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Predictability of Severe Thunderstorms with Fractal Dimension Approach

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Abstract: Thunderstorm is meso-scale weather with space scale varying from a few kilometres to a couple of 100 kilometres 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, down-bursts 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 around the globe. The rationale of the present study is, thus, to view the relative significance 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 the prevalence of severe 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 has more self-similarity than CAPE for the genesis of severe thunderstorms over Kolkata.

Key words: CAPE, CIN, severe thunderstorm, genesis, fractal dimension, LFC.

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, hail, lightning and occasional tornadoes. Such weather appears 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, 2006; Sharifi and Geograkakos, 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 et al., 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 et al. (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, 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., 1998, 2000; Kuligowski et al., 1998; Abraham et al., 2001; Chaudhuri, 2008a, b; Chaudhuri and Middey, 2009; and so on).

The purpose of the present article is to introduce the concept of fractal dimension 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 qualitative and quantitative measure. The endeavour of the study is to appraise the predictability of the genesis of severe thunderstorm using the concept of fractal dimension 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:

$$\text{CAPE}\,(z) = \int_{LFC}^{LNB} \left\{\left(T_p - T_e\right)/T_e\right\} g\,dz \quad \text{J/Kg} \tag{1}$$

where LNB is 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, and g is 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:

$$\text{CIN}\,(z) = \int_{Srf}^{LFC} \left\{\left(T_e - T_p\right)/T_e\right\} g\,dz \quad \text{J/Kg} \tag{2}$$

where *Srf* is 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 Bhowmik, 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 CAPE. The concept has been made valid in the present study by the application of fractal geometry.

Fractal Geometry—An Outline

The basic concept associated with fractal dimension 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, Hausdroff dimension (Barabasi and Stanley, 1995) is to be measured. 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

$$V(l) = N(l)\, l^{d_E} \tag{3}$$

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

$$d_f = \lim_{l \to 0} \frac{\ln N(l)}{\ln\left(\frac{1}{l}\right)} \tag{4}$$

In terms of Holder exponent α (Mandelbrot, 1985), the fractal dimension is defined as

$$d_f = 2 - \alpha \tag{5}$$

The term α gives the quantitative measure of the roughness within the system.

Existence of 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 fractality has to be estimated. CAPE and CIN represent the energy in J/Kg. 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_E} (Barabasi et al., 1995). We need *N(l)* balls to cover the same. Thus, fractality is not a property of *N(l)*. The *N(l)* is a component to measure the fractal dimension using equation (4) (Barabasi et al., 1995).

Equation (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 1). The fractal dimensions are observed to be below the straight line corresponding to the embedding dimension $d_E = 2$ on thunderstorm days (Figure 2). Objects with $d_f < d_E$ are called fractals (Barabasi et al., 1995). CIN is thus observed to hold the fractality (Figure 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 (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.

Data

The data used in the present study are collected from India Meteorological Department (www.imd.ernet.in)

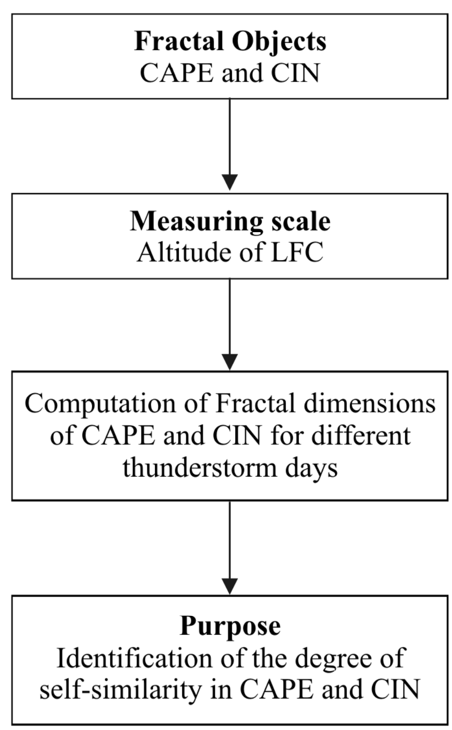

Figure 1: The implementation procedure.

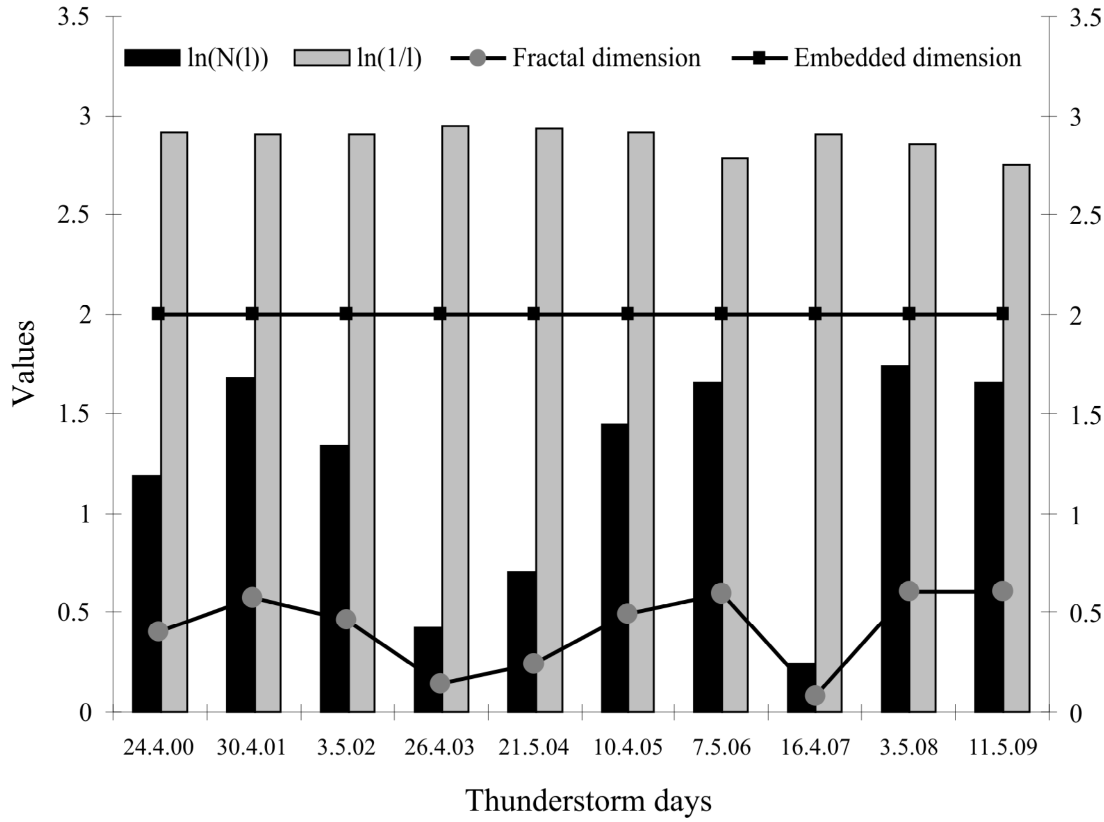

Figure 2: The histogram of ln (N(l)) and ln (1/l) with CIN as fractal. Fractal dimension and embedded dimension are shown in the figure.

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).

Results and Discussions

The fractal dimensions of CAPE and CIN are computed (Figure 3). It is apparent from the figure that CIN always possesses 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 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 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 (5) shows higher fractal dimension indicating lower roughness. Thus, CIN has lower degree of roughness, and thus higher degree of self-similarity than CAPE.

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.

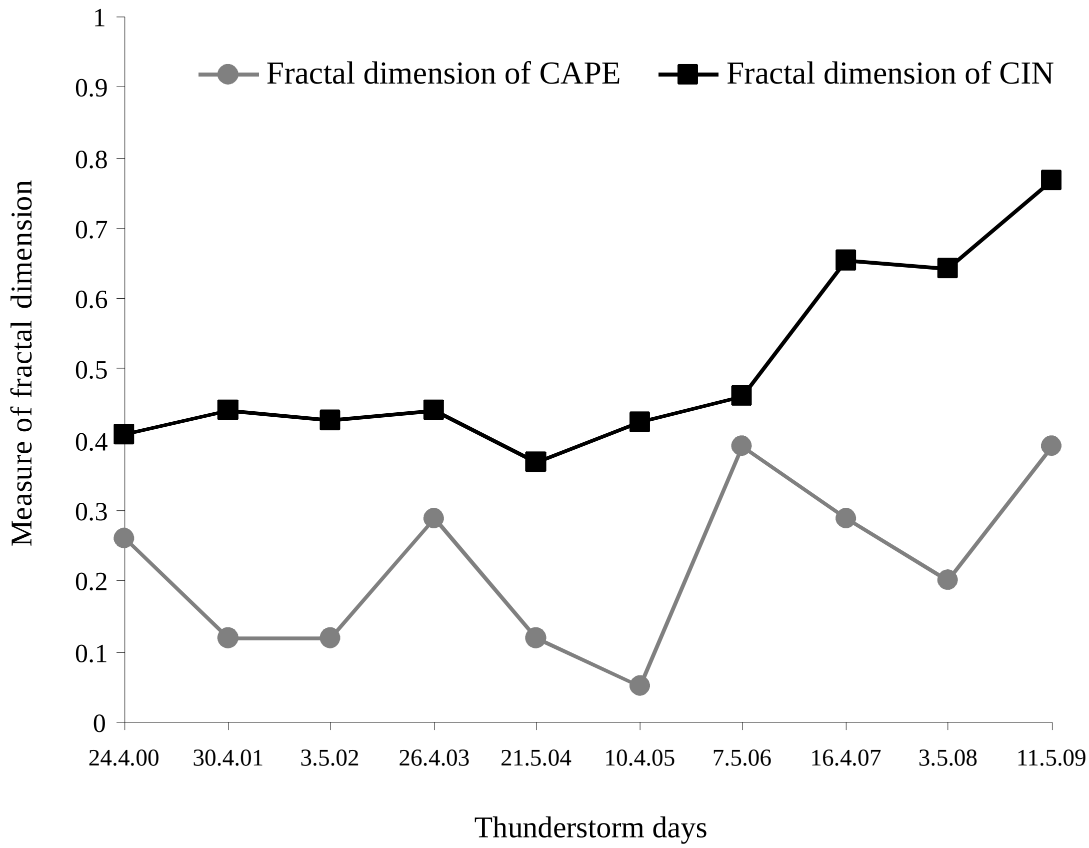

Figure 3: The fractal dimension of CAPE and CIN for thunderstorm days during the period 2000-2009.

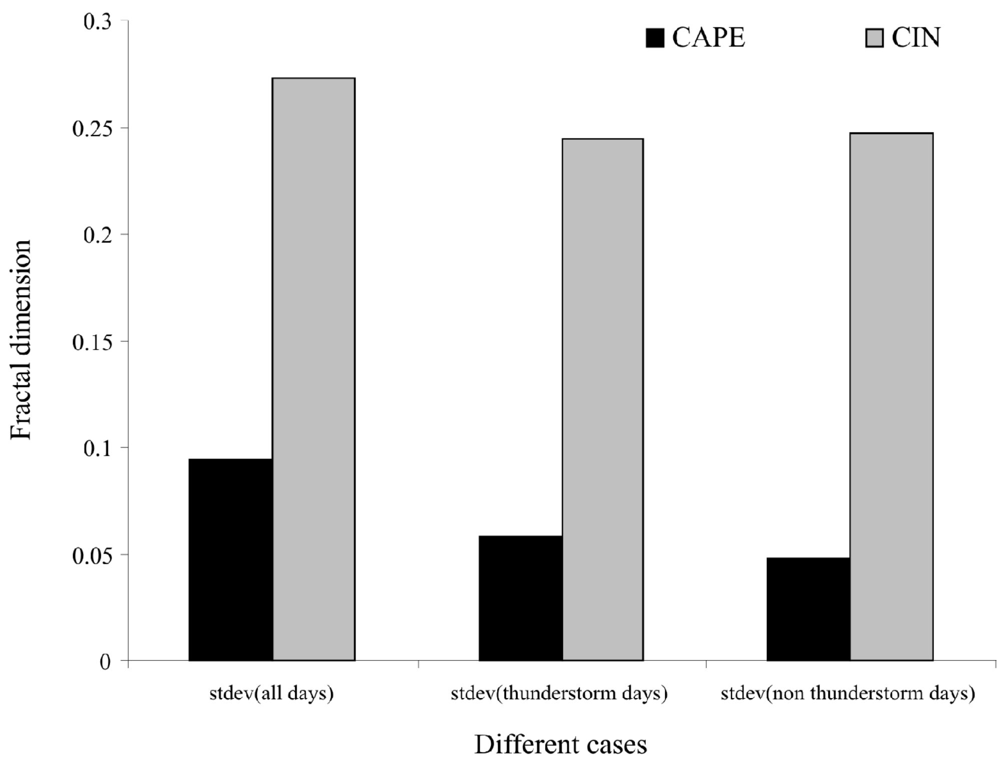

Figure 4: The standard deviation of all days, thunderstorm days and non-thunderstorm days.

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Calendar of Events

13th International Riversymposium
11 to 14 October 2010
Perth, Western Australia, Australia
Website: http://riversymposium.com
Contact name: Lynette Maxwell
Organized by: International Water Forum

Hydrology Conference 2010 - The Changing Physical and Social Environment: Hydrologic Impacts and Feedbacks
11 to 13 October 2010
San Diego, California
Website: http://www.hydrologyconference.com
Contact name: Claire Norris
Organized by: Journal of Hydrology / Elsevier

Water: Crisis and Choices — ADB and Partners Conference 2010
11 to 15 October 2010
Mandaluyong, Philippines
Website: http://www.adb.org/waterconference2010
Contact name: Ma. Consuelo Garcia
Organized by: Asian Development Bank

Water 2010
13 to 14 October 2010
London, United Kingdom
Website: http://www.marketforce.eu.com/Conferences/water10/
Contact name: Ross Hillitt
Organized by: Marketforce

International Conference on Environmental Challenges: A Global Concern
15 to 16 October 2010
Jalandhar, Punjab, India
Website: http://www.kmvjla.org/confevs
Contact name: Dr. Mrs. Atima Sharma
Organized by: Kanya Maha Vidyalaya, Jalandhar

Integrated Water Management
21 October 2010
London, United Kingdom
Website: http://www.coastms.co.uk/conferences/435
Contact name: Lauren Goozee
Organized by: CIWEM

ICEMT 2010 - The First International Conference on Environmental Management & Technologies
1 to 3 November 2010
Amman, Jordan
Website: http://icemt10.emtme.com/
Contact name: Sami Kamal
Organized by: Al-Atheen in collaboration with CSAAR

International Meeting on Marine Resources 2010
16 to 17 November 2010
Peniche, Leiria, Portugal
Website: http://www.immr.ipleiria.pt/
Contact name: Susana Mendes
Organized by: GIRM (Marine Resources Research Group) - Polytechnic Institute of Leiria (IPL), School of Tourism and Maritime Technology (ESTM)

4th International Conference on Water Resources and Arid Environments (2010)
5 to 8 December 2010
Riyadh, Saudi Arabia
Website: http://www.icwrae-psipw.org/
Contact name: Dr Abdulmalek A. Al Alsheikh
Organized by: King Saud University / Prince Sultan Bin Abdulaziz International Prize for Water / Saudi Ministry of Water & Electricity

IVth World Aqua Congress
8 to 10 December 2010
New Delhi, India
Website: http://www.worldaquacongress.org
Contact name: Praggya Sharmaa
Organized by: Aqua Foundation

International Conference on Environment 2010
13 to 15 December 2010
Penang, Malaysia
Website: http://chemical.eng.usm.my/ICENV2010/index.php
Contact name: The Secretariat ICENV 2010
Organized by: Universiti Sains Malaysia