



Trend Analysis of Rainfall in Southern Kerala based on Empirical Mode Decomposition

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Abstract: This study proposes an alternative approach for estimating the short term trend of rainfall southern Kerala, India using Empirical Mode Decomposition (EMD). The annual, monsoon and post-monsoon rainfall data for the recent 30 year period (1983-2012) from 8 stations pertaining to four southern Kerala districts were temporally decomposed and the trend components were extracted. The results were compared with the classical linear trend fitting and traditional Sen's slope and Mann-Kendall statistics. EMD is successful in capturing inherent non-linear trend of dataset, which cannot be estimated by the traditional approaches. The study showed a consistently increasing trend of annual, monsoon and post-monsoon rainfall at Cherthala station. Monsoon rainfall records of all stations except Cherthala showed a decreasing trend, while post-monsoon rainfall of 5 stations showed an increasing trend and annual rainfall of three stations showed a decreasing trend. The EMD method also depicts the specific shape of trend which is successful in capturing the recent change points of inherent trend in different datasets. EMD based decomposition showed major reduction of annual and post-monsoon rainfall from Alappuzha station and that in post-monsoon rainfall of Kollam and Thiruvalla stations since 2000 (~). The present study gives broad inferences on changing climate of southern Kerala in the recent past.

Keywords: Empirical Mode Decomposition, Kerala, Rainfall, Trend

1. Introduction

Trend analysis of rainfall has been of great concern in the recent past among the scientific community because of the recent evidences of global climate change. Trend analysis can help in better understanding of the changing pattern of the prominent climatic variables in a river basin or geographical region of interest. Precipitation is a key component of the hydrologic cycle and changes in its pattern would directly influence the water resources of a region, as it affects streamflow, soil moisture, and groundwater reserves [1, 2]. Thus, clear understanding of the spatial and temporal distribution of rainfall and its changing patterns will lead to a better planning and management of water resources in a region. Rainfall pattern of Kerala meteorological subdivision - which is known as the gateway of Indian summer monsoon - has attracted many researchers in the past. The principal rainy seasons in Kerala are the southwest monsoon (June–September) and the north-east monsoon (October–December). The pre-monsoon months (March–May) are characterized by major thunderstorm activity in the region, and the winter months (January–February) are marked by low clouding and low rainfall.

A number of studies were conducted to detect the trends of hydro-climatic variables in different parts of India. For example, Guhathakurtha and Rajeevan [3] used the linear regression analysis, while Kumar *et al.*, [4] used non-parametric Mann Kendall (MK test)

for trend analysis of rainfall at sub-divisional scale. In the past, few studies evaluated in spatial and temporal trends in rainfall of Kerala [5-10], following different approaches. Simon and Mohankumar [8] studied spatial variability in the occurrence of rainfall in the Kerala by using multi-variate statistical approach and noted that the spatial variability is significantly influenced by the physiography of the region. Pal and Al-Tabbaa [11, 12] performed rigorous trend analysis of Kerala subdivision using fine resolution rainfall data at a gridded scale. Raj and Azeez [13] performed a trend detection study for rainfall at the Bharathapuzha basin in Kerala using traditional linear regression, t - test and wavelets. Jagadeesh and Anupama [14] used Mann-Kendall Test, Sen's slope and linear fitting for trend and statistical analysis of annual and seasonal total rainfall over the above basin.

Recently, Adarsh and Janga Reddy [15] applied non-parametric methods like MK test and Sen's slope for estimation of trend of rainfall in four meteorological subdivisions in southern India. Moreover they reported a statistically significant increasing trend in post-monsoon rainfall of Kerala subdivision. They applied the Sequential Mann Kendall test for identifying the changing pattern of trend in post-monsoon rainfall of Kerala and applied Discrete Wavelet Transform for finding the dominant periodic component in deciding the trend of post-monsoon rainfall of Kerala subdivision.

Sonali and Nagesh Kumar [16] reviewed different methods available for trend analysis. In general, the magnitude of trend is determined by using a non-parametric method known as Sen's slope estimator [17] and statistical significance of the trend in the time series was analyzed by using Mann-Kendall (MK) test [18,19]. Even though Mann-Kendall and Sen's slope estimators are still the most popular trend detection methods, it is reported that the length of the dataset can significantly influence the trend [20]. Therefore Sang *et al.*, [20] proposed an alternative trend analysis method based on Empirical Mode Decomposition (EMD). They demonstrated the applicability of EMD by applying the method both for synthetic series and real field datasets of rainfall and runoff. EMD method is reported to be much efficient than classical approaches for estimation of trend in data sets of shorter length, which may be often masked by the classical MK-Sen's slope methods. However apart from the above study, the method is not yet applied for identification of short term trend of real field hydrologic data from any other part of the world. In the present study, EMD is used for analyzing the short term trends of annual rainfall and principal seasonal rainfalls (monsoon and post-monsoon) in Southern Kerala.

In the following section, the details of EMD are presented. Brief details of data used in this study are given in Section 3. Afterwards, the results of the trend analysis are discussed in Section 4. Finally, the conclusions of the study are summarized in Section 5.

2. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) is a signal decomposition method proposed by Huang *et al.*, [21], which decomposes a time series signal into different oscillatory modes having specific periodicity in purely empirical and data adaptive manner.

The different steps involved in the process are:

- (1) Identify all extrema (maxima and minima) of the signal $X(t)$
- (2) Connect these maxima with any interpolation function (for example, cubic spline) to construct an upper envelope ($E_{\max}(t)$); use the same procedure for minima to construct a lower envelope ($E_{\min}(t)$)
- (3) Compute the mean of the upper and lower envelope, $m(t)$
- (4) Calculate the difference time series $d(t) = X(t) - m(t)$
- (5) Let $d(t)$ be the new signal and repeat steps (1) to (4) until $d(t)$ becomes a zero-mean series with no riding waves (i.e., there are no negative local maxima and positive local minima) with smoothed amplitudes. Such an oscillatory signal is called an Intrinsic Mode Function (IMF). To satisfy step (5), an appropriate criterion is to be applied to stop the sifting iterations in order to guarantee that the IMF

retains enough physical sense of both amplitude and frequency modulations [22]. A number of stopping criteria have been reported in the literature and the popular modified Cauchy type stopping criterion [22] computed from two consecutive sifting results as:

$$\frac{\sum_{t=0}^T |d_{k,i-1}(t) - d_{ki}(t)|^2}{\sum_{t=0}^T |d_{k,i-1}(t)|^2} \leq \xi \quad (1)$$

Where, 'k' is the index for IMF; 'i' is the index for iteration for the sifting operation (to get k^{th} IMF); T is the data length; $d_{k,i}(t)$ is the deviation of the original time series from the mean in the i^{th} iteration to evolve the k^{th} IMF; ' ξ ' is the tolerance value specified by the user (normally, 0.2-0.3 as suggested in [22]).

- (6) On satisfying the zero-mean condition, $d(t)$ can be designated as the first intrinsic mode function IMF1
- (7) Compute the residue $RI(t)$ by subtracting IMF1 from original signal (i.e., $RI(t) = X(t) - IMF1(t)$) is used as new signal. The 'sifting' process is repeated upon this signal to get IMF2.
- (8) The higher oscillatory modes are obtained by treating the residue ($R_k(t)$) as the signal ($X(t)$), iteratively.

The k^{th} residue is defined as

$$R_k(t) = X(t) - \sum_{j=1}^k IMF_j(t) \quad (2)$$

The process will be continued till the resulting residue is a monotonic function or a function having only one extrema. The above process of extracting the IMFs from a time series $X(t)$ is called as 'sifting' process. The final component is called 'Residue' which indicates the long term inherent trend within the time series.

Then the original signal can be reconstructed as

$$X(t) = \sum_{k=1}^K [IMF_k(t)] + R_K(t) \quad (3)$$

where, K is the number of decomposed IMFs.

3. Study Area and Data

This study considers rainfall data from 8 meteorological stations, pertaining to four districts in southern Kerala. Monthly data of these stations for the period 1983-2012 were collected from IMD Trivandrum (<http://www.imdtvm.gov.in/>), for all stations except Thiruvalla. For Thiruvalla station, data for the period 1983-2010 only was available. The basic statistical properties (SP) such as Maximum (Max), Minimum (Min) Average (Avg), and % of Average Annual rainfall (AAR) of Annual (A), Monsoon (M) and Post-monsoon (PM) stations are

provided in Table 1. It is noticed that in all stations, more than 75 % of rainfall is contributed in these two seasons.

Table 1 Statistical properties of dataset

SP	Thiruvananthapuram			Nedumangadu		
	A	M	PM	A	M	PM
Avg	1750	792.77	560.77	1915	831.92	639.15
Max	2291	1319.1	1003.6	2567	1296.3	1134.7
Min	1193	338.20	226.90	477.2	236.50	115.00
% AAR	100	45.30	32.04	100	43.44	33.38
SP	Kollam			Punalur		
	A	M	PM	A	M	PM
Avg	2187	1190.2	548.86	2661	1350.8	709.55
Max	3065	1958.4	1063.0	3563	1762.7	1221.0
Min	1526	661.20	225.30	1769	883.40	208.80
% AAR	100	54.41	25.09	100	50.75	26.66
SP	Thiruvalla			Kayamkulam		
	A	M	PM	A	M	PM
Avg	2561.	1579.2	573.86	2567	1556.8	534.37
Max	3321	2300.7	1109.0	3749.	2252.4	1026.1
Min	1777	942.70	292.40	1724	1012.0	192.20
% AAR	100	61.65	22.4	100	60.64	20.8
SP	Alappuzha			Cherthala		
	AI	M	PM	A	M	PM
Avg	2816.	1714.2	565.71	2567	1592.1	463.79
Max	3339	2473.0	1046.2	3749	2270.4	884.90
Min	1725	1104.6	173.00	1724	914.90	120.70
% AAR	100	60.68	20.09	100	63.94	18.62

4. Results and Discussion

Annual rainfall time series of all the stations were decomposed into several IMF components by the EMD method. The number of modes produced for each case differs, as it depends both on the data length and complexity [23]. The number of IMFs for most of the stations varied between 3-5, except for Alappuzha and Cherthala stations, where 2 IMFs and residue were resulted by the decomposition. The decomposition for Monsoon and Post-monsoon rainfall time series of each station is also performed. The residue component (which represent the trend) along with annual time series of different station are presented in Figure 1. To comment on the significance of trend, statistical significance test (SST) of IMF components [24, 25] is performed (at 5% significance level) for the annual time series pertaining to different stations. The test is based on the postulate that the summation of logarithmic values of mean normalized energy and mean period of an IMF is zero. This test compares the spectral energy and the mean period relation between the IMFs of original signal and white noise. If the IMF energy of the observed data with a certain mean period is located above the specified confidence level, the corresponding IMF is considered as statistically significant at the given level. Basically it involves (i) the computation of energy density of IMFs and its normalization by considering first IMF as the

reference IMF;(ii) generation of white noise series by Monte Carlo simulations, its EMD and computation of the 'spread function'; (iii) estimation of the confidence band of spread function of white noise at a selected significance level, based on step (ii). Then the points having coordinates of mean normalized energy and mean period of IMFs are located in the 2D plane. This enables a comparison of the energy level of different IMFs with the spread function of white noise. The IMFs of original time series $X(t)$ that have their energy densities located above the upper confidence line of the white noise series can be considered to be statistically significant at the selected confidence level. More details on this test can be found elsewhere [19, 24, 25]. The results of SST of annual rainfall series from different stations are presented in Figure 2. Figure 2 clearly indicate that the trend component of all-time series passes the statistical significance test. Further, the Sen's slope estimator and MK and were used to estimate the behavior of trend and its statistical significance. The algorithm of these popular trend estimation methods can be found in literature [11,15,16]. The results of these tests are presented in Table 2. Moreover, linear trend of different annual time series were estimated and presented along with the respective time series, to enable a comparison with the EMD based estimates of non-linear trend.

The linear trend analysis captures the linear trend in the dataset, while most of the hydro-climatic time series possess non-linear trend [26-28]. Hence it is worthwhile to extract the true non-linear trend from the rainfall time series. Figure 1 shows that for the time series from Kollam and Thiruvalla stations, the actual non-linear trend is decreasing, while the linear trend analysis show an increasing behavior. Moreover, rainfall from some of the stations (Thiruvananthapuram, Nedumangadu, Alappuzha) show a reduction in rainfall in the past decade (since 2000), which cannot be captured by the linear trend fitting exercise. Table 2 shows the statistically significant trend only for rainfall from Cherthala station. But the SST suggests that the trend is to be monitored carefully.

EMD based non-linear trend and the linear trend estimates of monsoon and post-monsoon rainfall time series from different stations are presented in Figure 3 and Figure 4 respectively. Here also the SST is conducted and found that the rainfall trends pass the SST. For brevity the figures are not presented here. Figure 3 show that the monsoon rainfall of all stations except Cherthala showed a reducing trend. As EMD picturize the non-linear trend, EMD method also possesses an additional advantage that it can give information on the change point of trend. The results of post-monsoon rainfall (Figure 4) showed that 5 out of 8 stations show increase in post-monsoon rainfall while a noticeable reduction of post-monsoon rainfall

record of Kollam, Thiruvalla and Alappuzha stations in the recent past.

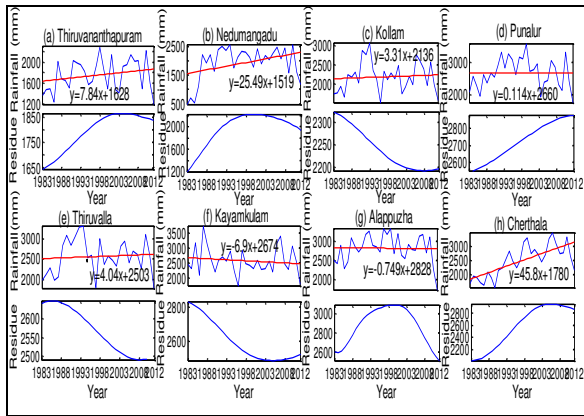


Figure 1 Results of trend analysis of annual rainfall from eight stations by EMD along with linear trend fit. For each station, the upper panels show the rainfall time series and linear fit, while lower panel show the non-linear trend extracted by EMD

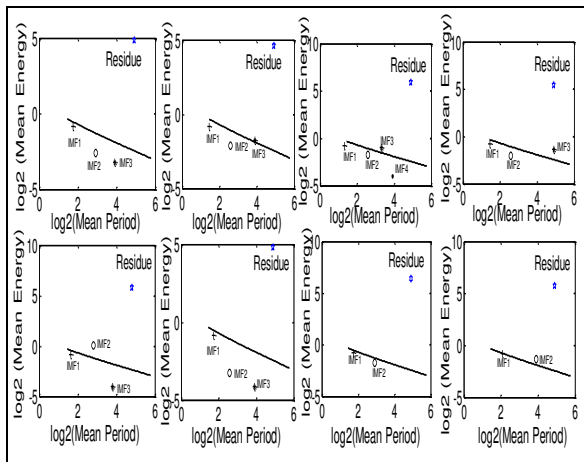


Figure 2 Statistical significance test of IMF components and residue of annual rainfall time series from different stations. The solid line represents upper confidence line of white noise series at 95 % confidence level

Table 2 MK and Sen's slope values of annual and seasonal rainfall time series from different stations. The bold figure indicate that the trend is significant

Station	Annual		Monsoon		Post-monsoon	
	MK Value	Sen's slope	MK Value	Sen's slope	MK Value	Sen's slope
Thiruvananthapuram	1.32	10.16	-0.36	-2.31	1.97	10.07
Nedumangadu	1.25	16.42	-0.07	-0.80	1.99	12.87
Kollam	0.53	7.89	-0.96	-5.75	1.17	4.84
Punalur	0.29	3.40	-1.43	-10.9	0.46	3.52
Thiruvalla	0.41	5.96	-0.29	2.43	1.00	5.28
Kayamkulam	-0.73	-5.31	-2.48	-21.1	1.27	5.92
Alappuzha	0.32	2.05	-1.46	-13.1	1.49	6.89
Cherthala	4.07	49.26	2.78	21.19	2.74	13.77

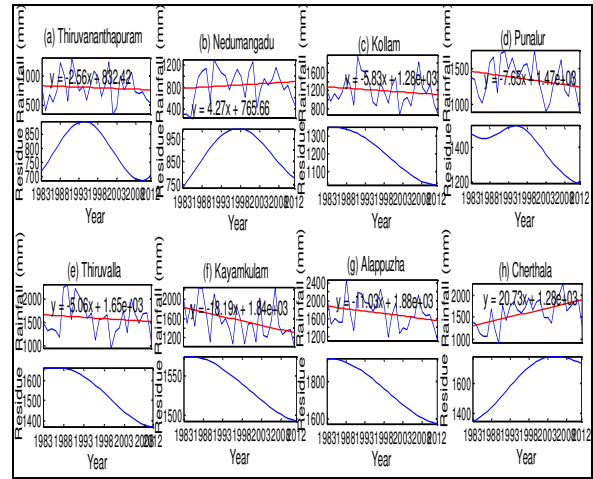


Figure 3 Results of trend analysis of monsoon rainfall from eight stations by EMD along with linear trend fit. For each station, the upper panels show the rainfall time series and linear fit, while lower panel show the non-linear trend extracted by EMD

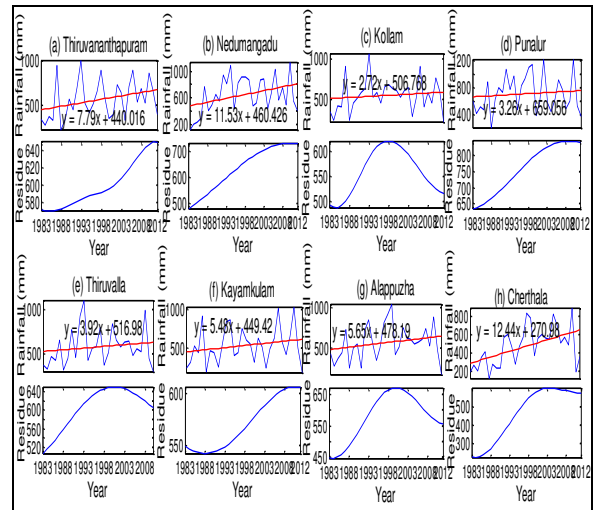


Figure 4 Results of trend analysis of post-monsoon rainfall from eight stations by EMD along with linear trend fit. For each station, the upper panels show the rainfall time series and linear fit, while lower panel show the non-linear trend extracted by EMD

Analysis for Monsoon rainfall show that the rainfall records from Kayamkulam station show a significant reduction, while that of Cherthala station show a significant increase. But both stations are located respectively at southern and northern part of Alappuzha district. This infers the role of spatial variability in rainfall trend and it clearly demonstrate the importance of station wide/grid wise analysis of hydro-meteorological studies

The EMD method is superior in trend analysis of hydro meteorological variables, as it provides information of non-linear trend, along with its change point and statistical significance of trend. The present study gives broad inferences of changing climate of southern Kerala. The study provides a background for hydrologic data generation, detailed investigations on

climate change, framing adaptation policies and hence it may help for overall management of water resources of Southern Kerala.

5. Conclusions

This study applied EMD for detection of non-linear trend of annual and two major seasonal rainfalls (monsoon and post-monsoon) in southern Kerala. EMD is found to be successful in capturing the non-linear trend cannot be extracted by the linear fitting or MK-Sen's slope estimators. EMD analysis showed that the annual, monsoon and post-monsoon rainfall of Cherthala station show a statistically increasing trend. Overall, the monsoon rainfall of Southern Kerala show a statistically significant reduction and post-monsoon rainfall show an increase.

The anomalous changes in rainfall in the recent past (~since 2000) are successfully captured by EMD, as it also gives the specific shape of inherent non-linear trend in the datasets. The EMD based decomposition showed major reduction of annual and post-monsoon rainfall from Alappuzha station and that in post-monsoon rainfall of Kollam and Thiruvalla stations since 2000 (~). The present study is helpful in hydrologic data generation and climate change related studies pertaining to Southern Kerala.

References

- [1] S.K. Jain, V. Kumar and M. Saharia, "Analysis of rainfall and temperature trends in north-east India", *International Journal of Climatology*, 33.4., 968-978., 2013.
- [2] S.K. Jain and V. Kumar, "Trend analysis of rainfall and temperature data for India-A Review", *Current Science*, 102.1., 37-49., 2012.
- [3] P. Guhathakurta and M. Rajeevan, "Trends in the rainfall pattern over India", *International Journal of Climatology*, 28.11., 1453-1469., 2007.
- [4] V. Kumar, S.K. Jain and Y. Singh, "Analysis of long-term rainfall trends in India", *Hydrological Sciences Journal*, 55.4., 484-496., 2010.
- [5] M.R. Soman, K. Krishnakumar and N. Singh, "Decreasing trend in the rainfall of Kerala", *Current Science*, 57.3, 7-12., 1988.
- [6] P.V. Joseph, A. Simon, V.G. Nair and A. Thomas, "Intra-Seasonal Oscillation (ISO) of south Kerala rainfall during the summer monsoons of 1901-1995", *Proceedings of Indian Academy of Science (Earth and Planetary Science Letters)*, 113.2., 139-150., 2004.
- [7] P. Guhathakurtha, "Long-range monsoon rainfall prediction of 2005 for the districts and subdivision Kerala with artificial neural network", *Current Science*, 90.6, 773-77., 2005.
- [8] A. Simon and K. Mohankumar, "Spatial variability and rainfall characteristics of Kerala", *Proceedings of Indian Academy of Science (Earth and Planetary Science)*, 113.2., 211-221., 2004.
- [9] K.N. Krishnakumar, G.S.L.H.V.P. Rao and C.S. Gopakumar, "Rainfall trends in twentieth century over Kerala, India", *Atmospheric Environment*, 43., 1940-1944., 2009.
- [10] A. Nair, K.A. Joseph and K.S. Nair, "Spatio-temporal analysis of rainfall trends over a maritime state (Kerala) of India during the last 100 years", *Atmospheric Environment*, 88., 123-132., 2014.
- [11] I. Pal and A. Al-Tabbaa, "Trends in seasonal precipitation extremes-An indicator of climate change in Kerala, India", *Journal of Hydrology*, 367., 62-69., 2009.
- [12] I. Pal and A. Al-Tabbaa, "Monsoon rainfall extreme indices and tendencies in Kerala, India for 1954-2003", *Climatic Change*, 106.3, 407-419., 2011.
- [13] P.P.N. Raj and P.A. Azeez, "Trend analysis of rainfall in Bharathapuzha River basin, Kerala, India", *International Journal of Climatology*, 32.4., 533-53., 2012.
- [14] P. JAGADEESH AND C. ANUPAMA, "STATISTICAL AND TREND ANALYSES OF RAINFALL: A CASE STUDY OF BHARATHAPUZHA RIVER BASIN, KERALA, INDIA", *ISH JOURNAL OF HYDRAULIC ENGINEERING*, 20.2., 119-132., 2014.
- [15] S. Adarsh and M. Janga Reddy, "Trend Analysis of Rainfall in four meteorological Subdivisions in Southern India Using Non Parametric Methods and Discrete Wavelet Transforms", *International Journal of Climatology*, 35.6., 1107-1124., 2015.
- [16] P. Sonali and D. Nagesh Kumar, "Review of trend detection methods and their application to detect temperature change in India", *Journal of Hydrology*, 476., 212-227., 2013.
- [17] P.K. SEN, "ESTIMATES OF THE REGRESSION COEFFICIENT BASED ON KENDALL'S TAU", *JOURNAL OF THE AMERICAN STATISTICAL ASSOCIATION*, 63., 1379-1389., 1968.
- [18] H.B. Mann, "Non-parametric tests against trend", *Econometrica*, 13.3, 245-259., 1945.
- [19] M.G. Kendall, *Rank Correlation Methods*, 4th Edition, Charles Griffin, London, UK, 1975.
- [20] Y F Sang, Z Wang and C Liu, "Comparison of the MK test and EMD method for trend identification in hydrological time series", *Journal of Hydrology*, 510., 293-298., 2013.
- [21] N.E. Huang, Z. Shen, S.R. Long, M.C. Wu, H.H. Shih, Q. Zheng, N.C. Yen, C.C. Tung and H.H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis" *Proceedings of Royal Society London, Series A*. 454., 903-995., (1998)
- [22] N.E. Huang and Z. Wu, "A review on Hilbert Huang Transform: Method and its applications to geophysical studies", *Reviews of Geophysics*, 46.2, doi: 10.1029/2007RG000228., 2008.
- [23] Y. Huang, F.G Schmitt, Z. Lu and Y. Liu, "Analysis of daily river flow fluctuations using empirical mode decomposition and arbitrary order Hilbert spectral analysis", *Journal of Hydrology*, 454., 103-111., 2009.

- [24] Z. Wu and N.E Huang, "A study of the characteristics of white noise using the empirical mode decomposition method" *Proceedings of Royal Society London*, A. 460., 1597–1611., 2004.
- [25] Z. Wu and N.E Huang, "Statistical significance Test of Intrinsic mode functions" *In Hilbert Huang Transform and its Applications*. Edited by: Norden E Huang (NASA Goddard Space Flight Center, USA), Samuel S P Shen (University of Alberta, Canada). World Scientific Publishing Singapore. 2005.
- [26] Z. Wu, N.E Huang, S.R Long and C.K Peng, "On the trend, detrending and variability of nonlinear and non-stationary time series", *Proceedings of National Academy of Science USA*, 104., 14889-14894., 2007.
- [27] A.M CARMONA AND G. POVEDA, "DETECTION OF LONG-TERM TRENDS IN MONTHLY HYDROCLIMATIC SERIES OF COLOMBIA THROUGH EMPIRICAL MODE DECOMPOSITION", *CLIMATIC CHANGE*, 123.4., 301-313., 2014.
- [28] C.L Franske, "Non-linear climate change", *Nature Climate change*, 4., 423-424., 2014.