CHAPTER 14

PREDICTABILITY OF SEVERE THUNDERSTORMS WITH FRAC TAL DIMENSION APPROACH 13

ABSTRACT:
Thunderstorm is meso-scale weather with space scale varying from a few kilometers to a couple of 100 kilometers and time scale varying from less than an hour to several hours. Severe thunderstorms however, produce strong surface wind squalls, lightning, heavy rain showers, occasional hail, downbursts and tornadoes leading to loss of life and property on the ground and aviation hazard aloft. Prediction of severe thunderstorm is a challenging task for the Atmospheric Scientists over the globe. The rationale of the present study is thus, to view the relative importance of two important convective energies, convective available potential energy (CAPE) and convective inhibition energy (CIN) in the genesis of severe thunderstorms during the pre-monsoon season (April – May) over Kolkata (22° 32’N, 88° 20’E). The concept of fractal dimension is applied in this study to observe the degree of self-similarity between CAPE and CIN for thunderstorms during the pre-monsoon season. Fractal dimension of CAPE and CIN is measured with the help of the level of free convection (LFC). The Fractal dimension is considered in this study as the measure of randomness. The result reveals that CIN possess more self similarity than CAPE for the genesis of severe thunderstorms over Kolkata.

14.1 INTRODUCTION
Thunderstorm is a meso-scale high frequency weather phenomenon. In general, thunderstorm is a perennial feature of India. However, the Meteorologists and Atmospheric Scientists of India are concerned about the disasters caused by severe thunderstorms accompanied with high wind gust,

13 Chaudhuri S. (2010), Predictability of Severe Thunderstorms with Fractal Dimension Approach, Asian journal of Water, air & Environmental Pollution, 7 (4), 81 – 87
hail, lightning and occasional tornadoes. Such weather appear every year during the pre – monsoon season (April – May) over Kolkata (22° 32'N, 88° 20'E), which is confined within the north-eastern part (20°N to 24°N latitude, 85°E to 93°E longitude) of India. The destructions and casualties associated with such severe thunderstorms necessitated extensive research in this field (Desai and Rao, 1954, Jacovides and Yonetani, (1990); Manohar et al. 1999, Kandalgaokar et al. 2002, Chaudhuri, 2005 and so on). The pre-monsoon thunderstorms have significant socio-economic impact over the region.

Forecasting severe thunderstorms is still a major challenge for the meteorologists and atmospheric scientists of India because the weather phenomenon is highly nonlinear, complex and chaotic. The deterministic chaos inherent in the time series of occurrence of severe thunderstorms is identified (Chaudhuri, 2006a; Sharifi et al. 1990; Sivakumar et al. 1998).

Artificial Intelligence (AI) have been progressively and successfully applied in modelling non-linear systems in different scientific and engineering fields (e.g. Seker et al. 2003; Perez and Reyes, 2001; Colulibaly et al. 2001; Shao, 1997). Application of AI in atmospheric sciences has become very popular since 1990s. The complex nature and non-linearity inherent in the atmospheric processes necessitated a way out from the existing conventional methods. Hsieh and Tang (1998) explored the meteorological and oceanography data using Artificial Neural Network for prediction purpose. Various studies in hydrology like precipitation-runoff modelling; river flows etc. have been done
using AI techniques (El-Shafie et al. 2007; Rajurkar et al. 2004; Elshorbagy and Simonovic, 2000; Tokar and Markus, 2000; Zealand et al. 1999; Fernando and Jayawardena, 1998). Jin et al. (2008) used genetic algorithm (GA) and artificial neural network (ANN) together as hybrid genetic neural network (GNN) model to predict the typhoon intensity and the hybrid model output are found to be more accurate than traditional single ANN model. The hybrid AI methods (Yu and Chen, 2000) are capable of better quality output than any single AI method. Wang et al. (2008) used hybrid neuro-fuzzy system to integrate shear and spectral signatures for tornado detection. Utilization of AI methods in the study of weather events has been studied by many (McCann 1992; Marzban et al. 1997, 1998, 2000; Kuligowski et al. 1998; Abraham et al. 2001; Chaudhuri, 2008a, b; Chaudhuri and Middey, 2009; and many others).

The purpose of the present study is to introduce the concept of fractal geometry in the study of thunderstorm. Convective available potential energy (CAPE) and convective inhibition energy (CIN) are established to be responsible for convective development (William, 1995). These energies are confined within areas on the temperature – entropy diagram with varying geometry and quantitative measure. The endeavour of the study is to appraise the predictability of the genesis of severe thunderstorm using the concept of fractal geometry by estimating the self similarity in CAPE and CIN.
ROLE OF CAPE AND CIN IN THE GENESIS OF THUNDERSTORMS

Conditional instability is known to be the mechanism by which thunderstorms are formed (William, 1995). The energy that drives conditional instability is convective available potential energy (CAPE) and is defined as:

$$\text{CAPE} (z) = \int_{LFC}^{LNB} \frac{(T_p - T_e)}{T_e} gdz \quad \text{Jkg}^{-1}$$  \hspace{1cm} (14.1)

Where,
- LNB → level of neutral buoyancy, where upward buoyancy vanishes
- LFC → level of free convection, the altitude at which the parcel first becomes upwardly buoyant
- $T_p$ → temperature of the parcel of air
- $T_e$ → environmental temperature
- $g$ → acceleration due to gravity.

CAPE represents the maximum limit of energy a parcel can extract from the environment, once it becomes buoyant. In order to release CAPE, a small negative energy identified as convective inhibition energy (CIN) must be supplied. CIN provides the measure of the energy barrier that must be surmounted and is defined as:

$$\text{CIN} (z) = \int_{Srf}^{LFC} \frac{(T_e - T_p)}{T_e} gdz \quad \text{Jkg}^{-1}$$  \hspace{1cm} (14.2)

Where, $Srf$ → Surface
In mid-latitude, the meteorologists put thrust on the enhancement of CAPE to estimate the energy release because the synoptic systems are available there in plenty to minimize CIN (Chaudhuri, 2005).

Observations show that, the quantitative value of CAPE is enhanced by the advection of cold air above the LFC for a given temperature and moisture content at the surface. CAPE pushes the air parcel upwards, while the upper level features like field of divergence ahead of a trough and rear of a ridge, or hydrodynamic pressure induced by wind shear pulls the parcel up. The occurrence of severe thunderstorms over Great Plains of America is unique in a sense that such events occur due to the enhancement of CAPE.

In tropics, on the other hand, Indian subcontinent is normally barotropic during the period of pre-monsoon season as the horizontal temperature gradient is less (Chaudhuri and Aich Bhowmick, 2006). Besides the presence of feeble induced low-pressure areas on the surface level, there exists no significant synoptic system, which can be observed from climatological charts. It is mentioned here that by strong or significant synoptic system, it is meant that the synoptic conditions could be expressed objectively. Attention is, therefore, drawn in tropics towards small-scale and lower level features that tend to minimize CIN. Thus, for forecasting the genesis of severe thunderstorms of pre–monsoon season over Kolkata, it is surmised that CIN should be more persistent than that of CAPE. The concept has been made valid in the present study by the application fractal geometry.
14.3 FRACTAL GEOMETRY – AN OUTLINE

The basic concept associated with fractal geometry is self-similarity. An object is said to be self-similar if it is formed by parts that are similar to the whole. An exactly self-similar object is called a deterministic fractal (Barabasi and Stanley, 1995). An object with randomness is called random fractal. To decide upon the fractality of an object, Hausdorff dimension is to be measured (Barabasi and Stanley, 1995). The volume $V(l)$ of an arbitrary object is measured by covering it with balls of linear size $l$, and volume $l^{d_E}$. The number of balls to cover $V(l)$ is $N(l)$ and are connected by

$$V(l) = N(l)l^{d_E}$$

(14.3)

Where $d_E$ represents the embedding dimension. Objects with $d_f < d_E$ are called fractals where $d_f$ is the fractal dimension (Barabasi and Stanley, 1995);

$$d_f = \lim_{l \to 0} \frac{\ln N(l)}{\ln \left(\frac{1}{l}\right)}$$

(14.4)

In terms of Holder exponent $\alpha$ the fractal dimension is defined as (Mandelbrot, 1982, 1985);

$$d_f = 2 - \alpha$$

(14.5)

The term $\alpha$ gives the quantitative measure of the roughness within the system.

14.4 FRACTALITY IN CAPE AND CIN

The purpose of the present study is to view the fractality or the self similarity within CAPE and CIN for the prevalence of severe thunderstorm during the
pre–monsoon season over Kolkata. The convective available potential energy (CAPE) and convective inhibition energy (CIN) represent the amount of positive and negative energy respectively acquired by a parcel of air lifted up through buoyancy.

The limit definition is used to compute the fractal dimension of CAPE and CIN in the present study. The level of free convection (LFC) is considered as the measuring stick and CAPE and CIN are considered as the random objects whose fractalinity has to be estimated. CAPE and CIN represent the energy in Jkg\(^{-1}\). The convective energies and the level of free convection are the functions of altitude. Thus, it is reasonable to consider the energies as \(N(l)\) and the pressure levels as \(l\). Values of \(\ln (N(l))\) and \(\ln (1/l)\) are found to be 1.2 and 2.92 respectively for a thunderstorm day. On the same thunderstorm day, after considering the standardized values of energy embedded in CIN and the LFC, the order of \(N(l)\) and \((1/l)\) are observed to be \((3.3)^k\) and \((18.5)^k\) respectively. The fractal dimension of the object CIN comes to be 0.41 (Handerson and Wells, 1988). Similar approach is adopted for rest of the thunderstorm days.

The quantity \(N(l)\) basically represents the number of balls as a function of the scale \(l\) required to cover the whole of a fractal object \(V(l)\). In the present study CAPE and CIN for different thunderstorm / non-thunderstorm days are represented by \(V(l)\)'s. The volume \(V(l)\) of an arbitrary object can be measured by covering it with balls of linear size \(l\) and volume \(l^d\) (Barabasi
and Stanley, 1995). We need \( N(I) \) balls to cover the same. Thus, fractality is not a property of \( N(I) \). \( N(l) \) is a component to measure the fractal dimension using equation (14.4) (Barabasi and Stanley, 1995).

Equation (14.4) is used to compute the fractal dimensions of CAPE and CIN with LFC as measuring stick. The implementation procedure is depicted as a flow chart (figure 14.1). The fractal dimensions are observed to be below the straight line corresponding to the embedding dimension \( d_E = 2 \) on thunderstorm days (figure 14.2). Objects with \( d_f < d_E \) are called fractals (Barabasi and Stanley, 1995). CIN is thus, observed to hold the fractality (figure 14.2).

The smallest Euclidean dimension of the space in which CIN can be embedded is 2. Thus, for CIN, with LFC as the measuring stick, the embedding dimension is 2. Logarithms for LFC and CIN are computed. Fractal dimensions are computed for ten thunderstorm days from the years 2000 to 2009 and one non-thunderstorm day using equation (14.3).

Similarly, for CAPE the embedding dimension is also found to be 2. Logarithms for LFC and CAPE are computed in the similar manner. The fractal dimensions corresponding to CIN and CAPE are found to be less than 2. Thus, both CAPE and CIN can be considered to hold fractality.

### 14.5 THE DATA

The data used in the present study are collected from India Meteorological Department (www.imd.ernet.in) during the pre-monsoon season (April and
May) for the years 2000 to 2009. The location of the study is Kolkata (22° 32'E, 88° 20'N). The raw data are the RS / RW sounding observations representing the near storm environment. These raw data are processed for computation of the convective available potential energy (CAPE) and convective inhibition energy (CIN).

14.6 RESULTS AND DISCUSSIONS

The fractal dimensions of CAPE and CIN are computed (table – 14.1) and plotted (figure 14.3). It is apparent from the figure that CIN always possess higher fractal dimension than CAPE. This indicates that CIN has higher degree of self - similarity within itself than CAPE. This leads to state that CIN has better fractality than CAPE for the prevalence of severe thunderstorms during pre –monsoon season over Kolkata. It is also apparent that the graph of fractal dimension of CIN is more flat than that of CAPE (figure 14.3). The less curvature indicates less uncertainty. Thus CIN, as a predictor for forecasting the severe thunderstorms would incorporate less uncertainty. CIN thus, is more persistent than CAPE for pre monsoon severe thunderstorms.

Standard deviation of the fractal dimensions of CAPE and CIN are computed. The standard deviations of thunderstorm and non - thunderstorm days are also computed (figure 14.4). It is evident from the figure that standard deviation in the self - similarity has more drastic change from thunderstorm day to non - thunderstorm day in case of CAPE than CIN. Thus, CIN is more consistent than CAPE for the occurrence of thunderstorms. This shows the significance
of CIN as a better predictor of thunderstorm than CAPE. Equation (14.5) shows higher fractal dimension indicating lower roughness. Thus, CIN has lower degree of roughness, and thus higher degree of self-similarity than CAPE.

14.7 CONCLUSION
The study leads to conclude that CIN is a persistent parameter with less uncertainty for forecasting severe thunderstorms of pre-monsoon season over Kolkata. CIN has higher degree of self-similarity than CAPE. Thus, inclusion of CIN as a predictor in the predictive model for forecasting severe thunderstorms over Kolkata during the period of pre-monsoon season would incorporate less degree of uncertainty and would provide better forecast.
Table 14.1 Fractal Dimensions of CAPE and CIN

<table>
<thead>
<tr>
<th>Dates</th>
<th>Station</th>
<th>UTC</th>
<th>Fractal dim. (CAPE)</th>
<th>Fractal dim. (CIN)</th>
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</thead>
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<tr>
<td>2.04.'97 (TS day)</td>
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<td>00</td>
<td>0.26</td>
<td>0.41</td>
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<td>0.54</td>
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<td>0.43</td>
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<td>0.84</td>
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<td>0.97</td>
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</tbody>
</table>

TS - Thunderstorm Day

NTS - Non Thunderstorm Day
Figure 14.1 The implementation procedure

Fractal Objects
CAPE and CIN

Measuring scale
Altitude of LFC

Computation of Fractal dimensions of CAPE and CIN for different thunderstorm and non-thunderstorm days

Purpose
Identification of the degree of self-similarity in CAPE and CIN
Figure 14.2 The diagram shows the histogram of $\ln(N(l))$ and $\ln(1/l)$ considering CIN as a Fractal dimension and embedding dimension are also presented in the figure.
Figure 14.3 The diagram showing the Fractal Dimensions of CAPE and CIN for thunderstorm and non-thunderstorm days.
Figure 14.4 The diagram shows the standard deviations corresponding to the thunderstorm and non-thunderstorm days. The overall (o.all) standard deviation is also shown for CAPE (blue) and CIN (red).