# Searching for decadal variations in ENSO precipitation teleconnections

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In many regions the strength of El Niño—Southern Oscillation (ENSO) teleconnections has varied over the last century. It is an active area of research to investigate how such changes can be related to long-term climate variability or climate change. However, fluctuations due to the limited observational record and the low signal/noise ratio also contribute to variations in the apparent strength of the teleconnections. These contributions are considered at 658 precipitation stations around the globe. For each station the probability is estimated that the observed decadal variations in the effect of ENSO on precipitation are explainable by random statistical fluctuations of a constant teleconnection.

The number of stations with statistically significant decadal variations is much lower than the number with statistically significant ENSO teleconnections. It is close to the number expected from chance alone. The observed period is too short to reliably detect multiplicative decadal variability in ENSO precipitation teleconnections.

## 1. Introduction

El Niño – Southern Oscillation (ENSO) affects the weather in many places in the world. As ENSO is well predictable at lead times up to at least half a year, these teleconnections form the basis for much of the skill in seasonal weather forecasts [*Sardeshmukh et al.*, 2000; *Palmer et al.*, 2004; *van Oldenborgh et al.*, 2005]. The strength of ENSO teleconnections, and hence the skill of seasonal forecasts, depends strongly on the location and the season [*Ropelewski and Halpert*, 1987; *Kiladis and Diaz*, 1989; *Mason and Goddard*, 2001]. Compared to the variability of the weather most teleconnections are relatively weak: the effect of ENSO on 3-month averaged precipitation explains less than half the variance with correlation coefficient $r < 0.7$ in all but the most directly affected regions. The exceptions are the core ENSO regions of eastern Indonesia and the western equatorial Pacific.

The strength of teleconnections also seems to vary over time during the last century for which reliable observations are available, complicating seasonal forecasting. These variations are often explored using running correlations, in which the correlation coefficient is computed in overlapping intervals and plotted as a function of the central year in this interval. The running correlations of the teleconnections to rainfall in India, North America and Europe and other regions exhibit large fluctuations [e.g., *Kumar et al.*, 1999; *Diaz et al.*, 2001; *Knippertz et al.*, 2003]. In some areas the strength has varied from $r = 0$ to 0.6 over the last 140 years. These variations have often been explained by changes in the background climate.

*Gershunov et al.* [2001] showed that the statistical variability in running correlations is quite large. For the ENSO teleconnection to All Indian Rainfall AIR the fluctuations in the running correlations were found to be *smaller* than expected from sampling alone. However, in other regions a similar analysis shows that the fluctuations are highly statistically significant, i.e., that they are unlikely to be due to chance. An example from *van Oldenborgh et al.* [2005] is a station in northern California, where El Niño was accompanied by drought at the end of the 19th century and the beginning of the 20th century ($r \approx -0.4$), but by excessive rain at the end of the 20th century ($r \approx +0.6$).

A well-known statistical problem is that chance alone will generate highly statistically significant results for some stations when enough stations are considered. Are the observed large decadal fluctuations in running fluctuations compatible with a null hypothesis of no physically varying teleconnections, or do they reliably indicate the effect of a change in the climate? In this paper we address this question by systematically scanning the world for decadal fluctuations in the strength of ENSO teleconnections, and comparing the fraction of stations with large fluctuations with the fraction expected by chance alone. Note that we do not adress non-ENSO decadal variability itself, only whether observations show ENSO teleconnections to be modulated by it.

## 2. One station

The significance test is first shown for a single station. For parochial reasons we consider seasonal precipitation at De Bilt, the Netherlands (WMO station 6260). The logarithm of precipitation is used, as in arid regions this quantity is more normally distributed than precipitation itself. (Zero seasonal precipitation is arbitrarily replaced by 1/5 of the lowest non-zero observed precipitation amount.) The logarithm of De Bilt precipitation shows a weak ENSO teleconnection in spring. The correlation with the Niño3.4 index $N_{3.4}$ [*Kaplan et al.*, 1998; *Reynolds and Smith*, 1994] over 1856–2003 is $r = 0.24^{+0.13}_{-0.14}$, the error bounds indicate the 95% confidence interval $0.10 < r < 0.37$ [*van Oldenborgh et al.*, 2000]. The 25-year running correlation for the observed rainfall data is shown in Fig. 1 and fluctuates from $r = -0.09^{+0.34}_{-0.32}$ around 1941 to $+0.58^{+0.20}_{-0.27}$ around 1975. The difference between highest and lowest correlation is expressed in $z$-values with $z = \log((1+r)/(1-r))/2$. This quantity is unbounded, estimates are more normally distributed around the true value, and the variance is to a first approximation independent of $r$. Over the 150 years with data in De Bilt we find that the fluctuations in running correlation correspond to $\Delta z = z_{\max} - z_{\min} = 0.75$.

The statistical significance of these fluctuations can be assessed with a Monte Carlo technique. 1000 precipitation time series $p_{\mathrm{MC}}$ are generated with the real observations replaced by synthetic observations with the same mean regression with the Niño3.4 index. The weather noise is approximated by a normal distribution, which is a good approximation to the distribution of the observed residues:

$$\log p_{\mathrm{MC}}(t) = a_0 + a_1 N_{3.4}(t) + \sigma_{\log p}\sqrt{1-r^2}\,\eta_p(t)\ , \quad (1)$$

with standard deviation $\sigma_{\log p}$ and fit parameters $a_0$ and $a_1 = r\sigma_{\log p}$ estimated from the observations, and noise $\eta_p(t)$

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0094-8276/05/$5.00

drawn from a normal distribution $N(0,1)$ with zero mean and unit variance. As the autocorrelation between seasonal rainfall in successive years $t$ and $t+1$ is small, the noise is uncorrelated in time. Neglecting serial correlations underestimates the statistical fluctuations.

These time series have, by construction, no decadal variability based on variations of the strength of the teleconnection, as the regression coefficient $a_1$ is constant in time. The running correlations of the first 10 synthetic time series with the observed Niño3.4 index are shown in Fig. 1. One sees that these already have extrema outside the range of the observed, indicating that the observed fluctuations are within the range due to sampling.

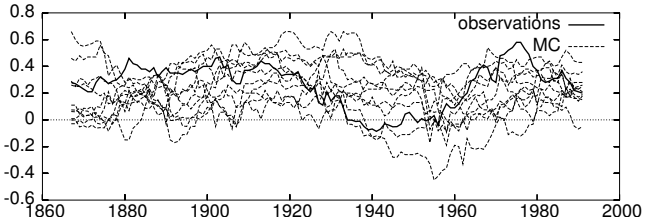


**Figure 1.** 25-yr running correlations of March–May precipitation at De Bilt with the simultaneous Niño3.4 index compared to 10 running correlations of random precipitation series with the same time-invariant statistical relationship with Niño3.4 as the observations.

To quantify the statistical significance of the observed decadal variations, for each synthetic series $\Delta z$ is computed. It turns out that 697 of the 1000 synthetic series have larger decadal fluctuations than the observed ones, so under the null hypothesis of constant teleconnections and the assumption (1) there is a probability of $P = 69.7\%$ of finding a larger $\Delta z$. There is no need to invoke changes in the background state to explain the difference between the 1940s with no teleconnection and the 1970s with a relatively strong one; sampling uncertainties (and the observed decadal ENSO variability) are probably enough to generate these kind of differences without changes in the strength of the teleconnection.

An alternative method is to replace the Niño3.4 index with a normally distributed random series with regression to the observed precipitation equal to the original:

$$N_{3.4}^{\mathrm{MC}}(t) = b \log p(t) + \sigma_N \sqrt{1-r^2}\, \eta_N(t) \ . \qquad (2)$$

This has the advantage that the precipitation does not need to be normally distributed. On the De Bilt series, this procedure gives $P = 71.3\%$, almost equal to the previous method. As the logarithm of precipitation is non-normal in most of the world, this method will be used in the remainder of the article. We checked that the results are almost indistinguishable from the findings when precipitation is replaced by a normal distribution. Decadal changes in the statistical properties of ENSO could also give rise to changes in the apparent strength of the teleconnection compared to the random series, but the observed Niño3.4 index is itself compatible with a stationary series [*Gershunov et al.*, 2001].

## 3. Power of the test

The statistical power of this MC test was investigated by constructing 100-year time series with fixed regression $c$ to the December–February averaged Niño3.4 index over 1900–2000 modulated by a prescribed sinusoidal decadal variation with amplitude $A$ and period $T$, plus noise $\eta_i(t)$ with unit amplitude

$$X_i(t) = [c + A\sin(2\pi(t/T + \phi_i))]N_{3.4}(t) + \eta_i(t) \ . \qquad (3)$$

The phase is chosen randomly per time series $i$. We compute the fraction of these time series that pass the 5% significance test on $\Delta z$. When the decadal variability $A = 0$ this should be 5%, but due to the use of the observed regression rather than the true one it is slightly lower at 4.5%. Lower significance levels are also overestimated by about 10%. This bias has been taken into account when the field significance is considered (section 5).

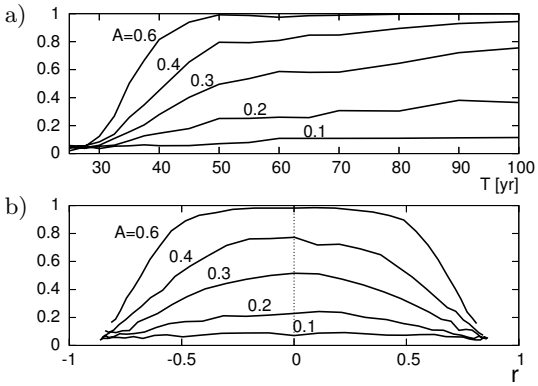


**Figure 2.** The fraction of time series that is significantly different from the null hypothesis of no decadal variability at 5% as a function of (a) the period $T$ for zero mean ENSO teleconnection and (b) the correlation $r$ of the ENSO teleconnection for $T = 50$ yr.

In Fig. 2a the fraction of time series (3) is shown that passes the test at 5% significance level as a function of the period $T$ and the amplitude of the decadal signal $A$. The test cannot discern periods smaller than about 35 years with a 25-yr window. Above this threshold, the power depends on the strength of the ENSO teleconnection. Where this is zero on average, decadal variability of 30% of the year-to-year random variability ($A = 0.3$) can be detected in a single station detected with 50% probability, and $A = 0.6$ almost always. In Fig. 2b the power for $T = 50$yr is shown as a function of the correlation coefficient $r$. The power decreases with the strength of the ENSO teleconnection. This is due to the inability to distinguish between decadal variations in the strength of ENSO and the strength of the teleconnection in a running correlation. A running regression would be less sensitive.

## 4. World maps

In order to investigate the spatial patterns of decadal variability of ENSO teleconnections and assess their statistical significance, the significance test is performed for 568 precipitation stations of the GHCN v2 database [*Vose et al.*, 1992] with at least 80 years of data in all 3-month seasons and at least 2° separation (to decrease spatial dependencies). Coverage is excellent in the U.S., Europe, India, South Africa, eastern Australia and Oceania, fair in West Africa, East Africa and (South) East Asia and spotty in South America.

In Figs 3(a,c,e,g) the linear precipitation teleconnections with ENSO are shown as the correlation coefficients with the

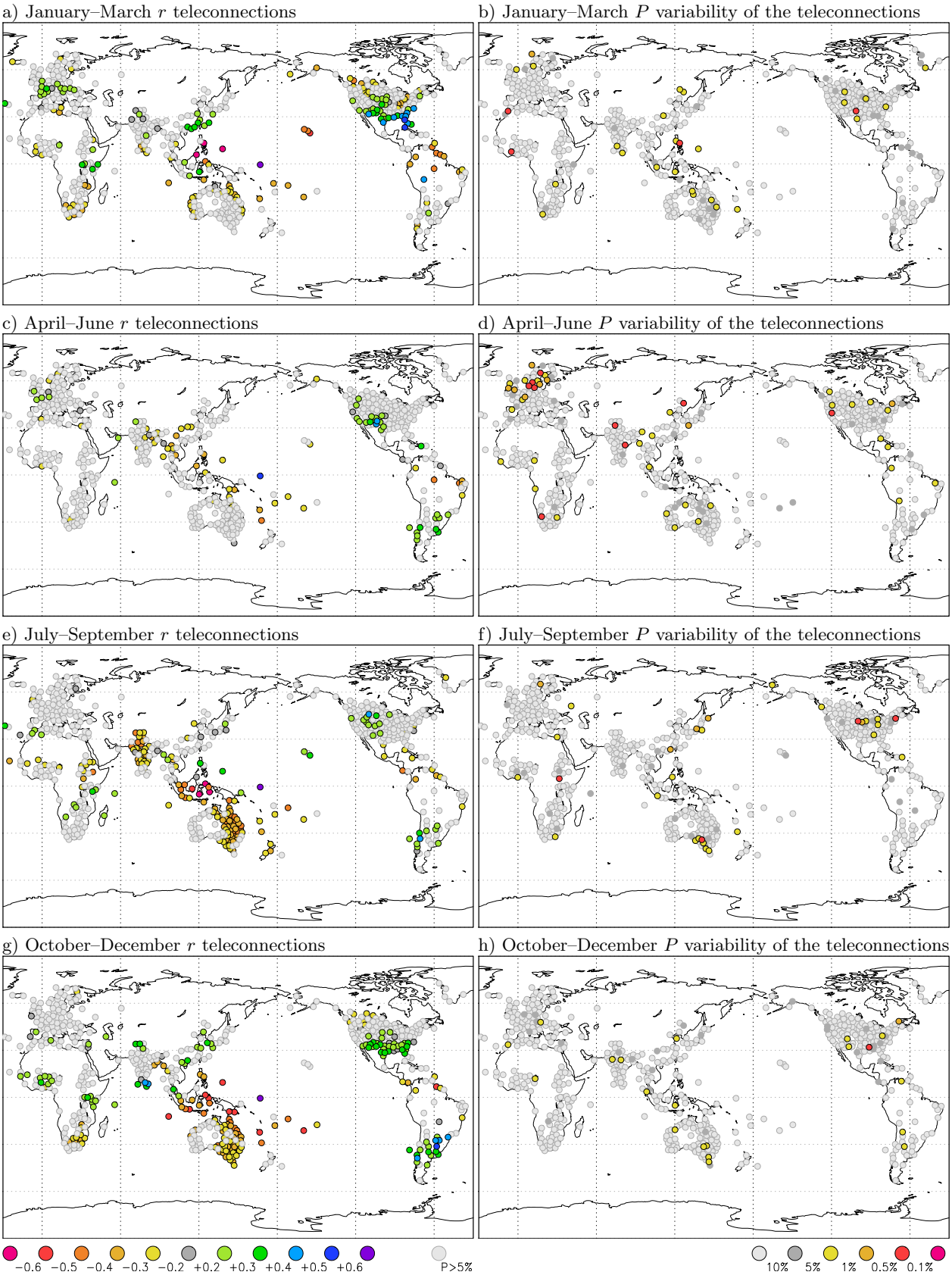


**Figure 3.** a) Overall correlation and b) statistical significance of variations in the 25-yr running correlation of the logarithm of GHCN v2 station precipitation with the Niño3.4 index in January–March. c), d) Same for April–June. e), f) Same for July–September. g), h) Same for October–December. Only stations with at least 80 years of data are shown.

Niño3.4 index for the four seasons January–March, April–June, July–September and October–December. Globally, these correspond as much as possible to local seasons in which ENSO teleconnections are active. The maps were made with the Climate Explorer web site (climexp.knmi.nl) and the reader is encouraged to make them for other seasons and smaller regions. These maps show the well-known teleconnection patterns [*Ropelewski and Halpert*, 1987; *Kiladis and Diaz*, 1989; *Mason and Goddard*, 2001] against the grey stations where the correlations are below $|r| = 0.2$ (for 80 years, $P < 5\%$ at $|r| = 0.19$). The only teleconnection that is not visible in the plots due to an absence of long time series is the increased summer rain in Kazakhstan during El Niño.

Figs 3(b,d,f,h) show the statistial significance of decadal fluctuations. Stations at which $1\% < P < 5\%$ are yellow, $0.5\% < P < 1\%$ orange, and $P < 0.5\%$ is denoted by red. In contrast to the teleconnection maps, the decadal variability maps do not show large regions in which there are obviously large signals. The largest coherent signal is in April–June in northern Europe, where El Niño in the late spring of 1940 and 1941 was accompanied by dry weather, but by wet weather in 1982 and 1983. Weaker signals are visible in southern Australia and the midwestern U.S. in July–September.

## 5. Field significance

In the absence of any decadal variability in ENSO teleconnections one would still expect about $n\%$ of the stations to have significance $P < n\%$. In Table 1 we show the number of stations expected (corrected for the bias) and observed for a few conventional cut-off values in the four seasons. There are far more stations than expected by chance alone that have statistically significant ENSO precipitation teleconnections: no further statistical analysis is needed to conclude that ENSO teleconnections have a physical origin and not a statistical artifact. However, for the decadal fluctuations the numbers are only slightly higher than the ones expected by chance alone. For three of the seasons the numbers fall within the expected Poisson distribution, so the null hypothesis that the numbers arose from stationary teleconnections can not be rejected. In April–June the number of stations with $P$ small is higher than expected if all stations were independent. The surplus is mainly due to the cluster of stations in northern Europe mentioned before.

**Table 1.** Number of stations with statistically significant ENSO precipitation teleconnections as a function of the cut-off value; same for the decadal variations in these teleconnections.

| $P$ | CL | *expected number* | *observed number* JFM | AMJ | JAS | OND |
|---|---|---|---|---|---|---|
| | | | *teleconnections* | | | |
| 0.1 | 90% | 56.8 | 243 | 137 | 233 | 252 |
| 0.05 | 95% | 28.4 | 180 | 95 | 183 | 204 |
| 0.01 | 99% | 5.7 | 120 | 45 | 113 | 134 |
| 0.005 | 99.5% | 2.8 | 97 | 36 | 100 | 118 |
| | | | *decadal variations* | | | |
| 0.1 | 90% | 51.2 | 59 | 76 | 55 | 47 |
| 0.05 | 95% | 25.6 | 29 | 47 | 29 | 21 |
| 0.01 | 99% | 5.1 | 5 | 17 | 9 | 3 |
| 0.005 | 99.5% | 2.6 | 4 | 9 | 5 | 1 |

## 6. Conclusions

Decadal variations in the strength of ENSO teleconnections to precipitation have been computed for 568 stations over the whole globe for four 3-month seasons by means of 25-year running correlations. Maps do not show large-scale areas of decadal variability. Moreover, the number of stations with statistically significant decadal fluctuations is only slightly higher than the number obtained by replacing the Niño3.4 index with synthetic series with constant teleconnections. We conclude that in the majority of stations, most of the observed variability in the strength of the teleconnections is due to statistical fluctuations in the short observed record.

**Acknowledgments.** We thank David Stephenson and Adri Buishand for many helpful suggestions.

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