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RESEARCH ARTICLE

ANALYSIS OF TAMILNADU CLIMATE DYNAMICS BY A CLIMATE PREDICTABILITY INDEX

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ABSTRACT

This paper quantifies the predictability of two major components comprising the climate i.e temperature and rainfall. The quantification is done using a Fractal dimensional analysis of the corresponding time series. The Climate Predictability Index for temperature and rainfall is estimated for four station of Tamilnadu, India. The predictability index gives an indication of how predictable the climate is for a given station. Further, since the predictability index gives a single dimensionless number for each process, it can be used to roughly quantify the interplay between temperature and rainfall.

INTRODUCTION

Fractal dimensional analysis of geophysical time series is a well established investigative tool for exploring the dynamics (Hurst *et al.,* 1965). However, these analyses have concentrated on obtaining the fractal dimensions for individual time series. In this paper we concentrate on investigating the Tamilnadu climatic dynamics through an analysis of the temperature and rainfall time series. At these three variables form the dominant dynamic component of climate, our emphasis on them is well justified. Since the Indian subcontinent lies at the heart of the classic monsoon region and is the area most sensitive to monsoon fluctuations, fractal dimensional analysis of its climatic time series can be expected to yield some insights into how the Indian climate variability is linked to monsoon fluctuations. In this paper, we undertake a detailed analysis of the Tamilnadu climate dynamics using the predictability indices as the main tool. Predictability indices are calculated for 4 recording stations of Tamilnadu, India. These indices are computed using temperature and rainfall time series data for these stations. We calculate these indices for a season South West Monsoon (June to September) and North East Monsoon (October, November).

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MATERIALS

Study area and data

The data for the temperature and rainfall of Tamilnadu stations - Kodaikanal, Meenambakkam, Nagapattinam, Salem stations were procured from Regional Meteorological centre, Chennai and also from IIT website. The data is categorised into June to September and October, November. Present paper adopts the method of measuring fractal dimension D and the climate predictability index to detect whether the climatic components are predictable or not in the time series pertaining to the temperature and rainfall concentration over Kodaikanal, Meenambakkam, Nagapattinam and Salem, Tamilnadu, India between 1985 -2011. Several techniques have been developed to find fractal dimension in the time series data. In the present paper we have employed the rescaled range (R/S) analysis. (Mandelbrot and Wallis, 1969). We then execute the climate predictability index (PI_C). Through the PI_C value, the given time series data is identified to be predictable or unpredictable. If one of the indices is close to zero, then the corresponding process approximates the usual Brownian motion and is therefore unpredictable. If it is close to one the process is predictable (Govindan Rangarajan, 1997).

METHODS

R/S analysis

Climate over any continent comprises of four major components, such as temperature, pressure, rainfall and geographic parameters. Geographic parameters (latitude, longitude, distance from the sea and elevation) are constant for a given location. We therefore concentrate on the time series for the two variables (temperature and rainfall) .consider a discrete time series specified by

$$(t_i, x(t_i)) \ (i = 1, 2, \ldots, N).$$

Here t denotes the time and x the amplitude of the variable under consideration (either temperature, rainfall in our case). For a fractional Brownian motion, the amplitude increments $x(t_j) - x(t_i)$ have a Gaussian distribution with variance [Vos.s, 1985]:

$$< [x(t_j) - x(t_i)]2 > (t_j - t_i)^{2H}$$

Where the brackets <> denote the average over many samples of *X (t)*. The parameter H *is* called the Hurst exponent and takes values between 0 and 1. If *H* =0.5, we obtain the usual Brownian motion. The Hurst exponent provides information on the length of memory of the series.

Fractal Dimension

The Hurst exponent is related to the fractal dimension *D of* the time series curve by the formula [Voss, 1985]

D =2- H.

If the fractal dimension *D* for the time series is 1.5, there is no correlation between amplitude changes corresponding to two successive time intervals. Therefore, no trend in amplitude can be discerned from the time series and hence the process is unpredictable. However, as the fractal dimension decreases to 1, the process becomes more and more predictable as it exhibits “persistence”. That is, the future trend is more and more likely to follow an established trend [Hsui *et al.,* 1993]. As the fractal dimension increases from 1.5 to 2, the process exhibits “anti-persistence”. That is, a decrease in the amplitude and the proce ss is more likely to lead to an increase in the future. Hence, the predictability again increases. However, we will be concerned only with persistence behaviour since all geophysical time records analysed till date [Mandet- brot and Wattis, 1969; Flucqernan and Snow, 1989; Hsnz ci. at., 1993; Ture.otte, 1992] exhibit this behaviour. We obtain the fractal dimensions of the time series corresponding to temperature and rainfall for a given location. The fractal dimensions are denoted by D_T and D_R respectively. These are obtained using the rescaled range (R/S) analysis [Man- deibrot and Wattis, 1969]. In R/S analysis, we first calculates the ratio R/S where H is the cumulated range of the process over different time intervals with the sample average removed and S is the square root of the sample variance. The R/S value is averaged over all time intervals with the same period. The slope of the log-log plot of the average R/S values versus time intervals gives the Hurst exponent *H* (Karin vibe, 1995) which in turn is related to the fractal dimension D through the formula given earlier.

A climate predictability index

The R/S analysis is used merely because it has been the conventional technique used for geophysical time records [Hurst *et al*., 1965; Mandetbrot and Wo.1- us, 1969; Fluegernun and Snow,1989; Hsuz ci.at., 1993; Turcotte, 1992]. Any other method would be equally adequate. Predictability indices (denoted by PIT and PIR respectively) for temperature and Rainfall are defined as follows:

$$PI_T = 2|D_T - 1.5|; \quad PI_R = 2|D_R - 1.5|;$$

Here |D| denotes the absolute value of the number D. single index. when the fractal dimension becomes less than 1.5 then we have correlation (persistence)behaviour and when it becomes greater than 1.5 then we have anti-correlation (anti-persistence) behaviour. However, in either case, the process becomes more predictable.The climate predictability index (PIc:) is defined as the collection of the above two indices:

$$PI_C = (PI_T; PI_R).$$

If any one of these index is close to zero, then the corresponding process is the usual Brownian motion and is therefore unpredictable. If it is close to one, the process is very predictable. The rationale for introducing the climate predictability index is as follows. In this paper, we are interested in studying the inter-relationships between the two climatic components from the viewpoint of fractal dimensions. Hence, it is useful to have two of them represented in a single index. Then it is easier to see how the two sub-indices change in relation to one another as the seasons change. Further, by introducing predictability indices instead of fractal dimensions, we focus on how predictable time process is. This is especially useful for rainfall. One possibility that arises at this point is to somehow combine these two indices into a single number using an appropriate norm. But this may not be appropriate if even one of time processes is quite independent of the others. Therefore, for the present, we take the Plc to be a collection of two indices.

RESULTS AND DISCUSSION

R/S analysis

Table 1 show that the Hurst exponent value of temperature and rainfall for the period 1985-2011. *H* describes the correlation between the past and future in the time series. A Hurst exponent of 0:5 < H < 1:0 corresponds to a profile like curve showing persistent behaviour, while for 0 < H < 0:5, we have an antipersistent behaviour. If H is more or less equal to 0.5 it

Table 1. Hurst Exponent Value of temperature and rainfall for the month of June –September and October – November

Station	Hurst Exponent for temperature (June – Sept)	Hurst Exponent for rainfall (June- Sept)	Hurst Exponent for temperature (Oct- Nov)	Hurst Exponent for Rainfall (Oct- Nov)
Kodaikanal	0.9407	0.3693	1.0147	0.4473
Meenambakkam	0.6344	0.4673	0.8237	0.5767
Nagapattinam	0.3858	0.4987	0.8271	0.6964
Salem	0.9127	0.4148	0.895	0.437

Table 2. Fractal dimension D for June –September and October – November

Station	D for temperature (June - Sept)	D for rainfall (June – Sept)	D for temperature (Oct - Nov)	D for rainfall (Oct - Nov)
Kodaikanal	1.0593	1.6307	0.9853	1.5527
Meenambakkam	1.3656	1.5327	1.1763	1.4233
Nagapattinam	1.6142	1.5013	1.1729	1.3036
Salem	1.0873	1.5852	1.105	1.563

Table 3. Change in PI_C with the season

Station	location	PI_C for June -September	PI_C for October -November
Kodaikanal	Latitude: 10°13′59″ N Longitude: 77°28′59″ E	(0.9,0.3)	(1.0,0.1)
Meenambakkam	Latitude: 13°05′16″ N Longitude: 80°16′42″ E	(0.3,0.1)	(0.6,0.2)
Nagapattinam	Latitude: 10°46′00″ N Longitude: 79°49′59″ E	(0.2,0.0)	(0.7,0.4)
Salem	Latitude: 11°39′00″ N Longitude: 78°10′00″ E	(0.8,0.2)	(0.1,0.1)

indicates that the time series is random. In this paper we observed that the H value of temperature for Kodaikanal, Meenambakkam and Salem shows the persistent behaviour and H value of temperature for Nagapattinam shows antipersistent behavior (June – Sept), also persistent behaviour for the month October - November. The H value of rainfall for all four stations shows the antipersistent behaviour for the month June – September and for the month of October- November Kodaikanal and Salem station shows the antipersistent behaviour, Meenambakkam and Nagapattinam shows the persistent behaviour.

Fractal Dimension

Table 2 show that the Fractal dimension value for the month of June – September and October – November. In this paper we observed that the D value of temperature for Kodaikanal, Meenambakkam and Salem exhibits the persistent behaviour, the process becomes predictable. The D value of temperature for Nagapattinam exhibits antipersistent behaviour (June – Sept), the chance of predictability becomes increasing and also for all four station exhibits the persistent behaviour for the month October - November. The D value of rainfall for Kodaikanal, Meenambakkam and Salem exhibits the antipersistent behaviour, the chance of predictability becomes increasing. The D value of rainfall for Nagapattinam is 1.5 exhibits no trend in amplitude can be discerned from the time series and hence the process is unpredictable. The D value of rainfall for all four stations shows that there is more chance of predictability.

A climate predictability index

Table 3 shows the climate predictability index for the month of June – September and October – November. If any one of these index is close to zero, then the corresponding process is the usual Brownian motion and is therefore unpredictable. If it is close to one, the process is very predictable. We observed that South West monsoon of Nagapattinam and Meenambakkam show that the process is unpredictable because one of the indexes is close to zero. South West monsoon of Kodaikanal and Salem show that the process is predictable because one of the indexes is close to one. Similarly North East monsoon of Salem is unpredictable and other three stations are predictable.

Conclusion

Present paper we obtained a climate predictability index through a fractal dimensional analysis of the time series for two major components of a climate (temperature and rainfall). For a given station, an indication of how to predict the climate is given by this climate predictability index. We demonstrated that predictability indices change significantly as the climate dynamics change from one season to the other. In climate prediction models, one looks for trends in the time series of climatic variables which can help to specify the developing climatic models for a region. For these cases one should avoid the stations which have low PI_C

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