OCEA 90: Fundamentals of Climate

Class Module 3: The El Niño Southern Oscillation (ENSO)

3.1. El Niño and La Niña

Key concepts from lectures and readings:
(a) Vanishing Coriolis force at the equator
(b) The Walker Circulation in the atmosphere
(c) Equatorial upwelling in the Pacific Ocean
(d) The Bjerknes feedback
(e) Equatorial Kelvin waves
(f) The Southern Oscillation
(g) Triggers for El Niño (westerly wind bursts and the Madden-Julian Oscillation)
(h) The random nature of ENSO and ENSO forecasting

3.2. The Southern Oscillation

3.2.1 Key concepts from lectures
(a) The Walker Circulation
(b) Tahiti and Darwin surface pressures
(c) The Bjerknes feedback
(d) The Southern Oscillation index

3.2.2 The correlation of two time series

In this section we will introduce the concepts of statistical correlation and significance and apply them to the Southern Oscillation introduced in lecture.

To illustrate the basic idea that underpins the correlation between two time series, Figure 3.1 shows several examples of pairs of regular time series described by \( x(t) = \sin(\omega t) \) and \( y(t) = 2\sin(\omega t + \phi) \) where \( \omega \) is a frequency, \( t \) denotes time, and \( \phi \) represents the phase difference between the two time series. The correlation coefficient between the two time series is defined by:

\[
r = \frac{\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N} (x_i - \bar{x})^2 \sum_{i=1}^{N} (y_i - \bar{y})^2}}
\]

(3.1)

where \( x_i \) and \( y_i \) are the time series values for \( i = 1, 2, \ldots, N \); \( N \) is the number of points in the time series; \( \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \) is the time-averaged value of \( x \); and \( \bar{y} = \frac{1}{N} \sum_{i=1}^{N} y_i \) is the time-averaged value of \( y \). By necessity, the correlation coefficient, \( r \), varies between +1 and -1. Positive values of \( r \) (i.e. \( r > 0 \)) indicate that variations in the two time series are in-phase with each other, while
negative values of $r$ (i.e. $r<0$) indicate that the variations are out-of-phase. The larger the value of $r$, the greater the degree of correspondence between the phase variations (i.e. in-phase when $r>0$ or out-of-phase when $r<0$) between the two time series. A correlation coefficient of zero indicates that there is no relation between the time series at all.

**Figure 3.1**: Time series of $x(t) = \sin(\omega t)$ (red curve) and $y(t) = 2\sin(\omega t + \phi)$ (black curve) for (a) $\phi = 0$, (b) $\phi = \pi/4$, (c) $\phi = \pi/2$, (d) $\phi = 3\pi/4$ and (e) $\phi = \pi$. The correlation coefficient $r$ between each pair of curves computed using equation (3.1) is also indicated.

The correlation coefficient, $r$, between each pair of time series computed using equation (3.1) is also shown in Fig. 3.1. When the two time series are completely in-phase (i.e. $\phi = 0$; Fig. 3.1a) the correlation coefficient $r=1$, indicating that the two curves are perfectly correlated, even though they have different amplitudes. In the case $\phi = \pi/4$, the two time series are offset by one quarter of a period, and the correlation coefficient $r=0.7$ indicating that the time series are still significantly correlated and largely in-phase. As $\phi$ increases towards $\pi/2$ the correlation coefficient $r$ decreases and when $\phi = \pi/2$ (i.e. the time-series are in “quadrature”), the correlation coefficient $r=0$, indicating that there is no correlation between the time series. As $\phi$ further increases towards $\pi$ the correlation coefficient becomes progressively more negative until $\phi = \pi$ at which point the time series are completely out-of-phase and $r=-1$.

Let’s now look at time series (as Sir Gilbert Walker would have done) of surface atmospheric pressure at two stations: one on the island of Tahiti in the central tropical Pacific ($17.6^\circ$S, $149.4^\circ$W) and another at Darwin in the Northern Territory of Australia ($12.4^\circ$S, $130.8^\circ$E). Time
series of the monthly averaged surface pressure from these two stations are shown in Fig. 3.2a for the period 1951-2013. The pressure at Tahiti is generally higher than at Darwin, which is to be expected since Darwin is located under the rising branch of the Walker Circulation and is characterized by relatively low surface pressures compared to the surrounding areas. However, if you look carefully you will notice that there are times when the pressure at Darwin is higher than at Tahiti – we will return to these events later. The seasonal variations in pressure at both stations are very evident, with pressure variations over the course of a year of ~5-10 mb. These changes in pressure are associated with the redistribution of solar energy throughout the year as the sun passes back-and-forth across the equator due to the tilt of the earth axis and the position of the earth in its orbit around the Sun. The surface pressure at both stations is generally lowest during the southern hemisphere summer when the Sun at both stations will be almost directly overhead.

Figure 3.2: (a) Time series of monthly mean surface pressure (in millibars (mb)) at Darwin (black curve) and Tahiti (red curve). (b) The average seasonal cycle of surface pressure at Darwin (black) and Tahiti
(red). (c) Time series of the surface pressure anomalies (i.e. monthly mean pressure minus the average seasonal cycle) at Darwin (black) and Tahiti (red). (d) A time series of the 3 month running mean of the monthly mean surface pressure anomalies at Darwin (black) and Tahiti (red). (Data are from the NOAA Climate Prediction Center).

It is clear from Fig. 3.2a that surface pressures at Darwin and Tahiti vary in unison, or as we would say they are “correlated.” The degree of correlation between two time series can be quantified by computing the correlation coefficient, \( r \), according to equation (3.1) which is now written as:

\[
\begin{align*}
   r &= \frac{\sum_{i=1}^{N} (D_i - \bar{D})(T_i - \bar{T})}{\sqrt{\sum_{i=1}^{N} (D_i - \bar{D})^2 \sum_{i=1}^{N} (T_i - \bar{T})^2}} \\
   &= \frac{1}{N\sigma_D\sigma_T} \sum_{i=1}^{N} (D_i - \bar{D})(T_i - \bar{T}) 
\end{align*}
\]

(3.2)

where \( D_i \) and \( T_i \) represent the time series of values of surface pressure at Darwin and Tahiti respectively; \( i=1,2,...,N \) where \( N=756 \) is the total number of monthly values at each station; \( \bar{D} \) and \( \bar{T} \) are the time-averaged pressures at each station; and \( \sigma_D \) and \( \sigma_T \) are the standard deviations of Darwin pressure and Tahiti pressure respectively. The time-averaged values are simply computed as the mean of the time series according to:

\[
\bar{D} = \frac{1}{N} \sum_{i=1}^{N} D_i \quad \text{and} \quad \bar{T} = \frac{1}{N} \sum_{i=1}^{N} T_i.
\]

(3.3)

Recall that the correlation coefficient, \( r \), varies between +1 and -1.

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Figure 3.3: Time series of the observed monthly surface pressure anomalies at Darwin (black curve) and Tahiti (red curve) after applying (a) a 3-month running mean, and (b) a 12-month running mean.
The correlation coefficient of the time series of Darwin and Tahiti surface pressure shown in Fig. 3.2a is $r=0.59$, indicating that variations in the two time series are generally in-phase with each other. The in-phase behavior of the pressure variations at Darwin and Tahiti is quite obvious in Fig. 3.2.a. Much of this correlation is due to the variations in solar radiation since both stations are in the same hemisphere. As Fig. 3.2a indicates, the seasonal variations in surface pressure at each station are very regular year-after-year, although the amplitude of the seasonal variations varies from one year to the next. It is these year-to-year variations (so-called “inter-annual” variations) in the amplitude of the seasonal cycle that are of interest for the study of climate. To explore the nature of the inter-annual climate variations, it is usual to first remove the average seasonal cycle from each time series. The average seasonal cycle is defined as the mean conditions for January, followed by the mean conditions for February, followed by the mean conditions for March, and so on. Figure 3.2b shows the average seasonal cycle of surface pressure at Darwin and Tahiti repeated each year. The difference between the surface pressure time series in Fig. 3.2a and the average seasonal cycle in Fig. 3.2b (i.e. the monthly mean surface pressure minus the seasonal cycle) defines the surface pressure “anomaly.” Time series of the surface pressure anomalies at Darwin and Tahiti are shown in Fig. 3.2c. These are time series of the monthly mean surface pressure at each station with the mean seasonal cycle removed. If you look carefully at Fig. 3.2c, you will notice that the two time series are out-of-phase: when pressure at Darwin is higher than the mean seasonal cycle (i.e. a positive anomaly), the pressure at Tahiti is generally lower than the mean seasonal cycle (i.e. a negative anomaly), and vice versa. The correlation coefficient of the two surface pressure anomaly time series in Fig. 3.2c can be computed using equations 3.2 and 3.3 where now $D$ and $T$ refer to Darwin and Tahiti surface pressure anomalies respectively. The correlation coefficient in this case is $r=-0.33$ confirming that the two time series of pressure anomalies in Fig. 3.2c are generally out-of-phase.

The negative correlation of the surface pressure anomaly time series in Fig. 3.2c is a direct consequence of the Southern Oscillation identified by Sir Gilbert Walker that we discussed in class. As the rising branch of the Walker circulation migrates backwards and forwards along the equator in the Pacific Ocean, the pressure changes at Darwin and Tahiti are out-of-phase. While the out-of-phase relation is quite evident in Fig. 3.2c, it is somewhat obscured by “noise” in the two time series – i.e. higher frequency spikes superimposed on lower frequency variations. This noise is due to other, energetic, atmospheric phenomena in the tropical Pacific that also affect surface pressure. In order to isolate the lower frequencies associated with climate, it is customary to smooth the time series. This can be conveniently achieved by applying a technique referred to as a “running mean.” The means of each time series over all 63 years are defined by equations (3.3). However, suppose instead of averaging over all $N$ records of the time series we compute the average over a shorter interval of, say, $M$ records, where $M \ll N$. Suppose we compute this new mean (let’s call it $\hat{D}_1$) using only the first $M$ records of the time series for $D$ so that

$$\hat{D}_1 = \frac{1}{M} \sum_{i=1}^{M} D_i.$$ 

Now further suppose that we repeat the calculation again, but now use records
2 through \( M+1 \), so that \( \hat{D}_2 = \frac{1}{M} \sum_{i=2}^{M+1} D_i \). Similarly if we repeat this sequence of calculations for \( \hat{D}_3 = \frac{1}{M} \sum_{i=3}^{M+2} D_i \), \( \hat{D}_4 = \frac{1}{M} \sum_{i=4}^{M+3} D_i \), and so on, we obtain a new time series of values of \( \hat{D}_j \) where \( j=1,2,\ldots,N-M+1 \). This new time series is referred to as the “running mean” and represents a smoothed version of the original time series \( D_i \). To illustrate, Fig. 3.2d shows time series of surface pressure anomalies (i.e. pressure after the mean seasonal cycle has been removed) at Darwin and Tahiti for \( M = 3 \) (a so-called “3 month running mean”). The time series of the 3 month running means are significantly smoother than the original time series shown in Fig. 3.2c. The out-of-phase relationship between the Darwin and Tahiti pressure anomalies is now clearer, which is reflected in the correlation coefficient of these two 3 month running mean time series which is now \( r=-0.53 \).

The larger the value of \( M \) that is used in the calculation of the running mean, the smoother the running mean time series will become. To illustrate this, Fig. 3.3 shows time series of the 3 month running mean surface pressure anomalies (i.e. \( M = 3 \)) and the 12 month running mean time series (i.e. \( M = 12 \)). The 12 month running mean time series of surface pressure anomalies at Darwin and Tahiti are now very smooth, and the out-of-phase relation between them is very evident. The correlation coefficient for the 12 month running mean time series is \( r=-0.67 \) which is significantly higher than both the original time series (Fig. 3.1c; \( r=-0.33 \)) and the 3 month running mean time series (Fig. 3.3a; \( r=-0.53 \)).

An important concept that accompanies the correlation coefficient is the notion of statistical significance. For example, even though we have established that inter-annual variations in surface pressure at Tahiti and Darwin are negatively correlated, there may in fact be no causal relation between the pressure at these two stations. Of course, we have a strong reason to believe that pressure variations at the two sites are causally related, but the possibility does exist that the pressure variations in, say, Fig. 3.3 are out-of-phase purely by chance. What we must therefore do is to estimate the probability that the pressure at Tahiti and Darwin could be out-of-phase by pure chance. If the probability of this occurring is small, then we are forced to conclude that the time series in Fig. 3.3 are not an outcome of pure chance, and that they are in fact related in some way. The notion that the two time series could be correlated by pure chance is referred to as the null hypothesis, and the procedure for proving or disproving the null hypothesis is referred to as significance testing. One very common measure of significance is the so-called \( p \)-value which is a measure of the probability that the null hypothesis is true. A discussion of the calculation of \( p \)-values is beyond the scope of this class, but nonetheless we can use the concept of the \( p \)-value (which can be readily computed using \( R \)) to evaluate the null hypothesis for the time series considered here. For the pressure anomaly time series in Figs. 3.2c, 3.2d and Fig. 3.3 the \( p \)-values are all smaller that \( 1 \times 10^{-16} \) (i.e. the \( p \)-value is effectively zero). In other words, there is less than a 1 in ten thousand trillion chance that the time series of Tahiti and Darwin surface pressure anomalies are correlated by pure chance, so the null hypothesis must be rejected.
3.2.3 The Southern Oscillation Index (SOI)

The difference between the surface pressure anomalies (i.e. surface pressure with the average seasonal cycle removed) at Tahiti and Darwin has traditionally been used as an indicator of El Niño and La Niña episodes. Figure 3.4a shows a time series of the 3 month running mean of Tahiti minus Darwin surface pressure anomalies. The large negative values during 1982 and 1997 indicate that pressure was anomalously low at Tahiti relative to Darwin, conditions that occur during large El Niño episodes when the trade winds collapse and the upward branch of the Walker circulation migrates east along the equator into the central Pacific Ocean.

**Figure 3.4:** (a) Time series of the 3 month running mean of Tahiti minus Darwin surface pressure anomalies. (b) Time series of the Southern Oscillation Index (SOI). Sustained values of SOI < -2 typically indicate El Niño conditions, while sustained values of SOI > 2 indicate La Niña conditions. These two thresholds are indicated by the dashed red lines.

Conversely, when the surface pressure is anomalously high at Tahiti relative to Darwin (e.g. as in 1988) this indicates a stronger than normal seasonal cycle indicative of La Niña conditions. Rather than using the straight difference between Tahiti and Darwin surface pressure anomalies, climate scientists monitor El Niño and La Niña conditions using the Southern Oscillation Index (SOI) which is defined as follows:

(1) First, the surface pressure anomaly at Tahiti is computed and divided by the standard deviation of the Tahiti pressure according to \( \tilde{T}_i = \frac{(T_i - \bar{T})}{\sigma_T} \) where \( \tilde{T}_i \) is referred to as the “standardized Tahiti anomaly.”

(2) Similarly the “standardized Darwin anomaly” \( \tilde{D}_i \) is computed according to \( \tilde{D}_i = \frac{(D_i - \bar{D})}{\sigma_D} \).
Next the root mean squared difference, $d$, between the standardized anomalies is computed as 

$$d = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\tilde{T}_i - \tilde{D}_i)^2}.$$ 

Finally, the Southern Oscillation Index is defined as 

$$\text{SOI} = \frac{\sum_{i=1}^{N} (\tilde{T}_i - \tilde{D}_i)}{d}.$$ 

A time series of the SOI is shown in Fig. 3.4b as a histogram to more clearly highlight the periods when SOI > 0 and when SOI < 0. Sustained negative values of the SOI < -2 are typically indicative of El Niño conditions, while sustained positive values of the SOI > 2 typically indicate La Niña conditions.

### 3.3. The tropical Pacific Ocean

As discussed in class, El Niño and La Niña are manifested in the ocean as large changes in the Sea Surface Temperature (SST) along the equator in the central and eastern tropical Pacific Ocean. As another way of monitoring El Niño and La Niña activity, the SST in the tropical Pacific is routinely monitored by averaging the SST over the various regions shown in Fig. 3.5.

![Figure 3.5: The regions commonly used for monitoring the SST variations associated with El Niño and La Niña.](image)

For example, Fig. 3.6a shows a time series (1950-2013) of the monthly mean SST averaged over the “Nino 3” region of Fig. 3.5 (i.e. 5°S-5°N, 150°W-90°W). The Nino3 SST time series is dominated by the seasonal variations in temperature which are the result of two effects: the passage of the sun across the equator twice each year (i.e. the solstices), and the seasonal periodic weakening of the equatorial trade winds during April-May. The expression of the latter effect is apparent in Fig. 3.2a – during April and May the pressure difference between Tahiti and Darwin reaches its lowest value, so the along-equator pressure gradient that drives the equatorial trade winds (recall that the Coriolis force vanishes at the equator) is at a minimum at this time of year. The weakening trade winds at this time lead to a reduction in equatorial upwelling, and an increase in SST in the Nino3 region.

Figure 3.6a reveals that there are significant year-to-year variations in SST (i.e. inter-annual variability) in the Nino3 region, and during some years the temperatures in this central-eastern Pacific region are very warm, almost 29°C. These years are characterized by El Niño conditions.
Conversely, during some years the Nino3 SST falls well below 24°C which is indicative of La Niña conditions.

Figure 3.6: (a) Time series of the monthly mean SST averaged over the Nino3 region shown in Fig. 3.5. (b) Time series of the monthly mean SST anomaly averaged over the Nino3 region, and computed by removing the average seasonal cycle of SST from the total SST.

As in the case of the Southern Oscillation Index discussed in section 3.2.3, it is advantageous to remove the average seasonal cycle of SST from the total SST in order to highlight the inter-annual departures from the mean. Following section 3.2.2, the average seasonal cycle is defined as the mean SST for January, followed by the mean SST for February, followed by the mean SST for March, and so on. Subtracting the average seasonal cycle from the original time series yields a time series for the SST anomalies which is plotted in Fig. 3.6b. This is referred to as the “Nino3 index.” Large positive SST anomalies (i.e. anomalously warm conditions) are present during some years (e.g. 1971-72, 1982-83, 1997-98) and are symptomatic of the very large amplitude El Niño episodes that occurred during these years. Similarly, large negative SST anomalies (i.e. anomalously cold conditions) are also apparent in the time series (e.g. 1955-56, 1973, 1975, 1988, 1999) and symptomatic of large amplitude La Niña episodes.

The different “Nino” regions illustrated in Fig. 3.5 can be used to compute other indices that highlight variability associated with El Niño and La Niña in other parts of the tropical Pacific. For example, the Nino1 and Nino2 indices capture variability in the far eastern equatorial Pacific and along the coast of Ecuador, while the Nino4 index characterizes variability in the western Pacific. A fifth Nino index, dubbed Nino3.4, has also been identified in the central Pacific that overlaps the regions spanned by the Nino3 and Nino4 indices. The Nino3.4 index is routinely used by the U.S. Climate Prediction Center (a branch of the National Weather Service) as an “official” indicator of El Niño and La Niña conditions. A threshold of ±0.5°C is used in conjunction with the 3 month running mean (see section 3.2.2) of the Nino3.4 index to identify
individual El Niño and La Niña episodes. The 3 month running mean of the Nino3.4 index is referred to as the Oceanic Niño Index (ONI). For historical purposes, El Niño (La Niña) episodes are defined when ONI surpasses the threshold +0.5°C (-0.5°C) for at least five consecutive overlapping values.

Figure 3.7: A time series of the Oceanic Niño Index used to define historical El Niño and La Niña events. Strong El Niño episodes are indicated in red, strong La Niña episodes in blue, and moderate events of either type in black. (From http://www.dartmouth.edu/~floods/ElNino.html).

Figure 3.7 shows a time series of the ONI for the period 1950-2013, and individual El Niño and La Niña episodes are identified along with the relative strength of each event.

3.4. Prediction of El Niño and La Niña

As we have seen in class, the development of an El Niño or La Niña episode can be triggered by other energetic phenomena in the atmosphere, such as westerly wind bursts. In addition, the development of an El Niño or La Niña event can be enhanced or disrupted by subsequent atmospheric disturbances. Since westerly wind bursts and other related disturbances are essentially random events, the initiation and evolution of individual El Niño or La Niña events will also be a random process (recall the randomly forced pendulum from class that we used as an analogue for ENSO). This means that in order to predict the occurrence and intensity of a specific kind of event, we need to consider the probability density function of all possible outcomes, and then decide on what the most likely outcome will be.

For example, let’s greatly simplify the problem for a moment and consider again the random coin toss. Suppose that “heads” represents El Niño and “tails” represents La Niña. Each toss of the coin represents a forecast. After a large number of coin tosses (i.e. “forecasts”) we can evaluate the probability distribution of the outcome. In this example, of course, if the coin is “fair” (i.e. unbiased) then there is an equally likely chance of forecasting El Niño as there is of forecasting La Niña. However, suppose that we attach a piece of gum to the “tails” side of the coin to mimic the effect of a sequence of several westerly wind bursts, one after another, just prior to making the forecast. A repeat of the coin tossing forecasts will (presumably) now favor
“heads” (i.e. El Niño) more than “tails” (i.e. La Niña) because the coin is no longer “fair” – it is biased towards the occurrence of El Niño which we conclude is the most likely outcome.

The procedure just outlined for the multiple coin toss “forecasts” in fact parallels what is done at operational weather forecasting centers around the world. In this case, however, instead of using a coin to predict El Niño and La Niña, a sophisticated computer model of the earth atmosphere, ocean, and land system is used. The repetition of forecasts in this way yields a so-called “ensemble” of forecasts which can be used to estimate the future probability density function of the earth system. Each member of the forecast ensemble is generated by running the forecast model starting from slightly different initial conditions. In order to forecast the state of the atmosphere or ocean several days, weeks or months into the future, it is necessary for us to know the current state of each system. However, because we cannot observe the atmosphere and ocean everywhere, the current state of the system can never be precisely known. Hence, the initial conditions for a forecast represent a random process with an associated probability density function. The initial conditions for each member of the forecast ensemble will belong to this probability density function, and by running the forecast model many times starting from different initial conditions, the probability density function of the future state of the atmosphere-ocean circulation can be estimated. This is illustrated schematically in Fig. 3.8.

Figure 3.8: A schematic representing the evolution of a normal probability distribution by a forecast model. Suppose that \( f(t) \) represents the time dependent state of the ocean-atmosphere system in the tropical Pacific (i.e. El Niño vs La Niña conditions). To make a forecast of ENSO for some future time T, we need to know the circulation at the present time which we will assume is time 0. Therefore we want to predict \( f(T) \) given knowledge of \( f(0) \). This will typically be done using a computer model. Since \( f \) is a random variable, it is described by a probability density function. In the left of the figure, the probability density function for the circulation at the present time, \( f(0) \), is assumed to be a normal distribution, with a mean given by \( \bar{f}(0) \). The probability density function for the forecast, \( f(T) \), is shown to the right and has a mean \( \bar{f}(T) \). The problem of ensemble forecasting of ENSO is to estimate \( \bar{f}(T) \) and the probability density function at time T given an estimate of the probability density \( f(0) \).
Figure 3.9 shows an example of an ensemble of forecasts of the Nino3.4 SST anomaly issued by the European Centre for Medium Range Weather Forecasts (ECMWF) in the United Kingdom. The forecasts are made using a computer model of the global atmosphere, ocean and land system and the case shown is for forecasts issued on 1 August, 2013.

Figure 3.9: An ensemble of 6 month forecasts of the Nino3.4 SST anomaly (i.e. the Nino3.4 index) all starting in August, 2013. The total number of ensemble members is 50, and each forecast is shown by the red curves. The observed Nino3.4 SST anomaly is indicated by the black dashed curve. (Courtesy of the ECMWF: http://www.ecmwf.int).

Figure 3.9 shows the time evolution of the Nino3.4 index for each member of a 50 member ensemble of forecasts, where the duration of each forecast is 6 months. At the start of the forecast period (August, 2013) the forecast initial conditions are clustered together, and close to a mean value of the Nino3.4 index that is about -0.1°C. However over time, the forecasts diverge from one another, and by the end of the forecast period (February, 2014) the forecasts are predicting a wide range of values of the Nino3.4 index, ranging from about -1°C to +1.2°C. The mean predicted value of the Nino3.4 SST index in February 2014 is about +0.5°C which is the most likely predicted value of the Nino3.4 index for a normal distribution. Also shown in Fig. 3.9 is the actual observed Nino3.4 index over the same forecast period. In February 2014, the observed value is about -0.5°C which is significantly different from the mean predicted value of +0.5°C. Nevertheless, the observed value of the Nino3.4 does fall within the predicted range of values indicating that there is value in the probabilistic forecast.