GEOPHYSICAL RESEARCH LETTERS, VOL. 36, L08811, doi:10.1029/2009GL037989, 2009

Can global warming make Indian monsoon weather less predictable?

Neena Joseph Mani,[1] E. Suhas,[1] and B. N. Goswami[1]

Received 2 March 2009; accepted 24 March 2009; published 23 April 2009.

[1] Reliable medium range prediction of monsoon weather is crucial for disaster preparedness. Weather in tropics, controlled by fast growing convective instabilities is, however, intrinsically less predictable than that in extra-tropics. Increased frequency and intensity of extreme rain events in the tropics in the backdrop of global warming has a potential for further decreasing the potential predictability of the tropical weather. Using nonlinear dynamical techniques on gridded daily rainfall data over India for 104 years (1901–2004), here we show that the deterministic predictability of monsoon weather over central India in the latest quarter of the period has indeed decreased significantly compared to that in the earlier three quarters. The decrease of initial error doubling time from approximately 3.0 days to 1.5 days is consistent with higher frequency of extreme events and increased potential instability of the atmosphere in the recent quarter. To overcome the increased difficulty in predicting monsoon weather, significant increase in efforts to improve models, observations and enhancement of computing power would be required. **Citation:** Mani, N. J., E. Suhas, and B. N. Goswami (2009), Can global warming make Indian monsoon weather less predictable?, *Geophys. Res. Lett.*, *36*, L08811, doi:10.1029/2009GL037989.

1. Introduction

[2] Monsoon synoptic systems namely lows and depression account for most of monsoon rain during the June–September monsoon season [*Mooley and Shukla*, 1989]. Reliable prediction of these events 5–7 days in advance is crucial for various agricultural practices, water resource and disaster management. In contrast to extra-tropics where the weather is primarily governed by baroclinic instability (vertical shear of zonal wind driven) [*Charney*, 1949; *Holton*, 1992], the tropical weather is largely governed by barotropic instability (horizontal shear of zonal winds across the tropical convergence zone, TCZ), while the feedback with organized convection determines its intensity and growth rate [*Mak*, 1987]. During Boreal summer, the large easterly jet at upper troposphere over the Indian monsoon region makes the vertical shear of zonal winds appreciable and combined barotropic-baroclinic instability becomes responsible for initiation of monsoon lows and depressions [*Shukla*, 1978]. However, feedback with active convection is crucial for their intensification and scale selection [*Goswami et al.*, 1980]. Small scale instabilities, such as convective activity, have very short timescales and are typically less predictable than the larger scales [*Lorenz*, 1969; *Dalcher and Kalnay*, 1987]. Errors in small unresolved scales grow fast and through non linear interactions, introduce finite errors in the synoptic scale, thus setting an upper limit to its predictability. As a result of the seminal role played by feedback with convection, tropical weather is much less predictable than extra-tropical weather [*Shukla*, 1989]. Increasing moisture in the atmosphere [*Trenberth et al.*, 2005] as a result of increasing global temperature makes the tropical atmosphere increasingly more unstable. The frequency of occurrence as well as the intensity of extreme rainfall events have shown a significant increasing trend in tropics in general [*Hegerl et al.*, 2007] and over the central Indian region during summer monsoon in particular [*Goswami et al.*, 2006], consistent with the warming environment. Such an increase in number of high frequency events is likely to lead to a faster growth of errors in the synoptic scales, lowering the predictability of the monsoon weather in recent times.

[3] Most studies on predictability use model simulations where growth rate of errors (e.g., error doubling time) is estimated from comparison between predictions with the model from a suite of perturbed initial conditions and a 'control' prediction. Almost all models' inability to reproduce the observed space-time spectra of tropical clouds [*Lin et al.*, 2006] may affect the model based estimation of potential predictability. For example, the estimate of error doubling time of 2.5 days for extratropical weather, estimated with a coarser version of ECMWF prediction model in eighties [*Lorenz*, 1982] has been revised to 1.5 days in the northern hemisphere and 1.7 days in the southern hemisphere [*Simmons et al.*, 1995; *Simmons and Hollingsworth*, 2002] due to use of higher resolution models in recent years. With the availability of good long records of daily rainfall data [*Rajeevan et al.*, 2008], it may be worthwhile to attempt to estimate the predictability of Indian monsoon weather from observations. Such an estimate will require a measurement of the growth rate of initial uncertainties. Lyapunov exponents are such a measure of sensitivity to initial conditions with the magnitude of the exponent reflecting the time scale at which the system becomes unpredictable. In any dissipative dynamical system, there is at least one negative exponent and the sum of all of the exponents is negative. In chaotic systems there would be at least one positive Lyapunov exponent. Different methods have been proposed to estimate the largest Lyapunov exponent from an observed single time series [*Wolf et al.*, 1985; *Rosenstein et al.*, 1993], or the whole spectrum of Lyapunov exponents [*Eckmann et al.*, 1986], and some of it has been adapted for short noisy time series [*Zeng et al.*, 1991]. An understanding of the total spectrum of Lyapunov exponents will give a measure of the total error growth in all possible modes. Applying *Zeng et al.* [1991] algorithm to recently available daily gridded rainfall data over India for 104 (1901–2004) years [*Rajeevan et al.*, 2008], we investigate the changes in

[1]Indian Institute of Tropical Meteorology, Pune, India.

0094-8276/09/2009GL037989$05.00

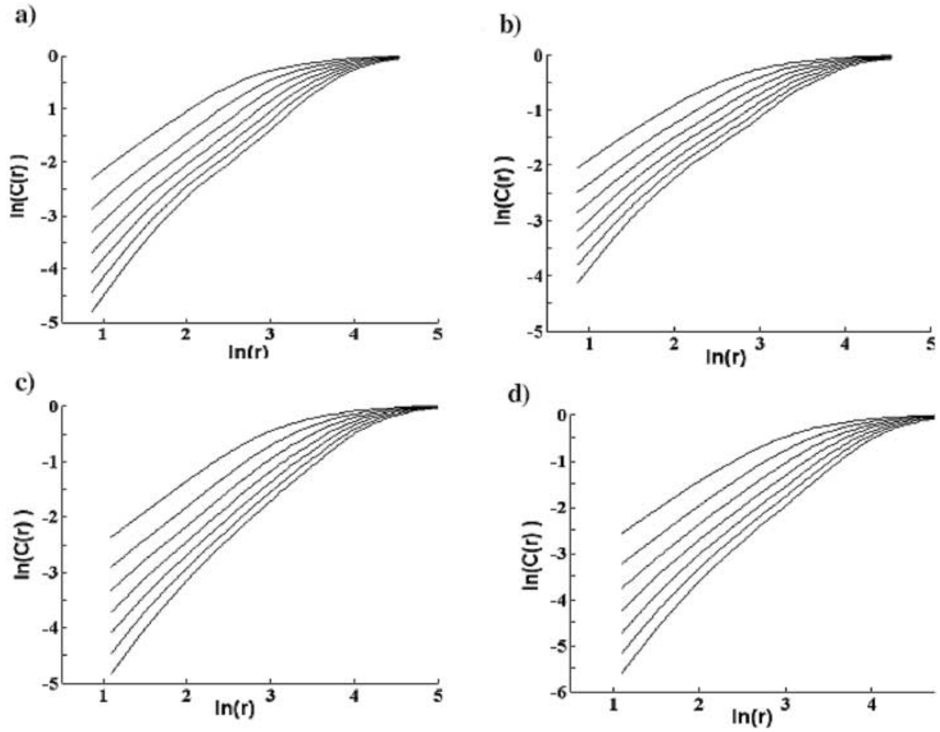

Figure 1. Computation of correlation dimension from the daily rainfall time series. Plots of ln(C(r)) versus ln(r) for embedding dimensions m = 2, 3, . . .8, ordered from left to right, at different locations, (a) 21°N 79°E, (b) 24°N 78°E, (c) 22°N 82°E, (d) 20°N 81°E.

the growth rate of small errors for the four quarters of the 104 year period.

2. Data and Methodology

[4] Our objective is to estimate the change in predictability over Central India (73°E–85°E, 18°N–27°N) as the track of monsoon lows and depressions largely follow the monsoon trough zone of central India [*Mooley and Shukla*, 1989]. The daily rainfall data used in our study [*Rajeevan et al.*, 2008], is based on daily accumulated rainfall from about 1384 stations and analyzed in to 1° × 1° grid boxes. Daily rainfall anomalies at each grid box are constructed as deviations of daily values from an annual cycle defined by sum of the annual mean and first three harmonics. The period from May 1 to October 31 is taken to represent the summer monsoon season. Spectra of the daily rainfall anomalies in this period shows large power in the synoptic time scale (2–8 days) and significant power in sub-seasonal time scales (10–60 days). Daily temperature and humidity data from ERA40 [*Uppala et al.*, 2005] have been used to calculate the convective available potential energy (CAPE) and convective inhibition energy (CINE).

[5] From the single time series of daily rainfall anomalies, the phase space of evolution of the monsoon weather is reconstructed by the method of time delay [*Takens*, 1981]. In preparation for estimating the positive Lyapunov exponents over central India, the correlation dimension (d_c) of rainfall time series at all grid point over the region is estimated following Grassberger and Procacia algorithm [*Grassberger and Procaccia*, 1983] using data between 1901 and 2004. The number of vectors which fall within a small radius ‘r’ (r greater than noise scales), C(r) versus r for different embedding dimensions ‘m’ is shown in Figure 1 for four different points. Slopes of these curves as a function of embedding dimension indicate that they reach a saturation level for embedding dimension between 5 and 7 giving d_c between 1.1 and 1.5 (not shown).

[6] With our objective of finding change in predictability of monsoon weather over central India, the total data was divided into four quarters of 26 years each, namely 1901–1926 (Q1), 1927–1952 (Q2), 1953–1978 (Q3) and 1979–2004 (Q4). Having obtained a measure of the attractor dimension of the monsoon daily rainfall time series at each grid boxes, an embedding dimension of 5 ($\sim 2d_c + 1$) was considered reasonable for computing the Lyapunov exponents following the *Zeng et al.* [1991] algorithm. Since the weather over the central Indian region is governed by the same lows and depressions, the estimated Lyapunov exponents (LEs) should be similar across the region. To test this, we estimate Lyapunov exponents at a number of grid boxes across the region for each quarter. In order to have better confidence in the estimation of LEs, we increase the length of the time series by combining 12 neighbouring 1 × 1 boxes in sixteen 3° × 4° boxes (Figure 2) over the central Indian region. Two 3° × 4° boxes in the north–east corner of the domain shown in Figure 2 are not considered as the rainfall over these boxes is influenced by topography and error growth characteristics could be different from the rest of the region. So, daily rainfall anomalies for 184 days and 26 years of each quarter from the twelve 1° × 1° boxes within each of the 3° × 4° boxes are combined to create a time series of length 57408 days and used to make stable estimates of LEs.

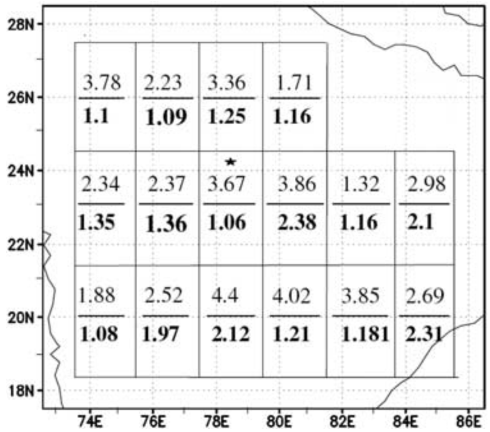

Figure 2. Error doubling time at sixteen 3° × 4° boxes in the region 18.5°N–27.5°N, 5.5°E–85.5°E. Light numbers are error doubling time for the period 1953–1978 (Q3) while the bold numbers are for the period 1979–2004 (Q4). Results of Monte Carlo simulations are shown in Figure S2 for the box with *.

[7] Lyapunov exponents are estimated using the *Zeng et al.* [1991] algorithm. For Lyapunov exponent computation, we determine the set of vectors x_j which fall within a short distance r (5% or 10% of the horizontal extent of attractor), from each vector x_i. After n time steps of evolution, the trajectories diverge and small vectors $x_j - x_i$ evolve to vectors $x_{j+n} - x_{i+n}$. A m X m matrix T_i is defined to describe the evolution of the system as

$$X_{j+n} - X_{i+n} = T_i(X_j - X_i)$$

The elements of T_i matrices are estimated by least square algorithm. Then each of the T_i matrix is QR decomposed into orthogonal matrices Q_j and upper triangular matrices R_j.The Lyapunov exponents are obtained by $\lambda_l = \frac{1}{\tau\kappa}\sum_{j=0}^{\kappa-1} \ln (R_j)_{ll}$ *where* $l = 1, 2, \ldots m$, where κ is the number of T_i matrices. The error doubling time is then found by the formula, ln(2)/(sum of all positive Lyapunov exponents).

3. Results and Discussions

[8] Using Grassberger Procacia algorithm on 19136 days of data (184 days × 104 years) at several locations over central India, we obtained a correlation dimension d_c between 1.1 and 1.5, which can be considered as a good approximation to the underlying attractor dimension. These are first such estimates of d_c of daily rainfall over India using long time series and the fractal nature of d_c supports our original premise that Indian monsoon rainfall time series is chaotic. The global tropical weather may be considered as comprised of a number of loosely coupled subsystems and hence may have a reasonably large correlation dimension [*Lorenz*, 1991]. Why then, the daily rainfall time series over the Indian monsoon region has small correlation dimension? It may be because the monsoon weather (lows and depressions) is characteristic of only the monsoon region and is a rather strongly convectively coupled subsystem of the tropical weather. For such strongly coupled subsystem, a small correlation dimension is possible [*Lorenz*, 1991].

[9] The rainfall time series for each quarter invariably gave two positive Lyapunov exponents in almost all locations over our central Indian domain. Error doubling time calculated from the Lyapunov exponents for the two recent quarters (Figure 2) show that there is a systematic decrease in error doubling time during Q4 compared to that during Q3. The average error doubling time over the region has reduced from 3.0 days during Q3 to 1.5 days in Q4. The statistical significance of the decrease in the mean error doubling time is tested using t-test and found to be significant at 99% level. The potential predictability of monsoon weather, therefore, has decreased significantly in recent couple of decades compared to in fifties and sixties. Therefore, it is not surprising that even though the weather prediction systems have improved in recent years, predicting the daily rainfall over the Indian monsoon region has remained a challenging problem.

[10] Robustness of our results depends on the confidence in the estimates of Lyapunov exponents from the time series. Our confidence is based on the fact that we use Zeng et al's methodology for estimating the Lyapunov exponents designed to provide reliable estimate even when the data length is not too long. We also took additional care to increase the length of the time series to 57408 days. The embedding dimension of five and the number of nearest neighbors are chosen through a series of sensitivity experiments to provide stable and robust estimates. The fact that both the exponents are homogeneous and continuous over the region (Figure S1 of the auxiliary material) also provides some support to our confidence in our estimates.[1] One could still ask whether any of these estimates of error doubling time could have been obtained purely by chance. To answer this question, we carried out Monte-Carlo simulations at several locations. For both periods, Lyapunov exponents were calculated for 1000 surrogate time series created from the original time series by keeping the spectral powers intact and by giving a small random perturbation on the phases. The pdf of the doubling time obtained with the surrogate time series for the box shown by (*) in Figure 2 for both the periods shows (Figure S2) that there is less than 5% chance that the values 3.76 and 1.06 could have been obtained by chance. Thus, null hypothesis that it could be obtained by chance is rejected with 95% confidence. This is tested at other boxes and other periods and uniformly similar results are found.

[11] Although the decrease in the error doubling time comes from a systematic increase in the magnitude of both the Lyapunov exponents (Figure S1) during Q4 compared to that in Q3, major contribution comes primarily from increase in the first Lyapunov exponent (λ_1). As there is higher level of confidence in estimation of the first Lyapunov exponent compared to the second, the fact that our main result is primarily due to the first Lyapunov exponent gives us little more confidence in our result. λ_1 is significantly larger than λ_2 everywhere and in both the periods. While the error growth associated with (λ_1) and (λ_2) are both likely to be related the weather disturbances with high frequency end

[1]Auxiliary materials are available in the HTML. doi:10.1029/2009GL037989.

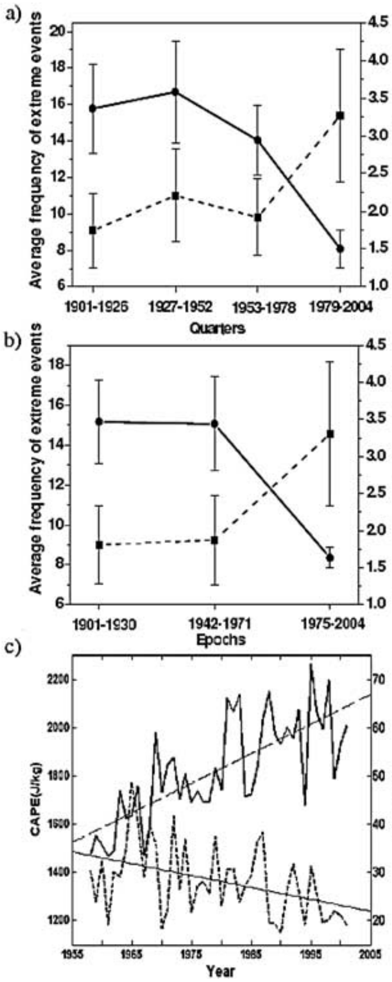

Figure 3. (a) Average error doubling time over central India (solid line) and frequency of extreme events (rainfall >150 mm/day) (dashed line) for four quarters. Vertical bars show one spatial s.d. of the error doubling time and one temporal s.d. of extreme events. (b) Same as Figure 3a But for three different 30 year periods. (c) Daily CAPE and CINE averaged over central India and over monsoon season from ERA40.

of the spectrum (period < 10 days), we are unable to identify them to any specific frequency or mode of variability at this time. While we recognize that in depth understanding of these aspects would require much further work, we believe that the clear and present danger presented by the gross decrease in potential predictability is worth noting even at this time.

[12] Similar estimates of Lyapunov exponents at each $3^\circ \times 4^\circ$ boxes were made for Q1 and Q2 as well and it is found that the averaged initial error doubling time over central India during both these periods is closer to that during Q3 (Figure 3a). Close correspondence between relatively high initial error doubling time during the first three quarters and low error doubling time during the fourth quarter are consistent with the fact that the average frequency of extreme events (daily rainfall > 150 mm) over central India during the first three quarters is relatively low and similar while that during Q4 is much larger (Figure 3a). As there is a multidecadal variation of the extreme events (EEs) [*Rajeevan et al.*, 2008] could our choice of four equal quarters affected the relationship between error doubling time and frequency of extreme events? To answer this question, we identified two regimes with equal low level EEs and another regime with high level of EEs, each of 30 year duration (Figure S3). Repetition of LE calculation for the three regimes show (Figure 3b), that the average error doubling time over central India in the two regimes with smaller number of extreme events is much higher than that during the recent high extreme event regime.

[13] Extreme events are results of convective instability of the atmosphere. If our hypothesis is correct, an increasing trend of the convective available potential energy (CAPE) over the region during June–September may be expected. Calculation of daily CAPE and CINE from ERA40 data averaged over the season and over central India indicates that CAPE has an increasing trend significant at 99% level (Figure 3c) [*Riemann-Campe et al.*, 2008] while CINE shows a clear decreasing trend (Figure 3c) indicating that the convective instability is increasing and becoming increasing easier to realize. These results support our original hypothesis that the global warming may be seriously decreasing the potential predictability of monsoon weather.

4. Conclusions

[14] The increased instabilities in the tropical atmosphere manifesting as increase in frequency of occurrence and intensity of fast growing high frequency events may lead to the faster initial error growth rate of tropical weather. This is likely to bring down the potential predictability of tropical weather. The hypothesis is tested in the context of Indian summer monsoon weather. Estimates of predictability of Indian monsoon weather, in this study, brings out clear evidence of significant decrease in predictability over the monsoon trough region of central India during the past couple of decades compared to earlier parts of this century. While the error doubling time over central India was close to 3 days during the first three quarters of the century, it has decreased to 1.5 day during the most recent quarter throwing up new challenges in predicting the monsoon weather. To improve the poor skill of current weather prediction systems would, therefore, require a quantum leap in improvement of prediction models, better initial conditions (observations) and large computing power.

[15] **Acknowledgments.** We thank Roger. A. Pielke, Xubin Zeng and J. P. Eckmann for providing algorithms and timely help and to IMD for making the newly constructed gridded daily rainfall for 104 years available to us. We thank J. Shukla for critical comments on an earlier version of the manuscript. NJM and SE acknowledge CSIR for financial support. BNG and I.I.T.M are fully supported by Ministry of Earth Sciences, Govt. India, New Delhi.

References

Charney, J. G. (1949), The dynamics of long waves in a baroclinic westerly current, *J. Meteorol.*, *4*, 135–162.

Dalcher, A., and E. Kalnay (1987), Error growth and predictability in operational ECMWF forecasts, *Tellus, Ser. A*, *39*, 474–491.

Eckmann, J. P., S. O. Kamphorst, D. Ruelle, and S. Ciliberto (1986), Lyapunov exponents from time series, *Phys. Rev. A*, *34*, 4971.

Goswami, B. N., R. N. Keshavamurty, and V. Satyan (1980), Role of barotropic-baroclinic instability on the growth of monsoon depressions and mid-tropospheric cyclones, *Proc. Indian Acad. Sci. Earth Planet. Sci.*, *89*, 79–97.

Goswami, B. N., V. Venugopal, D. Sengupta, M. S. Madhusoodanan, and P. K. Xavier (2006), Increasing trend of extreme rain events over India in a warming environment, *Science*, *314*, 1442–1445.
Grassberger, P., and I. Procaccia (1983), Characterization of strange attractors, *Phys. Rev. Lett.*, *50*, 346–349.
Hegerl, G. C., et al. (2007), Understanding and attributing climate change, in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by S. Solomon et al., pp. 664–745, Cambridge Univ. Press, Cambridge, U. K.
Holton, J. R. (1992), *An Introduction to Dynamic Meteorology*, 3rd ed., 511 pp., Academic, San Diego, Calif.
Lin, J. L., et al. (2006), Tropical intraseasonal variability in 14 IPCC AR4 climate models. Part I: Convective signals, *J. Clim.*, *19*, 2665–2690.
Lorenz, E. N. (1969), The predictability of a flow which possesses many scales of motion, *Tellus*, *21*, 289–307.
Lorenz, E. N. (1982), Atmospheric predictability experiments with a large numerical model, *Tellus*, *34*, 505–513.
Lorenz, E. N. (1991), Dimension of weather and climate attractors, *Nature*, *353*, 241–244.
Mak, M. (1987), Synoptic-scale disturbances in the summer monsoon, in *Monsoon Meteorology*, edited by C. P. Chang and T. N. Krishnamurti, pp. 435–460, Oxford Univ. Press, Oxford, U. K.
Mooley, D. A., and J. Shukla (1989), Main features of the westward-moving low pressure systems which form over the Indian region during the summer monsoon season and their relation to the monsoon rainfall, *Mausam*, *40*, 137–152.
Rajeevan, M., J. Bhate, and A. K. Jaswal (2008), Analysis of variability and trends of extreme rainfall events over India using 104 years of gridded daily rainfall data, *Geophys. Res. Lett.*, *35*, L18707, doi:10.1029/2008GL035143.
Riemann-Campe, K., K. Fraedrich, and F. Lunkeit (2008), Global climatology of Convective Available Potential Energy (CAPE) and Convective Inhibition (CIN) in ERA-40 reanalysis, *Atmos. Res.*, doi:10.1016/j.atmosres.2008.09.037, in press.
Rosenstein, M. T., J. C. James, and J. D. Carlo (1993), A practical method for calculating largest Lyapunov exponents from small data sets, *Physica D*, *65*, 117–134.
Shukla, J. (1978), CISK-barotropic-baroclinic instability and the growth of monsoon depressions, *J. Atmos. Sci.*, *35*, 495–508.
Shukla, J. (1989), Tropical forecasting: Predictability perspective, *Aust. Meteorol. Mag.*, *37*, 141–153.
Simmons, A. J., and A. Hollingsworth (2002), Some aspects of improvement of skill of numerical weather prediction, *Q. J. R. Meteorol. Soc.*, *128*, 647–677.
Simmons, A. J., R. Mureau, and P. Petroliagis (1995), Error growth and estimates of predictability from the ECMWF forecasting system, *Q. J. R. Meteorol. Soc.*, *121*, 1739–1772.
Takens, F. (1981), *Dynamical Systems and Turbulence, Warwick 1980*, edited by D. A. Rand and L.-S. Young, pp. 366–381, Springer, Berlin.
Trenberth, K. E., J. Fasullo, and L. Smith (2005), Trends and variability in column-integrated water vapor, *Clim. Dyn.*, *24*, 741–758.
Uppala, S. M., et al. (2005), The ERA-40 re-analysis, *Q. J. R. Meteorol. Soc.*, *131*, 2961–3012.
Wolf, A., J. B. Swift, H. L. Swinney, and J. A. Vastano (1985), Determining Lyapunov exponents from a time series, *Physica D*, *16*, 285–317.
Zeng, X., R. Eykholt, and R. A. Pielke (1991), Estimating the Lyapunov time series from the short time series of low precision, *Phys. Rev. Lett.*, *66*, 3229–3232.

B. N. Goswami, N. J. Mani, and E. Suhas, Indian Institute of Tropical Meteorology, Dr. Homi Bhabha Road, Pune, Maharastra 41008, India. (goswami@tropmet.res.in)