}\) during the DJF season, significantly lower than the reference dataset (8.4 mm day\(^{-1}\)), a bias of –0.5 mm day\(^{-1}\) or –0.6 standard deviations. The dry bias in the model is adjusted to the multi-reference dataset climatology by applying a constant shift, given by the difference between ensemble mean and reference climatology, to each model ensemble member (Jain et al. 2020, Squire et al. 2021). Bias adjustment may not be applicable in situations where there are large differences between observed and model distributions, which could point to a poor representation of important processes (Maraun et al. 2017). However, in this case, the distributions are statistically consistent, and taking the simplest mean shift approach to bias adjustment has no effect on the other moments of the distribution.
The model captures a predictable signal in the rainfall, as indicated by the significant correlation ($r = 0.77$) of model ensemble mean and reference data over the 1982–2016 period (figure 1(f)). Figure 1(F) also illustrates how the whole distribution of members shifts towards drier than normal conditions during El Niño events. Therefore, the likelihood of seeing extreme or unprecedented dry conditions in North Brazil is demonstrably dependent upon the state of the tropical Pacific and is reproduced at least qualitatively by the model simulations.

By sub-selecting the ensemble according to the ENSO state, it becomes possible to estimate the chance of unprecedented low North Brazil rainfall during El Niño. To increase confidence in a conditional assessment of chance based upon a specified relationship, we first establish that the teleconnection is simulated in a manner consistent with the observed relationship—El Niño/dry North Brazil—under investigation in this study. As expected, correlation of North Brazil rainfall with gridpoint SSTs (figure 2(a)) reveals the distinctive ENSO structure of the relationship in the Pacific. The best estimate of the observed correlation is calculated using the mean of the seven reference rainfall/N34 correlation coefficients. This value lies within, albeit at the upper end of, the 95% confidence intervals of the model correlation (figure 2(b)) which, as before, are obtained through bootstrap sampling ($n = 10000$). Composite rainfall anomalies display the expected pattern of dry conditions across northern South America (figures 2(c) and (d)). The warmest 15% of N34 comprises five events in the reference data and 53 events in model. The mean of the five-event composites for each reference rainfall dataset represents the best estimate. This is compared against confidence intervals made through $n = 10000$ bootstrap samples of five-event composites randomly selected from the model pool of 53 events. The reference value sits near the middle.
of the distribution of model composite anomalies (figure 2(e)), showing that the model simulates well El Niño-connected dry events.

Based on these tests, the teleconnection between El Niño and North Brazil rainfall simulated by the model is regarded as consistent with that in the reference data. This gives confidence in the assessment of the chance of unprecedented low rainfall in North Brazil during El Niño.

4. Conditional chance of unprecedented low rainfall

Sub-selection of the model ensemble according to El Niño provides a set of events from which the chance of unprecedented low rainfall in North Brazil during El Niño can be calculated. We start with a weak El Niño threshold where DJF N34 $\geq 0.5$ K (Yeh et al. 2009, Chakraborty 2018). To provide sets of events of increasing El Niño intensity, the lower temperature anomaly bound is increased in steps of 0.5 K up to 2 K, i.e. all cases with N34 $\geq 0.5$ K, $\geq 1$ K, $\geq 1.5$ K, $\geq 2$ K. As lower magnitude events are progressively excluded, the number of El Niño events in each set decreases, comprising 120, 71, 39 and 28 events, respectively. As an illustration, the $\geq 2$ K set, which includes the observed major El Niños of 1982/83, 1997/98 and 2015/16, is marked on the North Brazil rainfall timeseries in figure 1(f). In discussion that follows, ‘major’ El Niños refer to the N34 $\geq 2$ K set.

Minimum DJF rainfall is taken from the best estimate reference timeseries, and comes during the 2015/16 El Niño (figure 1(f)). The chance of unprecedented dry conditions in North Brazil is measured against that minimum (figure 3). If there is no sub-selection based on El Niño, and the likelihood estimate is made using all of the data, it comes out as 7% each year. Given an El Niño year where N34 $\geq 0.5$ K, there is a 20% chance that rainfall rates across the DJF season could fall below the minimum, but as the magnitude of El Niño increases, so too does the chance, up to a little below 60% during a major El Niño. A reduction of 10% (0.8 mm day$^{-1}$) below the reference minimum is more likely during a major El Niño at $\sim$9% (central estimate) compared with $\sim$2% for all El Niños (figure 3(a)) and the largest simulated reduction is of 1 mm day$^{-1}$ or $\sim$30 mm month$^{-1}$ below the minimum.

This analysis indicates that more severe rainfall deficits are possible in the current climate than those seen during El Niño events in the 1982–2016 period, and the chance of unprecedented low rainfall increases with El Niño magnitude. A $\sim$60% chance of unprecedented low rainfall during major El Niños is very high and could be important information for planning purposes.

5. A range of outcomes for North Brazil given a major El Niño

Considering the three major El Niños in the period: 1982/83, 1997/98 and 2015/16, the reference area-mean North Brazil DJF rainfall anomalies are similar and strongly negative in each case. In the model, too, many of the driest simulated DJFs in North Brazil come during these three years (figure 1(f)). However, multiple realisations of the atmosphere in the ensemble present the opportunity to assess the spread in possible responses over North Brazil. While the rainfall anomalies for the three
events are negative in all ensemble members, there is a wide range in the magnitude of these anomalies from just under 3 mm day\(^{-1}\) below the climatological mean, which is considerably lower than the reference data anomalies, to close to normal (figure 4(a)). This suggests that even in the presence of strong El Niño forcing, internal variability in the atmospheric teleconnection modifies the rainfall response over North Brazil. While there is a raised likelihood of unprecedented dry conditions, a rainfall deficit that is moderate or slight is still possible.

Through splitting the ensemble according to North Brazil rainfall response, we can see the wider conditions associated with the ensemble spread during major El Niños. For each of the three years, the three driest and three wettest of the ten members are identified. Selecting on these groups of ensemble members, difference composites of a range of variables are calculated to identify the atmospheric anomalies responsible for the differences in rainfall. A year-by-year approach is taken to ensure that a single year does not dominate, and the results reflect the spread within the ensemble. The mean of the year-specific differences (figures 4(b)–(d) and 5) is used to represent the difference in conditions between major El Niño/very dry and major El Niño/dry North Brazil.

By design, the very dry-dry precipitation difference anomalies (figure 4(b)) display drier conditions over North Brazil, but there are areas of significant difference outside the immediate area of interest, including in the northern extratropics. In the Niño 3.4 box, and in the equatorial Pacific in general, SST differences are not significant (figure 4(c)), although there are consistent associated locally-significant rainfall anomalies. SST anomalies in the North Atlantic subpolar gyre (SPG) region (figure 4(c)) have previously been shown to influence tropical Atlantic atmospheric circulation and the position of the intertropical convergence zone (ITCZ) (Kang et al 2009, Smith et al 2010, Dunstone et al 2011). Warm SST anomalies in the SPG are associated with an increase in tropical Atlantic SSTs and a northward shift of the ITCZ (Smith et al 2010). The positive SST anomalies in the tropical northern Pacific and Atlantic oceans may also be related to the areas of significant low pressure (figure 4(d)) further north, which reduce the wind speed of the low-level trades, and hence the evaporation and heat transfer to the atmosphere (not shown). Positive SST anomalies in the tropical north Atlantic inhibit the southward migration of the ITCZ, which could play a part in producing drier conditions over North Brazil.

The significant mean sea level pressure anomalies are suggestive of a potential role for the extratropics in the ensemble range in rainfall response, and additional circulation fields illustrate this further (figure 5).

Suppressed convection over North Brazil in the very dry compared with the dry members are shown in cross sections of the anomalous local Walker and Hadley circulations (figures 5(a) and (b)) as anomalous descent. The zonal circulation has areas of local anomalous ascent and descent in the region of the Maritime Continent and the central Pacific, which
Figure 5. Characterising the spread in response in North Brazil during major El Niños. Each panel shows the very dry-dry difference anomaly composite. Pressure-longitude and pressure-latitude cross sections represent the anomalous (a) Walker and (b) Hadley circulations, formed from the vertical velocity in pressure coordinates (omega) (*−1) and divergent component of zonal and meridional winds, respectively, with means taken over the longitude/latitude bands of North Brazil, 13° S–5° N for the Walker circulation, and 74° W–46° W for the Hadley circulation (pink shading). Panel (c) shows meridional wind anomalies at 250 hPa and (d) is omega at 500 hPa, where positive anomalies indicate descent. Stippling in panels (c) and (d) indicate significant differences at the 95% confidence level obtained via bootstrap sampling of 10,000 sets of the intra-ensemble difference between two groups of nine members selected from the three major El Niño years, and overlaid are contours of 250 hPa streamfunction anomalies from −3 to 3, interval of 1 \text{10^{6} m^2 s^{-1}}. The black box marks the Niño 3.4 domain.

are also reflected in the rainfall field (figure 4(b)), but there is no apparent direct zonal link with North Brazil. On the other hand, there is a more coherent anomalous circulation in the meridional plane, marked by anomalous ascent to the north and south of the zone of descent in North Brazil. The anomalous ascent could represent a compensating response to the descent over North Brazil and, particularly in the Northern Hemisphere at around 25° N, it appears to form part of a larger-scale pattern of circulation anomalies that extends from the extratropics to the tropics. There is a clear wave pattern, visible in the meridional wind and streamfunction anomalies in the upper troposphere (figure 5(c)), which follows the western coast of North America and into the Caribbean. The southwest-northeast phase tilt of the anomalies indicates an equatorward propagation of the wave train (Hoskins et al 1983, Drouard et al 2015). Ascent and descent associated with this wave (e.g. Matthews and Kiladis 2000) is captured by the mid-tropospheric vertical velocity anomaly field (figure 5(d)). There is a zone of anomalous ascent—and enhanced rainfall—in the Caribbean that forms the rising limb of the anomalous local Hadley circulation (figure 5(b)). Although the wave is clearest along the western coast of North America, there are circulation anomalies around the boundary of the North Pacific, and the presence of symmetric anomalies in the Southern Hemisphere may ultimately point to a possible tropical origin in the west Pacific. Sensitivity experiments would enable further investigation of the source of the wave train.

6. Summary and discussion

Large climate model ensembles present the opportunity to improve assessments of the chance of unprecedented extremes. North Brazil DJF rainfall is strongly influenced by El Niño, and by subsetting a large ensemble, we have quantified the likelihood of unprecedented low rainfall during El Niño events. Within a conditional framework the assessment of likelihood of unprecedented climate outcomes is predicated on a specified relationship. We extended the standard UNSEEN statistical testing of the model against reference data to assess the fidelity of the simulation of the El Niño-North Brazil teleconnection and found it to be consistent with that of the reference data. This increases confidence in the UNSEEN estimates of chance of very low rainfall conditioned upon El Niño.

We found that rainfall rates lower than those seen during the major El Niños of 1982/83, 1997/98 and 2015/16 are possible in today’s climate. The chance of unprecedented low rainfall rises as the strength of El Niño increases from 20% when considering all El Niños (N34 ⩾ 0.5 K), to ~60% for major El Niños like the three listed above (N34 ⩾ 2 K). This can be set against an unconditional estimate, i.e. with no sub-selection of the ensemble based on El Niño, of 7%. This information could be useful...
in implementing strategies designed to mitigate the impacts of drought, especially when a major El Niño is forecast to develop. Deficits could reach ~30 mm month$^{-1}$ below the reference minimum over the DJF season, a reduction of around a third with respect to climatological conditions.

The use of UNSEEN, and the chance estimates that it yields, depend to a large extent upon the observations—or reference datasets—against which the model ensemble is compared. It is therefore important to highlight the challenge that sparse data presents when applying UNSEEN. Here we address some of the discrepancies between rainfall datasets by using several available gridded products. By taking the mean of the properties of the datasets we aim to provide an improved estimate of ‘truth’ but recognise that significant uncertainty remains.

A growing body of research is concerned with ENSO diversity, in particular the so-called East Pacific and Central Pacific flavours of El Niño, and their teleconnections (Ashok et al 2007, Yeh et al 2009, Amaya and Foltz 2014, Jiménez-Muñoz et al 2016, Cai et al 2020, Jimenez et al 2021). This could provide a different way of sub-selecting the model ensemble and an interesting extension of this work, although introducing additional categories of El Niño would reduce the sample size. Because the model ensemble is initialised each year in November, it is constrained to observations, and hence diversity in, and magnitude of, El Niño events is limited. The ensemble does, however, provide sample sizes an order of magnitude greater than are available from the observations, and could offer valuable insight into the dynamics of different observed types of El Niño and their teleconnections.

The North Brazil area-mean rainfall response to the three major observed El Niños was similarly strongly negative in each case. An important insight to emerge from the ensemble is that even under major El Niño conditions, a wide range of rainfall outcomes over North Brazil is possible, from extreme deficits to only a little below the climatological mean. From an impacts and planning perspective, while the conditional UNSEEN analysis estimates a high chance of unprecedented rainfall during major El Niños, it is important to communicate that near-normal rainfall is also possible.

We characterised the spread of the ensemble by sub-selecting dry and very dry members. There is evidence of an equatorward-propagating wave train from the northern extratropics along the western coast of North America and into the Caribbean, which then forms part of an anomalous local Hadley circulation. This corresponds to enhanced uplift in the Caribbean and greater subsidence over North Brazil in the very dry ensemble members. This analysis suggests that in addition to the predictable signal from the tropical Pacific, an additional unpredictable component from the extratropics may play a role in modulating the seasonal response over North Brazil, which could be worth monitoring during El Niño development. This does not preclude the existence of other processes at play (Goddard and Gershunov 2021), nor does it take into account potential effects on the circulation of biases prevalent in current-generation coupled climate models (e.g. Feng et al 2021).

ENSO is a long-recognised driver of rainfall variability in North Brazil, particularly during its DJF peak, and while the driest DJF seasons of the last four decades have occurred in response to El Niño-modified circulation, UNSEEN demonstrates that more extreme dry conditions than those experienced are possible in the current climate. ENSO is well predicted several months in advance, which presents an important opportunity for putting in place measures to mitigate the risks of associated extremes (Yuan and Wood 2013, Goddard and Gershunov 2021). Combining the forecast of an El Niño with (a) improved information on the background chance of extremely low rainfall given El Niño conditions, and (b) monitoring of wider extratropical atmospheric conditions during El Niño events, could feed into a better assessment of risk as an El Niño event develops, and increase resilience to extremes. There is also the potential to extend this conditional approach to other regions that are under strong influence of a predictable climate driver.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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