CONVECTIVE AVAILABLE POTENTIAL ENERGY VARIABILITY OVER INDIA

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***Abstract:** The convection developed due to temperature and moisture stratification in the atmosphere is main cause for precipitation and can be measured with Convective available potential energy (CAPE). Convection takes place before monsoon starts and as it is measured in CAPE reaches to maximum value at a place and after monsoon ends CAPE takes minimum value. In this way we have a cycle of convection over the year. There is variation in convection from station to station. In this study we have inspected dominant frequency components in CAPE for 15 meteorological station over India by applying EMD and Lomb-Scargle periodogram (LSP) algorithm for a period of 30 years (1987-2016) using Integrated Global Radiosonde Archive (IGRA) radiosonde data. We have observed significant variation in periodicity of convective activity for different stations. We have observed regional (3-4 months), semiannual (6 months), annual (12 months), quasi-biennial (20-35 months), ENSO (40-80 months), solar cycles (100-140 months), periodicities.*

***Key words:** CAPE, EMD, IMF, LSP*

1. Introduction

The convective available potential energy (CAPE) is one of the instability indices developed due to unstable lapse rate and moisture to measure atmospheric convection. Deep convection in the tropical atmosphere occurs due to the unstable lapse rate can be studied by CAPE. Environmental conditions also plays crucial role in the development of deep convention. Convection feed on the potential energy inherent in the temperature and moisture stratification, the so called CAPE resulting from lifting of the air mass due to thermal instability or some kind of dynamical mechanism. Apart from this there were several complex atmospheric and oceanic process evolving at different time scales might be involved. Globally there is indication of low frequency variability in CAPE reported by Riemann-Campe et al.(2009). Masatsuga and Youshiko (2007) shown that the influence of seasonal auto correlation can not be neglected in their analysis of seasonality of air temperature. Zhang and Chou (1999) studied variability of water vapor, infrared radiative cooling and atmospheric instability for deep convection in the equatorial western pacific. Several studies have been carried out on atmospheric stability indices using radiosonde data sets (Gettlemann et al., 2002). Using high resolution radiosonde data Alappattu and Kunhikrishnan (2009) estimated the CAPE and convective inhibition (CIN) during spring season over the oceanic region surrounding the Indian sub continent. Y.D.Shanti et al., (2014) reported diurnal variation in CAPE using cosmic GPS RO data over Gadanki. In this study we have implemented an adaptive and effective method to process and analyze nonlinear and non stationary data, called empirical mode decomposition (EMD) and found intrinsic mode function (IMF) and tried to give information of periodicity in convective activity in a year and different atmospheric oscillations. For each IMF Lomb-Scargle periodogram algorithm is applied to find the periodicity in a signal.

2. Data

The Integrated Global Radiosonde Archive (IGRA) consists of radiosonde and pilot balloon observations at over 2,700 globally distributed stations. The earliest data date back to 1905, and recent data become available in near real time. Observations are available at standard and variable pressure levels, fixed- and variable-height wind levels, and the surface and tropopause. Variables include pressure, temperature, geopotential height, relative humidity, dew point depression, wind direction and speed, and elapsed time since launch. Sounding-derived parameters are available for a subset of the soundings in IGRA. This subset includes soundings at fixed observing stations on land that contain temperature observations and a surface pressure level. The parameters include precipitable water between the surface and 500 hPa, the refractive index, vertical gradients of several variables, and various measures of boundary-layer characteristics and stability.

In this study we have taken CAPE data of 15 different meteorological stations over India for 30 years from 1987-2016, calculated monthly mean. For this mean values we have applied to EMD and found 7-8 IMFs. For each IMF, LSP is applied and found dominant periodicity.

3. Methodology

CAPE is the positive buoyancy of an air parcel and is an indicator of atmospheric instability which is useful in predicting severe weather. CAPE is expressed in J/kg and it provides energy to lift the parcel from level of free convection (LFC) to environmental level (EL). CAPE is given by the equation 1,

$$\mathrm{CAPE} = \int_{\mathrm{EL}}^{\mathrm{LFC}} g\left(\frac{T_p - T_e}{T_e}\right) ------(1)$$

Where Tp is parcel temperature and Te is environmental temperature, g is acceleration due to gravity. As the CAPE data is directly available every day at 00z and 12z UTC in the above mentioned site, the data is collected and missing data is interpolated linearly. Yearly and monthly mean is calculated for the duration.

Empirical mode decomposition (EMD) is an adaptive and data driven multi resolution technique in which multi component wave form is resolved into several components without leaving the time domain. These components referred to as intrinsic mode function (IMF) are expected to be single component in nature. The function IMF is therefore sufficient to describe the signal even though they are not necessarily orthogonal. The reasons are given in Huang et al. for some special data the neighboring components could certainly have sections of data carrying same frequency at different time durations but locally any two components should be orthogonal for all practical purposes.

***The EMD steps are*:**

1. Identify local maxima and minima of a signal x(t).
2. Perform cubic spline interpolation between maximum and minimum to obtain envelops emax(t) and emin(t) and find mean m(t)= (emax(t) + emin(t))/2.
3. Extract intrinsic mode function (IMF), C1(t) = S (t) – m (t).
4. If the number of local extrema of C1 is equal to or differs from the number of zero crossing by one, and the average of C1 reasonably zero. If C1 is not IMF then repeat steps 1 to 3 on C1 instead of S(t) until C1 obtained satisfies the condition of an IMF.
5. Compute the residue r1= S(t) – C(t), if the residue is above a threshold value of error tolerance then repeat steps 1 to 4 on r1 to obtain IMF and a new residue.

The first IMF consists of highest frequency components of information. The subsequent IMFs contain lower frequencies. If n orthogonal IMFs are obtained in this iterative process the original may be reconstructed as $S(t) = \sum_{i=1}^{N} \mathrm{Ci}(t) + r(t)$

The final residue exhibits any general trends followed by the original. For each IMF obtained LSP algorithm is applied to find the frequency components.

Generally periodograms identify periodicity of a time series signal applying Fourier or least square fitting method. The Lomb-Scargle periodogram is a mathematical tool to find spectral analysis of a time series of unknown periodicities. It is based on least squares technique developed by Lomb and Scargle. In this study we have applied LSP as it has more advantages than other. It is faster as it will not depend on NFFT algorithm and weights unevenly sampled data. LSP provides optimal statistics and detects false alarm probability to asses the significance of a signal with noise

Power spectral Density (PSD) of LSP:

Let us consider N data points Xi= Xi(t) collected at times ti where i=1,2,…N, and its mean is Xm. PSD of LSP is given as

$$\mathrm{PN}(\omega) = \frac{1}{2\sigma^2}\left\{\frac{\left[\sum_i (X_i - X_m)\cos\omega(\mathrm{t_i} - \tau)\right]^2}{\sum_i cos^2\omega(\mathrm{t_i} - \tau)} + \frac{\left[\sum_i (X_i - X_m)\sin\omega(\mathrm{t_i} - \tau)\right]^2}{\sum_i sin^2\omega(\mathrm{t_i} - \tau)}\right\} - - - 2$$

Where tau τ is defined as

$$\tau = \left(\frac{1}{2\omega}\right)\tan^{-1}\left[\frac{\sum_i \sin 2\omega(\mathrm{t_i})}{\sum_i \cos 2\omega(\mathrm{t_i})}\right]$$

PN gives the normalized power as a function of angular frequency (ω=2π/P) for all periods (P) tested (Lomb, 1976; Scargle, 1982). The periods were restricted to T= tmax –tmin.

The false alarm probability (p) in LSP is given by

$$p(PNmax) = 1 - (1 - e^{-PNmax})^M - - - - 3$$

Where the variable M depends on the number of data points, their spacing and on the number of independent frequencies tested (Scargle, 1982). In general M can be set equal to N provided that only periods longer than twice the average sampling interval are investigated.

4. Results and discussion:

Monthly mean of CAPE of 15 different meteorological stations over India is shown in Fig A below. On average CAPE varies between 2000 to 4000 J/kg for all stations and it is shown for few southern stations of India in fig B.

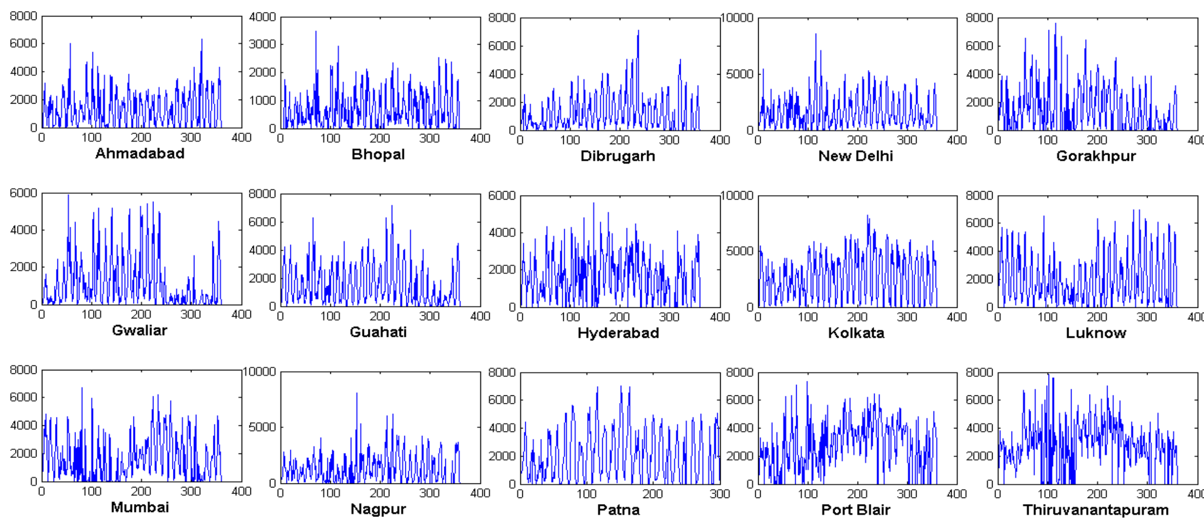

Fig A: Monthly mean of CAPE of 15 meteorological stations over India

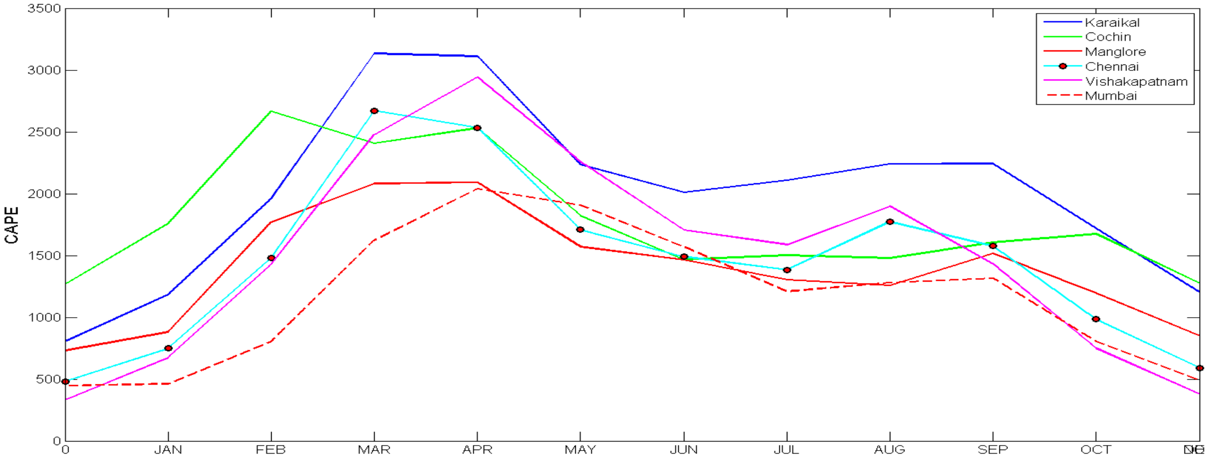

Fig B : Monthly mean CAPE for the years 1980 to 2017

For these mean values we have applied to EMD algorithm and found 7-8 IMFs. On applying LSP for each we found dominant period for each station at 95% significance level. Each period describes regional, semiannual, annual, quasi-biennial, ENSO, solar cycles as shown from figures 1 to 15. The dominant periods of 15 stations are noted in Table 1. It is observed that the first IMFs of all stations show semi annual oscillation having 6 months, where as Dibrugarh, Ahmadabad and Hyderabad show regional oscillations having 3-4 months. Second IMFs LSP show 12 months periods indicate annual oscillations. Third and fourth IMFs LSP show 20-40 months periods indicate quasi-biennial oscillations, fourth and fifth IMFs LSP show 40-80 and 100-140months periods indicate ENSO and solar cycles. The sixth and seventh IMFs LSP show trends indicating increasing or decreasing CAPE. Few stations Luknow, Mumbai, Ahmadabad, and Thiruvanantapuram show increasing trend and the remaining stations show decreasing trend.

Table 1

S.No	Station	Dominant Periods in Months						
	IMFs	1	2	3	4	5	6	7
1	NEW DELHI	6	12	18	59	122	251	
2	PATNA	6	12	38	68	122	269	
3	LUCKNOW	6	12	15	38	86	256	
4	GORAKHPUR	6	12	12	30	58	162	
5	GWALIOR	6	12	18	31	80	145	
6	DIBRUGARH	4	12	12	31	104	162	
7	GUWAHATI	6	12	51	65	117	270	
8	KOLKATA	4	12	15	60	93	155	
9	BHOPAL	6,40	12	12	24	53	112	
10	NAGPUR	9	12	12	27	57	72	182
11	BOMBAY	6	12	12	25	56	231	
12	AHMADABAD	4	12	12	39	57	120	
13	HYDERABAD	3,6	12	21	30	56	256	
14	THIRUVANANTHAPURA M	6	6	12	47	56	236	321
15	PORT BLAIR	6	12	12	36	57	253	

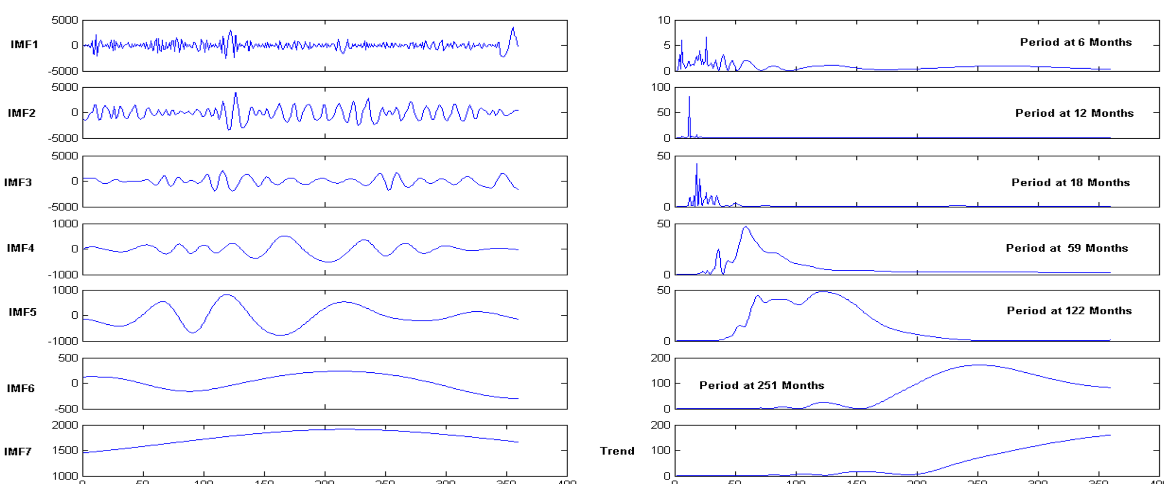

Fig1: IMFs of CAPE of New Delhi and their corresponding LSPs Periods,

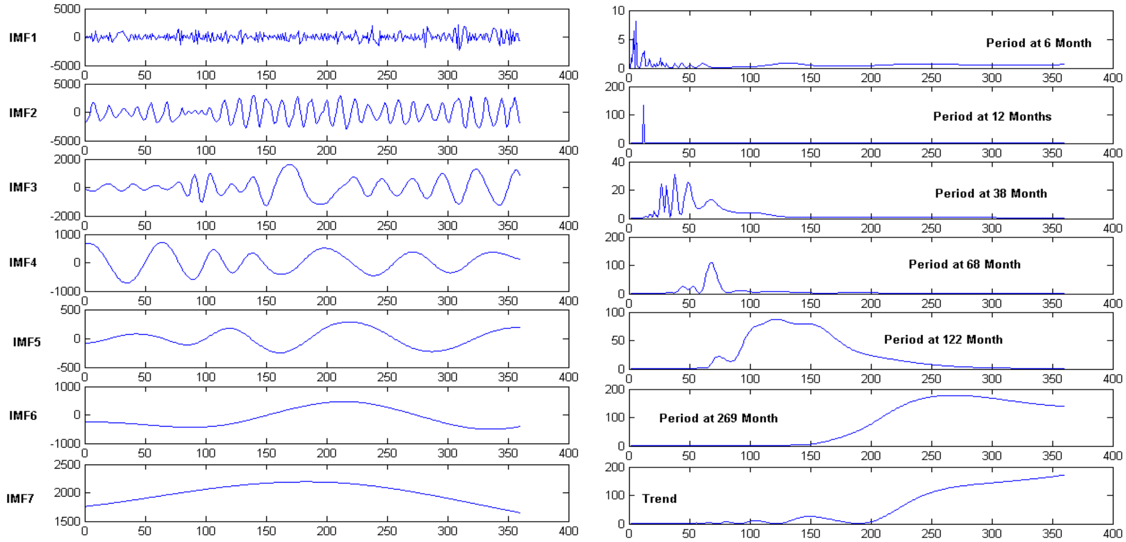

Fig2: IMFs of CAPE of Patna and their corresponding LSPs Periods

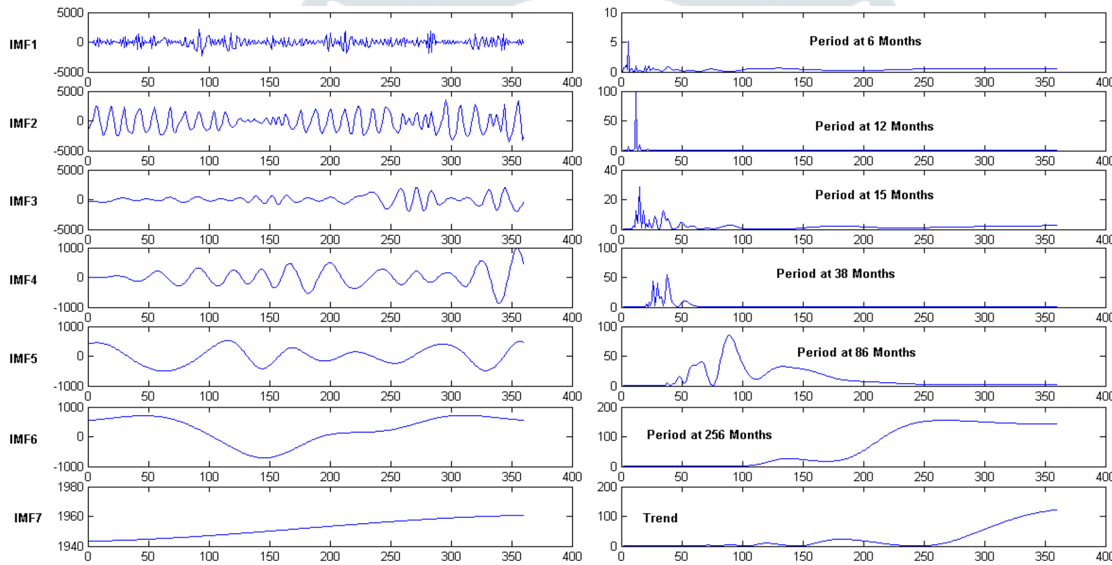

Fig3: IMFs of CAPE of Luknow and their corresponding LSPs Periods

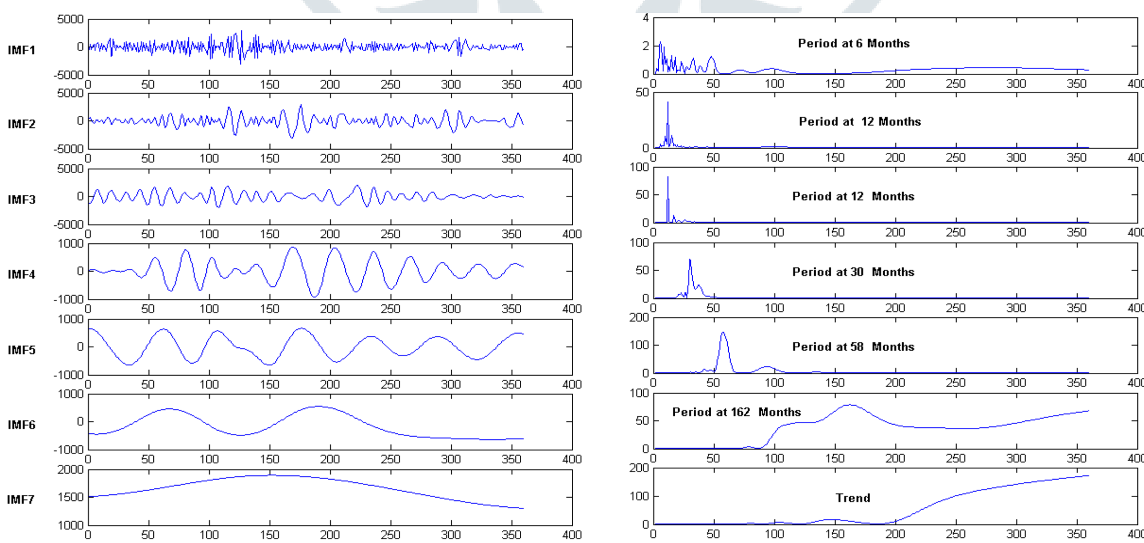

Fig4: IMFs of CAPE of Gorakhpur and their corresponding LSPs Periods,

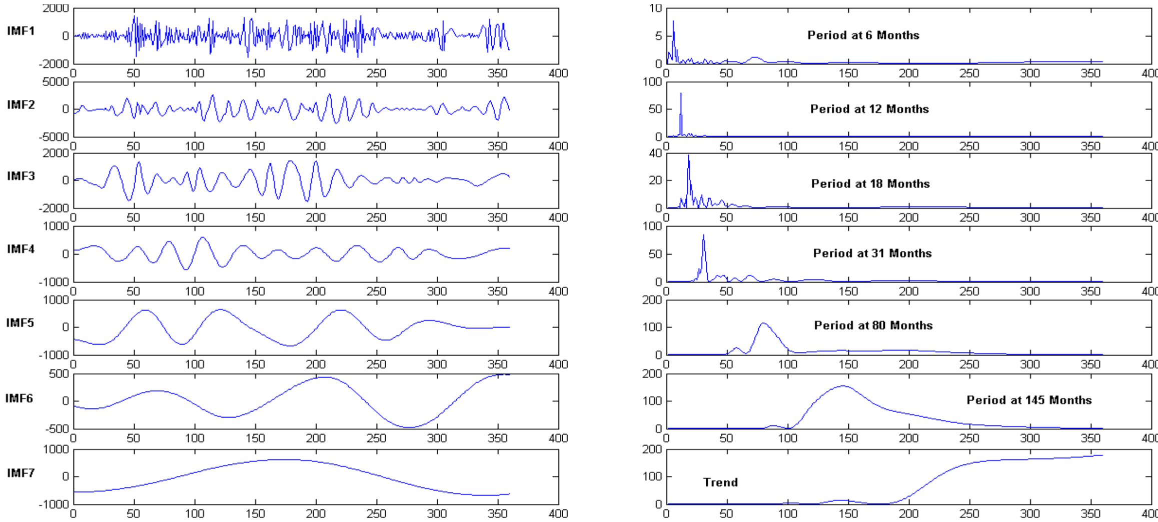

Fig5: IMFs of CAPE of Gwaliar and their corresponding LSPs Periods,

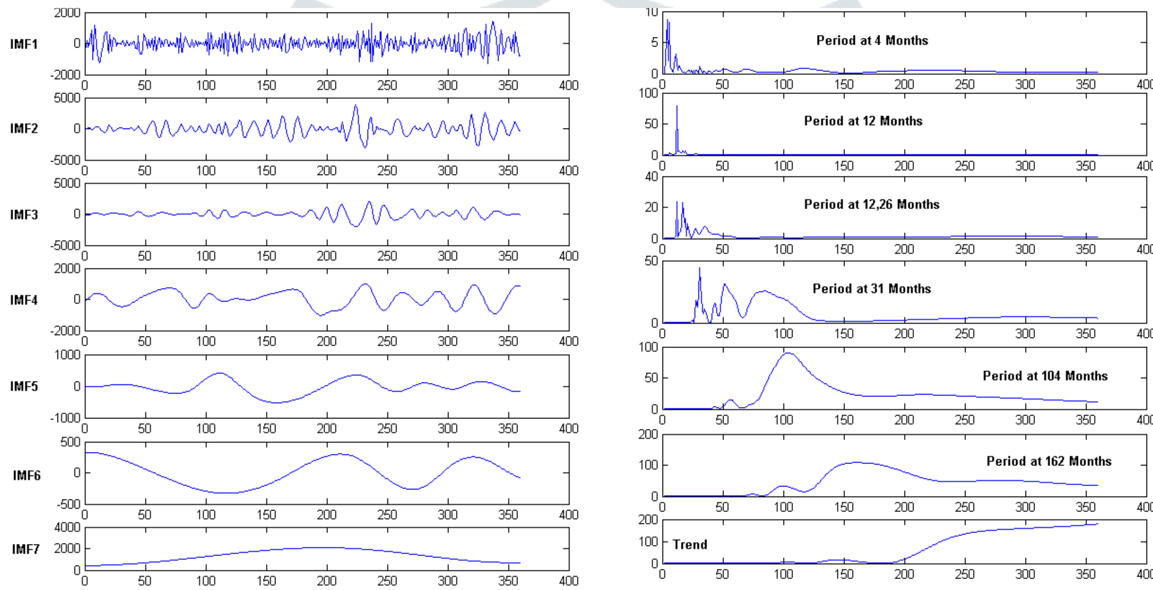

Fig6: IMFs of CAPE of Dibrugarh and their corresponding LSPs Periods,

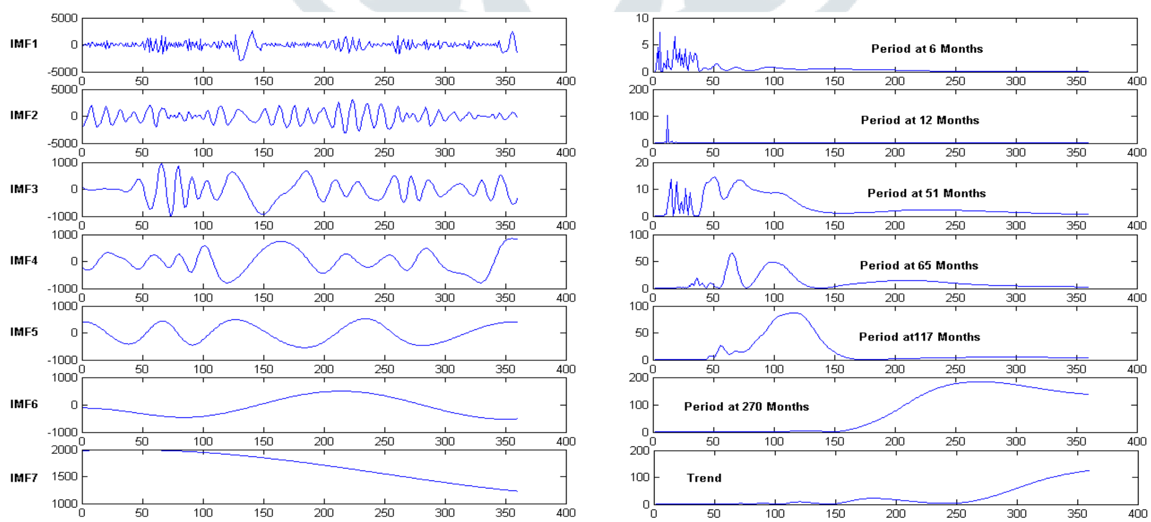

Fig7: IMFs of CAPE of Guahati and their corresponding LSPs Periods,

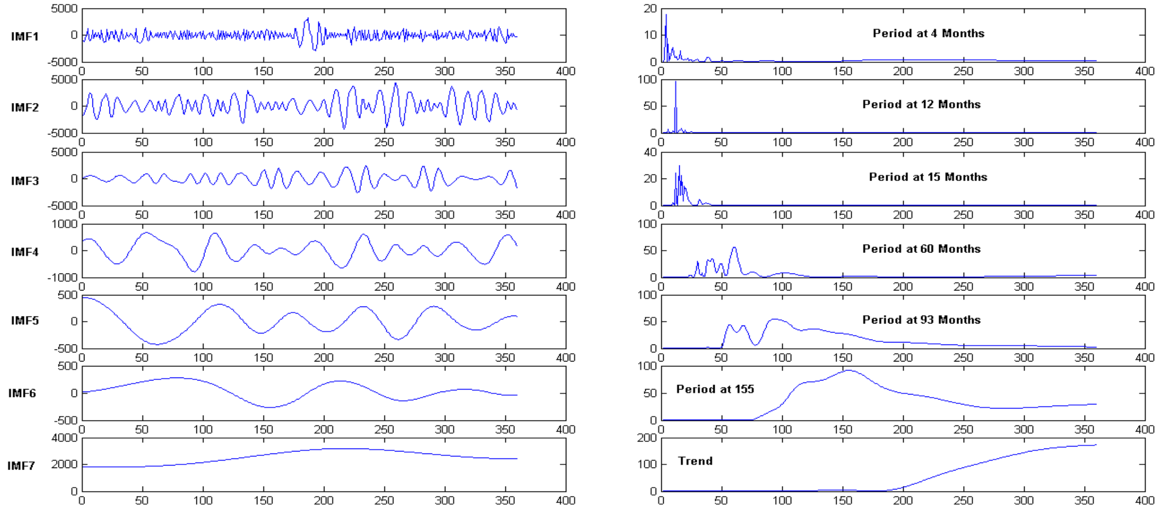

Fig8: IMFs of CAPE of Kolkota and their corresponding LSPs Periods,

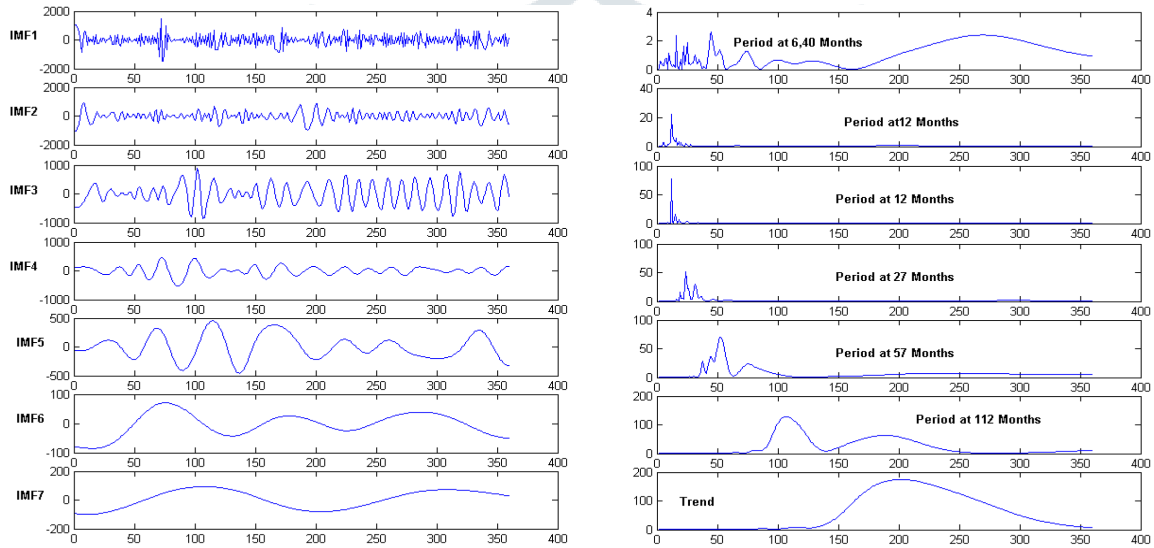

Fig9: IMFs of CAPE of Bhopal and their corresponding LSPs Periods,

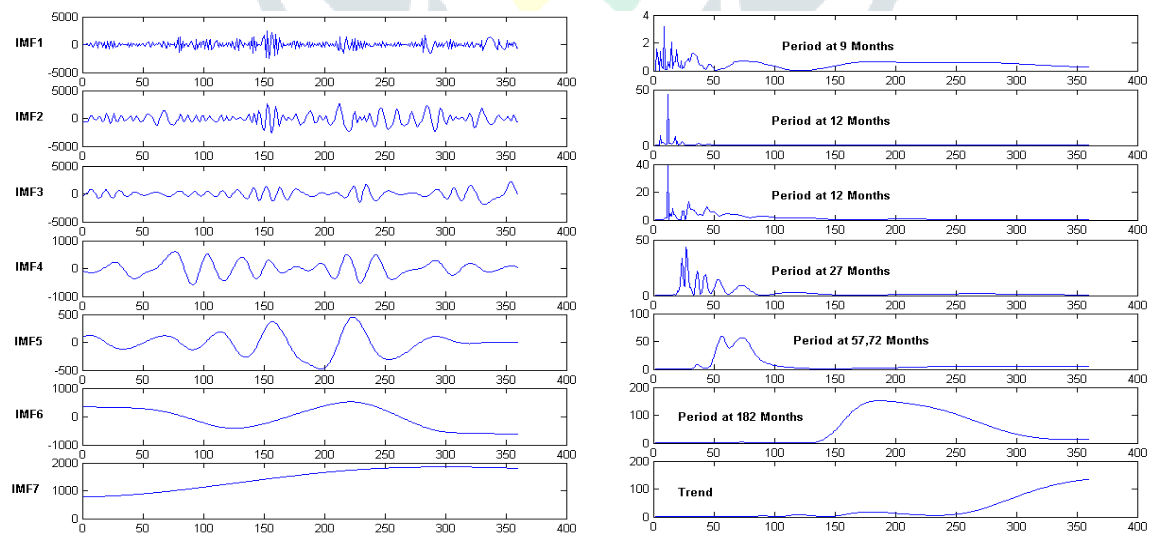

Fig10: IMFs of CAPE of Nagpur and their corresponding LSPs Periods,

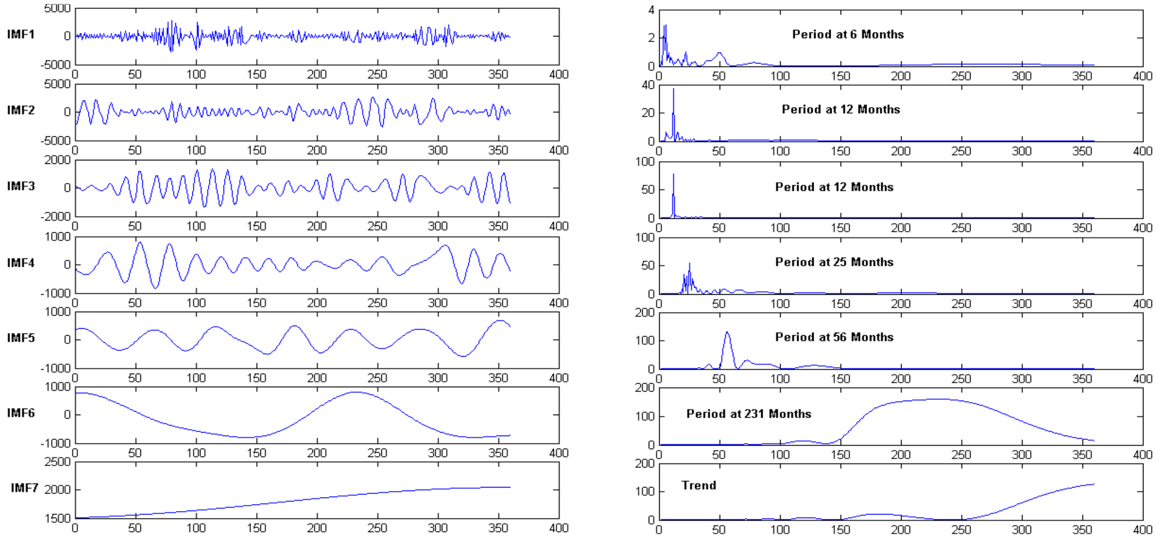

Fig11: IMFs of CAPE of Mumbai and their corresponding LSPs Periods,

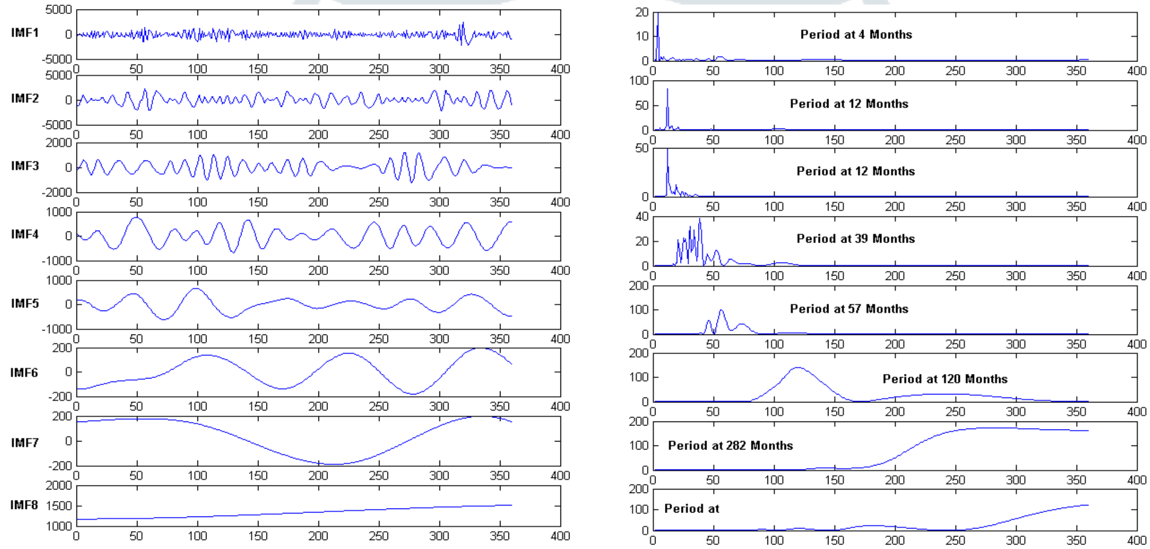

Fig12: IMFs of CAPE of Ahmadabad and their corresponding LSPs Periods,

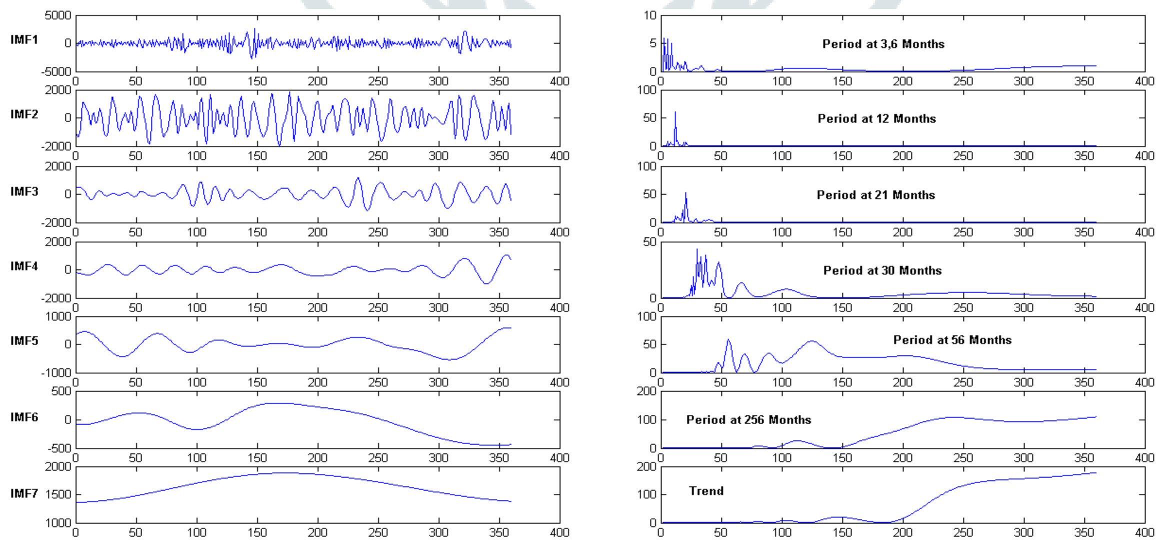

Fig13: IMFs of CAPE of Hyderabad and their corresponding LSPs Periods,

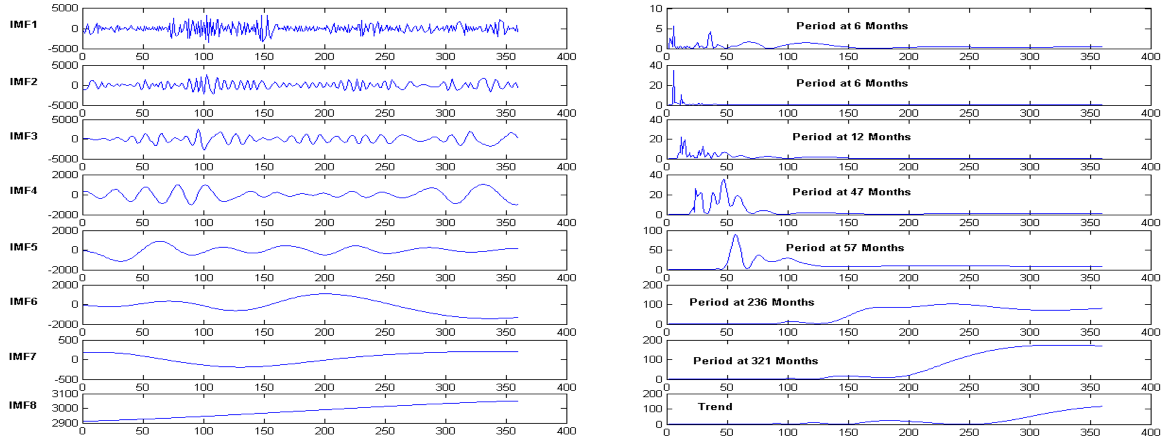

Fig14: IMFs of CAPE of Tiruvanantapuram and their corresponding LSPs Periods,

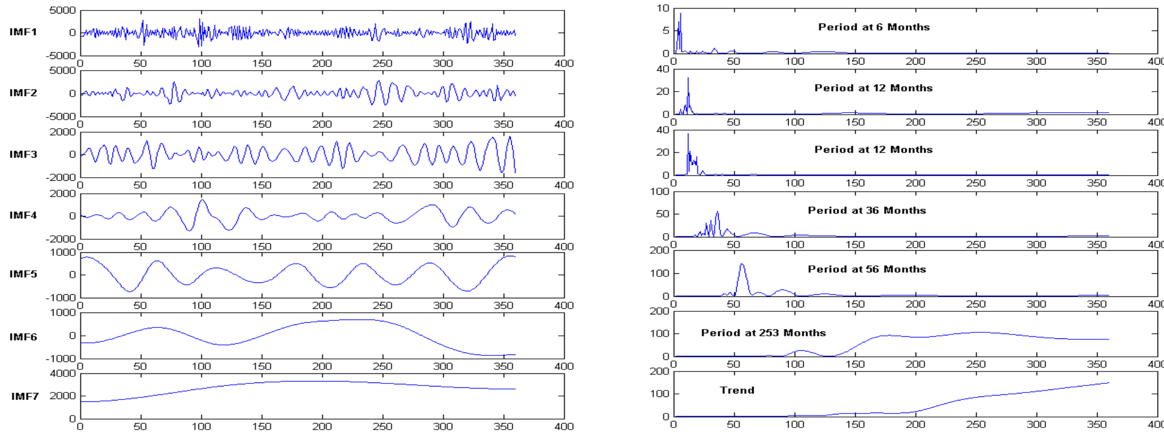

Fig15: IMFs of CAPE of Port Blair and their corresponding LSPs Periods,

Conclusions:

CAPE is one of the indices to measure the stability of atmosphere. In this paper we have used 30 years of CAPE data over India and found the different dominant modes of atmospheric oscillations. The dominant periodicities observed ranging from regional, semiannual, annual, quasi biennial and solar activity oscillations. Using EMD and LSP algorithm we could also detect the trend of CAPE.

5. Acknowledgement

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7. References

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