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Extraction of Periodic Components and Time Adaptive Long-term Trends of Temperature and Precipitation as Climate Variables in Langtang River Basin, Nepal Using Empirical Mode Decomposition

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Abstract: Climatic time series data are often nonlinear and non-stationary and hence the use of traditional techniques may not be suitable for their analysis. This research is focused on the monthly series of air temperature and precipitation data of 25 years from 1988 to 2012 at Langtang Meteorological Station (LMS), Kyangjing in Langtang River basin, Nepal to extract multi-scale cycles and trends. To address the non-linearity and non-stationary of these time series, we used Empirical Mode Decomposition (EMD) method. EMD decomposed LMS temperature and precipitation series into different oscillatory modes called Intrinsic Mode Functions (IMFs) and residue called trend. The extracted IMFs are subjected to Fast Fourier Transform (FFT) to determine their average period along with their power density. There exist oscillations of 1 year, 3.13 years, 6.25 years, 8.33 years and 12.5 years in temperature data. Among these cycles, only 1 year cycle is distinguished from Gaussian white noise at 95% confidence level. The air temperature at LMS, Kyangjing reflects monotonic positive trend till 2006 but remains as nearly steady state around 3°C from the end of 2006. Similarly, the precipitation data is embedded with cycles of 6 months, 1 year, 2.08 years, 2.27 years and 8.33 years of which only the first three are statistically significant at 95% confidence level. The precipitation shows a mixed trend with decreasing pattern till mid 1990s, increasing pattern till mid 2000s and again decreasing pattern till 2012. One year cycle is dominant in both the time series data. The above results reflect that temperature and precipitation fluctuates on various time scales. The effect of the changes in temperature and precipitation has already been manifested in the form of melting glaciers in this region. The causes for these oscillations might be related to phenomenon like Quasi-biennial Oscillation (QBO), solar activity, El Nino, monsoon climate dynamics and other local characteristics of the basin.

Keywords: Temperature; Empirical Mode Decomposition (EMD); Intrinsic Mode Function (IMF); Fast Fourier Transform (FFT); Periodicities; Trend.

Introduction

The evidences from scientific research show that climate change has started to manifest itself in the form of melting glacier, temperature rise, increasing weather extremes, etc. Temperature and precipitation are fundamental components of climate. The analysis of temperature data from 1906 to 2005 shows a linear trend of 0.74°C (IPCC, 2007) and 30 years period from 1983 to 2012 had likely been warmest during last 1400

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years in the Northern Hemisphere (IPCC, 2014). The analysis of precipitation gauge data shows that there is a positive trend of 0.89 mm/decade in global land precipitation (excluding Antarctica) (New et al., 2001).

The impact of global and regional climate changes on temperature and precipitation, and the factors associated with these changes have become a major issue in climate science. To address such issues, understanding the spatial and temporal characteristics of the changes and their possible causes are very important. Decomposing climatic time series data into different frequency components may give valuable clue about the physical processes that affect global and regional climate systems. The embedded frequency components may occur at different time scales ranging from inter-annual to decadal and multi-decadal. These cycles represent physical phenomena like QBO, El Niño Southern Oscillation (ENSO) and solar cycles.

The identification of trend in climatic series is also very important because it gives clue about the climate change provided that the temporal resolution of the series is long enough. The change can occur gradually, abruptly or in a complex form (Kundzewicz and Robson, 2004). Trend analysis is the analysis in the variation of observations over time in order to extract useful information and to quantify them (Esterby, 1996). Trend is generally associated with the change caused by cumulative artificial or natural processes (Kite, 1989). But trend assessment is challenging because the stochastic nature of time series can induce trend-like feature even in stationary time series (Fatichi et al., 2009).

Shrestha et al. (1999) studied mean monthly value of daily maximum temperature from 49 stations of Nepal since 1971 to 1994 using linear regression, Mann Kendall and Spermann Tests. They concluded that the maximum mean annual temperature is increasing from 1978 by more than 0.06°C in most of northern belt but terai region shows less than 0.306°C or even decreasing trend. Shrestha et al. (2000) analyzed the time series of precipitation data from 78 stations of Nepal using spline method and fast Fourier Transform (FFT). They concluded that there is no significant trend in rainfall. They extracted two dominant cycles of 2.5 and 11 years but 2.5 years cycle is not consistent with QBO and 11 years cycle is statistically insignificant with Zurich sunspot numbers. Sherma et al. (2000) found that the temperature and precipitation data of Koshi River basin increased significantly in some area but most stations do not show any trend.

Climatic time series data are often non-linear and non-stationary. So the use of traditional techniques may not be suitable. For example, Fourier analysis can be used when the series is stationary and linear. Although Wavelet analysis has the ability to deal with non-stationary series, it cannot handle non-linear series. To tackle with the issue of both non-linearity and non-stationary of the series, Haung et al. (1998) developed a method named Empirical Mode Decomposition (EMD). Since then, EMD has been widely used to analyze the non-linear and non-stationary time series.

This research aims to extract the multi-scale cycles and non-linear trend embedded in temperature time series at LMS, Kyangjing of Langtang River basin by EMD and calculate the average period of each cycle using Fast Fourier Transform Algorithm.

Study Area

The Langtang River basin lies in the Langtang Valley of Rasuwa district in Nepal (Figure 1). It is about 60 km in aerial distance toward the North of Kathmandu. It is the riverhead of Trisuli River in the Narayani River System and has the total basin area of 359.23 km^2. Out of the total area, 20.65% is covered in snow and ice, 7.5% in glacier covered debris and the remaining in rock and vegetation. The catchment has an elevation between 3800 m a.s.l up 7234 m a.s.l (Langtang Lirung peak). The average altitude (5169 m a.s.l) reflects the high potential relief energy of the catchment with a mean slope of 26.7°. The meteorological station in Langtang Valley that has longest time series of temperature is Langtang Meteorological Station at Kyangjing with latitude 28.21081^o and longitude 85.56948^o at an elevation of 3862 m a.s.l. Green triangle in Figure 1 represents LMS.

Material and Methodology

Materials

Mean monthly temperature and precipitation data of LMS, Kyangjing is obtained from Department of Hydrology and Meteorology (DHM), Nepal, for the period of 25 years from 1988 to 2012. There are less than 3% missing values in the data. The missing values for temperature are filled by calculating the average of previous and following values. Missing values for precipitation are filled by taking the historical average of rainfall for the same month during analysis period. There are no stations in the adjoining areas having similar topography and could be used to fill the gaps

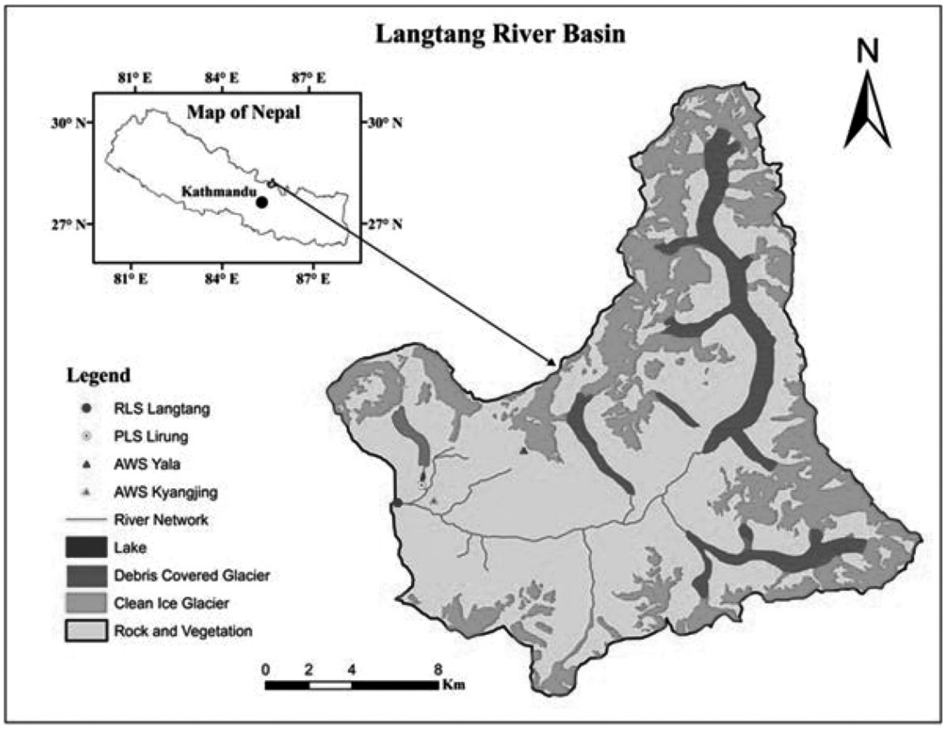

Figure 1: Location map of Langtang River basin (Pradhananga et al., 2014).

for LMS. So we used simple approach to fill the gap. Since the missing data were very few, we believe that it does not mislead our work.

Methods

Empirical Mode Decomposition

The temperature data is being decomposed by using EMD. EMD is a data driven technique developed by Haung et al. (1998) to analyze non-linear and non-stationary signals. This method allows the data to speak themselves. Robustness in terms of non-stationary and non-linearity makes this method very useful for hydro-climatology where the data are usually non-linear and non-stationary. Compared to other decomposition method, EMD is empirical, intuitive, direct and adaptive (Wu and Haung, 2009). The main idea of EMD is to decompose the data locally into different oscillatory components called Intrinsic Mode Function (IMF). To qualify each extracted oscillatory component as IMF, each oscillatory component should follow two criteria: (1) the number of maxima and the number of zero crossing should differ at most by one and (2) the mean of envelopes of local maxima and minima should be zero at any point. The lower IMFs represent fast oscillation components and the higher IMFs represent slow oscillations (Zang et al., 2010). The final component will not have cycle and is a constant or a monotonic function that represents the general trend of the time series.

Process for Empirical Mode Decomposition

1. Create lower envelope $l(t)$ by connecting all the local minima and upper envelope $h(t)$ by connecting all the local maxima using cubical spline of the data $x(t)$.
2. Calculate the mean envelope by averaging the lower and upper envelope $[m(t) = \{h(t) + l(t)\}/2]$.
3. Subtract the mean from the original data $[g_1(t) = x(t) - m(t)]$.
4. If $g_1(t)$ satisfies the two criteria of IMF then $g_1(t)$ is designated as first intrinsic mode function $[C_1(t)]$, if not then the difference is treated as the original signal and above steps are repeated until the criteria of IMF is satisfied.
5. After first IMF is identified, it is subtracted from the original signal and the residual $[r_1(t) = x(t) - C_1(t)]$ is treated as the original signals and subjected to the above steps to get IMF_2, IMF_3 and so on. The process is repeated until the final residue is constant or monotone.

In the end the signal is decomposed as

$x(t) = \Sigma C_i(t) + m(t)$, $i = 1: n$; where n is the number of IMFs and $m(t)$ is final residue.

We have used EMD toolbox for Matlab software available on *http://rcada.ncu.edu.tw.*

Fast Fourier Transform
FFT analysis decomposes the given signal into sin and cosine functions. It helps to convert the given time dependent function into frequency domain. The information that are often unknown from time domain can be gathered from frequency domain. Fourier analysis gives information about the frequencies and periods of the signal. We have used 'fft' function in Matlab to find the periods of extracted IMFs.

Statistical Significance Test
The extracted IMFs are not always rich in information as these may contain some noise. Before interpretation of the extracted IMFs, significance test can be performed. Wu and Haung (2004) have developed statistical method to identify whether the extracted IMFs can be differentiating from white noise or not. In this method, the spread function of various percentiles is calculated using the statistical characteristics of artificial white noise derived in Wu and Haung (2004). Confidence limit level is defined and the upper and lower spread lines are determined. Finally, the energy density of the IMFs from the data is compared with the spread functions. If the IMFs have their energy located above the upper bound and below the lower bound, they are considered to contain information at the predefined confidence level. This test does not include the residual IMF. The detail about the statistical significance of extracted IMFs is discussed in Wu and Haung (2004).

Results

EMD of Temperature Data
EMD based analysis of temperature time series extracted seven embedded modes and a trend as shown in Figure 2. The time scale characteristics increase with the mode index i.e. frequency of each IMF has gradually reduced from IMF_1 to IMF_7. The last residual component has represented the overall trend of the series. The plot of extracted IMFs for temperature data shows that IMFs higher than 6 are lacking the modulation and hence these are added to form a single component that represents the trend. This reduces the periodic components of temperature to five plus a trend.

EMD of Precipitation Data
EMD based decomposition of precipitation data also resulted in seven components and trend. Figure 3 depicts the cycles and trend embedded in precipitation data. It is evident that the precipitation components are excessively extracted after IMF_6. So, the sum of 6th, 7th and 8th components already satisfied the definition of trend. Thus, the precipitation at LMS, Kyangjing is embedded with five cycles and a trend.

Time Adaptive and Non-linear Trend
Figure 4 illustrates the time adaptive and non-linear trends of precipitation and temperature data. The top panel portrays that temperature series at LMS, Kyangjing is showing positive trend till 2006 but more or less stabilizes around 3°C after 2006. The trend of

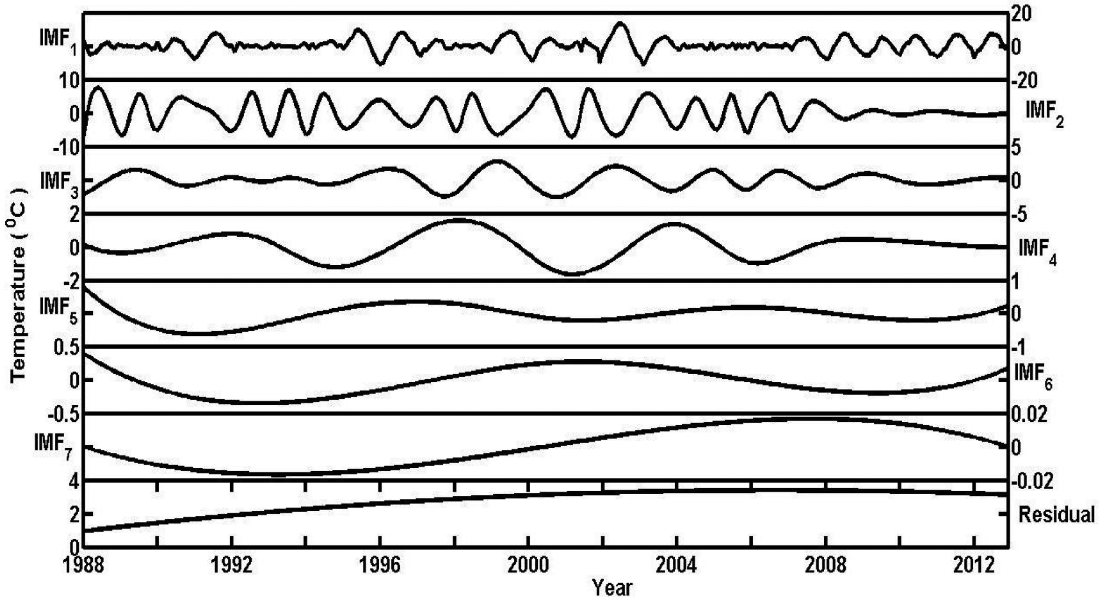

Figure 2: Extracted IMFs for temperature time series using EMD. Panels from top to bottom represent the plots of IMF_1, IMF_2, IMF_3, IMF_4, IMF_5, IMF_6, IMF_7 and a trend.

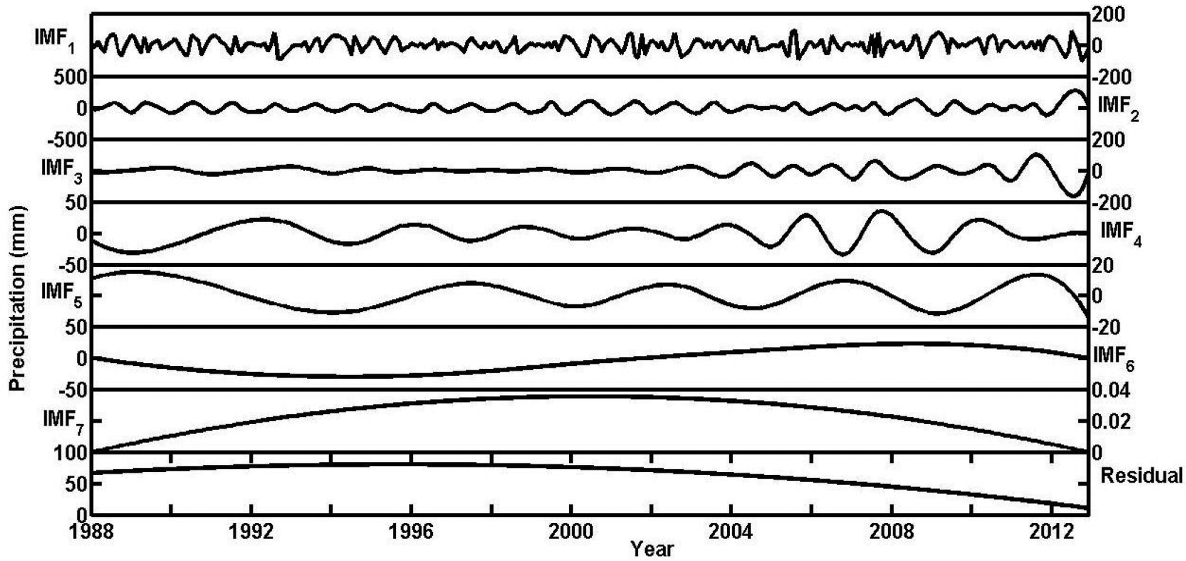

Figure 3: Extracted IMFs for precipitation time series using EMD.

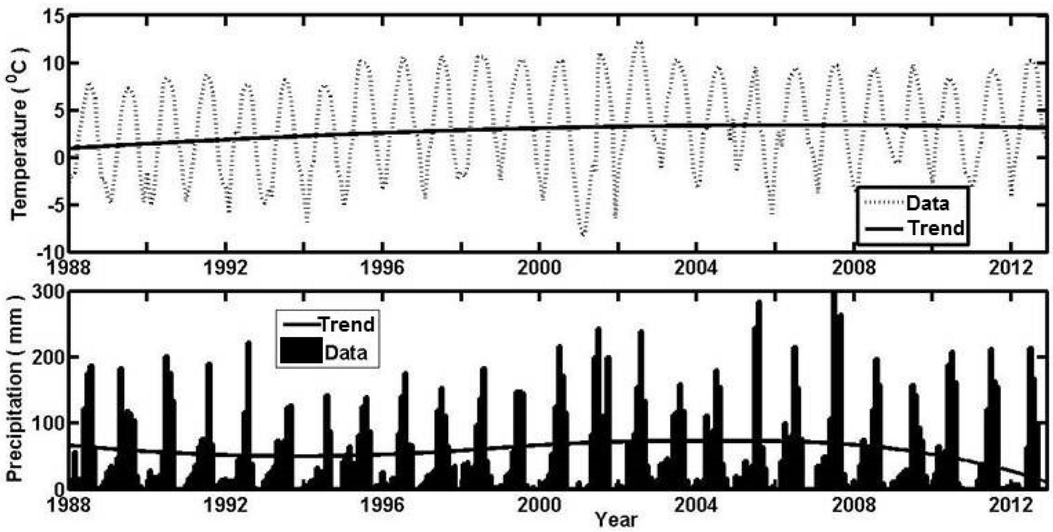

Figure 4: Time adaptive trend of temperature (top) and precipitation (bottom) calculated from the residuals resulting from EMD.

precipitation data, shown in bottom panel of Figure 4 reveals a unique pattern. The LMS precipitation series started decreasing from 1988 to November, 1993 but started to increase at low rate till September, 2004 and after that the trend again shows decreasing pattern.

FFT Analysis of Extracted Cycles

The cycles embedded in temperature and precipitation data have different periods. In order to determine their periodicities, the cycles are subjected to FFT analysis. FFT gives the average period of the components along with the power density. The periods of respective components extracted from temperature and precipitation are shown in Tables 1 and 2.

The FFT of temperature data shows that the power concentrates around 12 months for IMF_1, 12 months for IMF_2, 37.5 months for IMF_3, 75 months for IMF_4, 100 months for IMF_5 and 150 months for IMF_6. IMF_1 and IMF_2 have equal time period. The reason is a mode mixing problem, a major limitation of EMD as explained by Haung et al. (2009). Similarly, the precipitation data has been composed of the cycles of six months, 1 year, 2.08 years, 2.27 years and 8.33 years. It is evident from Tables 1 and 2 that annual cycle has the highest power density in both temperature and precipitation series.

Table 1: Periodicity and power density of extracted IMFs for temperature data based on FFT

IMF (temperature)	*1*	*2*	*3*	*4*	*5*	*6*
Maximum power	282587	151047.9	19904.67	17943.43	1409.819	805.9437
Months for max power	12	12	37.5	75	100	150
Periodic component (years)	1	1	3.13	6.25	8.33	12.5

Table 2: Same as Table 1 but for precipitation data

IMF (precipitation)	*1*	*2*	*3*	*4*	*5*
Maximum power	14729260	99225459	4236881	1799623	667286
Months for max power	6	12	25	27.2727	100
Periodic component (years)	1/2	1	2.08	2.27	8.33

Statistical Significance of Extracted Cycles

For temperature data, it is evident from Figure 7 that only IMF_1 and IMF_2 are significant. IMF_3, IMF_4, IMF_5 and IMF_6 are located between the 95% (solid black line) and 5% confidence levels (dashed black line). Therefore, these IMFs could not be distinguished from the IMFs of the Gaussian white noise at 95% confidence level. Similarly, the significance test of precipitation shows that the cycles of half year, 1 year and 2.08 years are significant as shown in Figure 8.

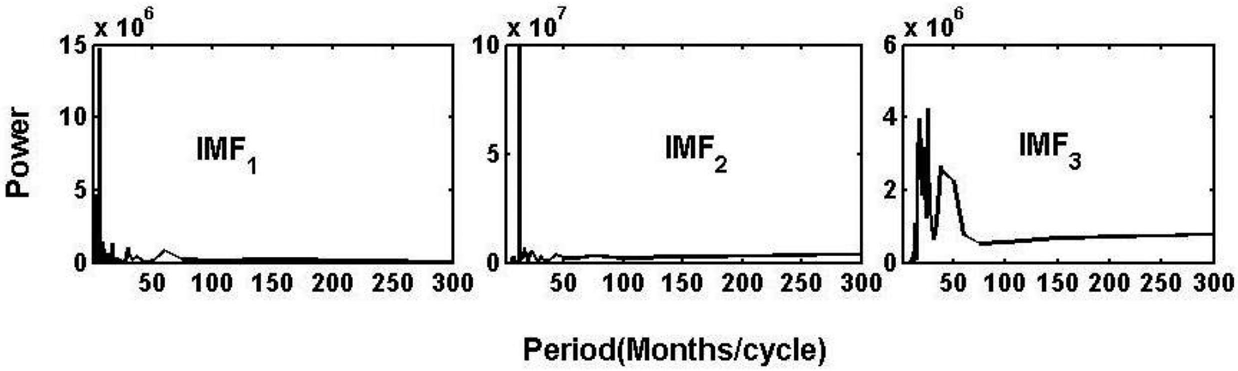

Figure 5: Periodogram of statistically significant cycles extracted from precipitation data.

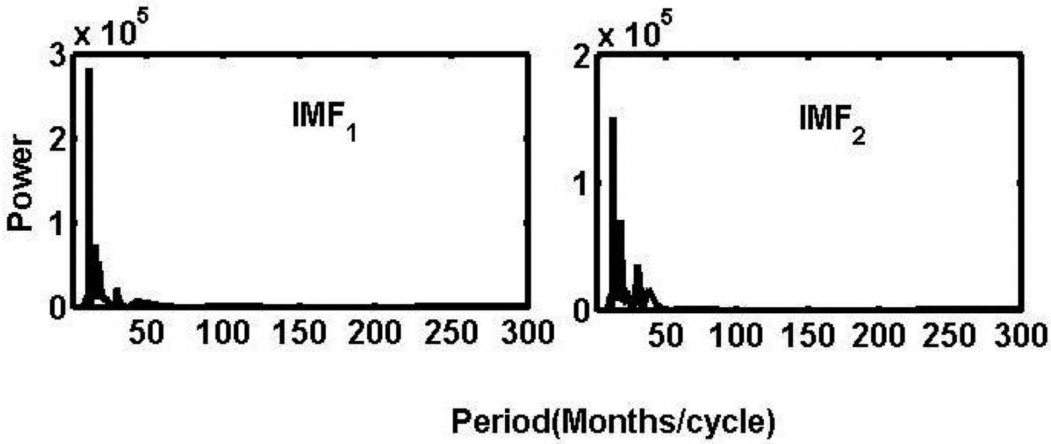

Figure 6: Periodogram of statistically significant cycles extracted from temperature data.

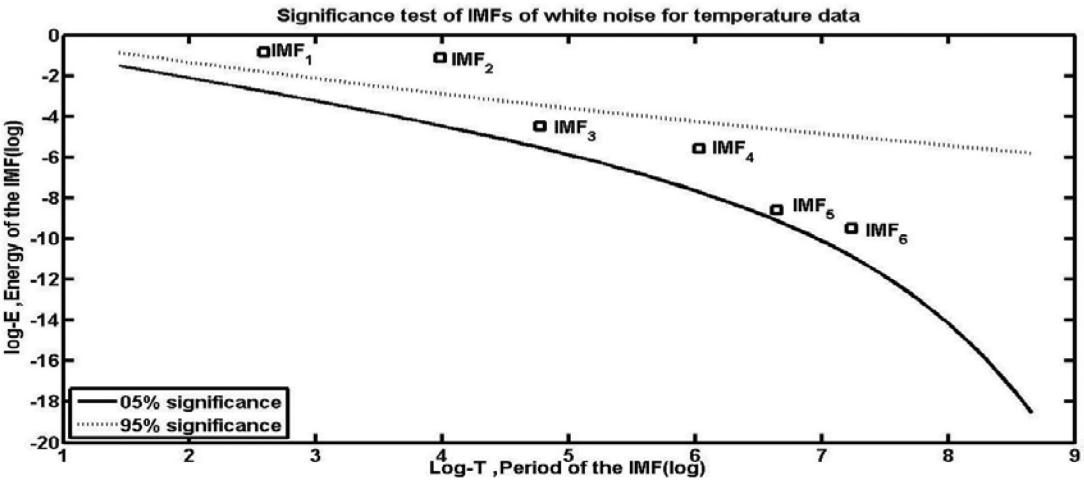

Figure 7: Significance test of cycles extracted from temperature. The black dots are the energy density as a function of spectrum weighed mean period for IMF_1 to IMF_6 based on Fourier spectra.

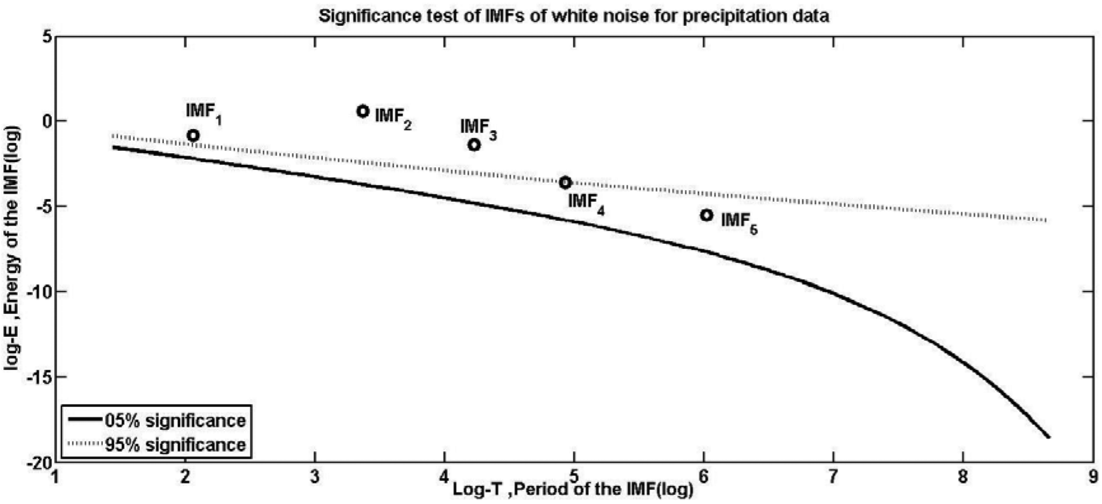

Figure 8: Significance test of cycles extracted from precipitation data.

Discussion

The only statistically significant one year cycle for temperature data at LMS, Kyangjing is resulted from the geometry of the Sun and the Earth. This is the cycle that has the highest power density representing the dominancy. As Earth takes one year to revolve around the Sun, one year cycle is obviously reflected in most of the climatic time series. One year cycle found in this study is in agreement with the result of Yang et al. (2009) who analyzed the monthly temperature data of Shapingba in Chongqing. Other cycles obtained from temperature series are statistically insignificant and hence could not be differentiated from noise. We could not link these cycles to the specific causes. The cycle of 12.5 years is a multiple of cycle 3.13 and 6.25 years. These cycles might be resulting from same physical process which we could not address in this study. Another cycle that is extracted from LMS temperature is of 8.33 years. The cycles of 8.33 and 12.5 years are very close to those of solar activity. This signifies that the activities of Sun can result in multi-scale characteristics of temperature fluctuation. A cycle of 3.13 years is similar to result of Shan and Xian (2006) who have also identified a cycle of 3-4 years in global mean temperature.

The half year cycle in precipitation data is due to the lag between summer and winter seasons. One year cycle is the annual variation resulting from monsoon dynamics, a dominant phenomenon for precipitation as verified by the high value of power density. The cycle of 2.08 years is QBO like mode. This signifies that precipitation at LMS, Kyangjing may have teleconnection with the regional climate. The precipitation data is also embedded with cycles of 2.27 and 8.33 years. These cycles correspond to the periods of El Nino but are statistically insignificant. Inter-annual variation of precipitation data from Nepal and the association of precipitation in Nepal with ENSO events are also found in previous study by Shrestha et al. (2000). Both temperature and precipitation data have a cycle of 8.33 years signifying the influence of same phenomenon. Though this cycle is near to the period of El Niño, it is noise corrupted. The complexity in explaining the reasons for extracted cycles can be attributed to the influence of human activities on climate change.

Temperature series at LMS, Kyangjing is showing positive trend till 2006 which correlates with the result from Pradhananga et al. (2014) who used linear method to analyze the trend. The temperature is in nearly steady state after 2006 which are not reported in earlier studies. The precipitation trend determined in this study is not in agreement with the previous studies. Pradhananga et al. (2014) concluded that precipitation is increasing at Kyangjing from 1988 to 2012 but our study shows that precipitation series started decreasing from 1988 to 1993, increasing at low rate till 2004 and then decreasing till 2012. The reason behind this is we used EMD which is capable to determine time adaptive trend. In 1990s, temperature is in increasing order and precipitation is in decreasing order. The impact of this phenomenon on glacier during this period might have been negative verified by the glacier terminus retreat (Fujita et al., 1998). After 1990s, the temperature is in steady state and precipitation in decreasing trend which might have also impacted glacier negatively. Many studies show that the impact of the change in precipitation and temperature has already been reflected in the form of melting glaciers in this region (Sugiyama et al., 2009; Baral et al., 2014).

Conclusion

Empirical Mode Decomposition method is one of the best available techniques to deal with non-linear and non-stationary hydro-climatic series. The analysis of air temperature and precipitation data at Langtang Meteorological Station (LMS), Kyangjing for 25 years from 1988 to 2012 using EMD show that the temperature is embedded with cycles of 1 year, 3.13 years, 6.25 years, 8.33 years and 12.5 years and precipitation is embedded with cycles of 6 months, 1 year, 2.08 years, 2.27 years and 8.33 years. The FFT analysis shows that the annual cycle has maximum power density for both temperature and precipitation series among others. The statistical test of the extracted IMFs shows that most of the quasi-periodic components embedded in the data are a stochastic noise except the cycle of 1 year in temperature series and 6 months, 1 year and 2.08 years in precipitation series at 95% confidence level. The causes for the oscillation of these series might be related to phenomenon like QBO, solar activity, El Nino and other local characteristics of the basin. But in order to completely understand the physical causes of these temperature fluctuations, the internal properties of the atmospheric system should be analyzed. The trend of the temperature series shows monotonically increasing pattern till 2006. After 2006, the trend of the temperature remains around 3°C. Similarly, precipitation series started decreasing till 1993, increasing at low rate till 2004 and then decreasing till 2012. The impact of the change in precipitation and temperature has already been reflected in the form of melting glaciers in this region.

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