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Indexing of driving rain exposure in India based on daily gridded data

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ABSTRACT

The severity of rainfall exposure endured by vertical building facades is often quantified using the "annual driving rain index (*aDRI*)" subjected to the availability of adequate wind and rainfall data. The present endeavor adopts the instance of Indian subcontinent to demonstrate the suitability of gridded data, which represent the average climatic conditions prevailing over approximately square grids, for estimating *aDRI* over continuous spatial positions including locations for which conventional station data are not available. The wind and rainfall records used pertain to the sixty-year period of 1951–2010. The study compares the quality of *aDRI* estimates as a function of the temporal resolution of gridded data by evaluating the total, non co-occurring and averaging errors. Regression models have been developed to facilitate a refined estimation of the index for those locations for which only monthly or annual data sets are available. An *aDRI* map for India at $1^0 \times 1^0$ (lat./long.) resolution has been constituted and the dominant directions of driving rain have been identified based on the analysis of daily gridded data. The discourse concludes with a statistical analysis of yearly driving rain indices to deduce the magnitude and significance of the trends pertinent to individual grids.

1. Introduction

Moisture accumulating in the porous fabric of a building envelope under the influence of ambient environment instigates its gradual deterioration and also affects the serviceability of indoor spaces. The physical damage inflicted on the envelope commonly manifests itself in the form of cracking and spalling of surface-layers. This occurs in consequence of the dissolution and crystallization of salts or due to the formation of expansive compounds as end products of reactions occurring within the porous matrix (Litvan, 1980; Charola, 2000; Idorn, 1992). Elements subjected to the persistent action of wetting-drying cycles lose stiffness and strength and also fall susceptible to the attack of corrosion (Benavente et al., 2008; Lopez and Gonzalez, 1993; Andrade et al., 2002). Moisture buildup in building materials also promotes microbial growth leading to the physical deterioration of the envelope and of the quality of indoor air through the emission of mycotoxins and organic volatiles (Gaylarde et al., 2003; Bornehag et al., 2001). Dampening of the envelope also lowers its insulating efficiency causing a consequent escalation of indoor heating and cooling loads (Bhattacharjee, 2013). The pertinence becomes especially critical for severe hydric influences such as rains (Abuku et al., 2009).

The co-occurrence of wind and rain gives rise to an oblique *driving rain* vector that wets exposed building facades and consequently influences their performance over varying time scales. The necessity to make a building envelope robust against the onslaught of *driving rain* has, over the course of the past century, driven continuing research towards its empirical, semi-empirical and numerical characterization (Blocken and Carmeliet, 2004). Studies based on field observation and numerical simulation of *driving rain* have ascertained its non-uniform distribution over windward facades wherein the top corners find the maximum exposure followed by the top and side edges (Abuku et al., 2009; Blocken et al., 2009). This has subsequently led to the constitution of *catch ratios and local factors* to facilitate the estimation of moisture loads at different points of an exposed facade (Karagiozis et al., 1997; Choi, 1994). A few studies have also been carried out to analyse the interaction of driving rain with exposed surfaces at the scale of an impinging water drop to comprehend the phenomena of spreading, bouncing, partial absorption, and runoff generation (Abuku et al., 2009a, 2009b, 2009c; Blocken et al., 2013). Efforts such as these are fundamental to the better understanding of rain-induced moisture intrusion in building facades.

Field studies on driving rain have also established the proportionality of wind-driven rain intensity (the horizontal component of driving rain) to wind speed and horizontal rainfall intensity (Lacy, 1965; Hoppestad, 1955). The annual driving rain index *aDRI,* was therefore defined as the

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product of average wind speed and average total rainfall, to quantify the severity of wind-driven rain intensity. This subsequently led to the development of driving rain maps for various countries in Europe, America, Asia and Africa (Boyd, 1963; Lacy, 1964; Grimm, 1982; Sauer, 1987; Chand and Bhargava, 2002; Akingbade, 2004; Sahal, 2006; Giarma and Aravantinos, 2011, 2014; Pérez-Bella et al., 2012; Domínguez-Hernández et al., 2016; Pérez-Bella et al., 2013, 2014; Narula et al., 2017). These maps depicted the spatial distribution of *aDRI* values at different locations, thereby enabling a relative assessment of the prevailing exposure severity and account for the same in the design of building envelopes of desired robustness. For a climatologically diverse country such as India which encompasses vast stretches of cold, hot and dry, warm and humid, temperate and composite regions, the importance of a driving rain map is even more critical.

The *aDRI* values used to constitute driving rain maps can be determined using data of various time resolutions such as hourly, daily or monthly based on their availability. *aDRI* values computed with data of finer temporal resolutions provide improved estimates of actual exposure due to their ability to encompass information of individual wind and rainfall occurrences to a greater detail (Blocken and Carmeliet, 2007). However, the insufficient availability of finer climatic records at most locations compels the use of daily, monthly or annual data in the determination of *aDRI,* designated respectively as *daDRI*, *maDRI* and *aaDRI* with increasing levels of errors (Pérez-Bella et al., 2012; Giarma and Aravantinos, 2014).

Semi-empirical relations have also been extensively used to quantify the actual moisture loads imposed on vertical surfaces oriented in different directions. These models represent free driving rain conditions and are essentially of the form $I_\theta = (2/9)\sum W_h(R_h)^{8/9}\cos(D-\theta)$, where, θ (degrees) is the direction of normal to the facade, D (degrees) is the direction of wind, I_θ (mm) is the total amount of driving rain, W (m/s) is the hourly mean wind speed and R (mm) is the hourly horizontal rainfall and with the summation being taken over only positive exposure values on a desired interval. Zhu et al. used the model based on records of hourly data for various Canadian cities. Researchers have also used a direction independent form of the model i.e., $I = (2/9)\sum W_d(R_d)^{8/9}$ (Zhu et al., 1995). The model was used with daily data to determine the moisture loads corresponding to discrete rainfall spells (referred to as the *absolute wet spells*) pertaining to a year and subsequently to deduce I_{AS} (*absolute spell index*) as a measure of severity from Gumbel distribution fitted with the set of maximum yearly values of I (Pérez-Bella et al., 2012; Giarma and Aravantinos, 2014).

This paper discusses the genesis of gridded data and establishes its reliability in facilitating the determination of location specific annual driving rain indices. Subsequently, the errors inherent to *maDRI* and *aaDRI* in relation to *daDRI* have been characterized. Furthermore, a set of regression lines have been fitted to relate *daDRI* to *maDRI* and *aaDRI* values. These models have been developed to aid indexing of the driving rain scenario in terms of *daDRI* for those locations at which only monthly or annual climatic records are available. A driving rain map of India has also been developed. The gridded map by the virtue of having a complete spatial coverage is especially useful to designers concerned with sites for which no climatic data is available. The discourse concludes with an analysis to characterize the trends of yearly indices at individual grids to obtain an impression of its historical evolution and probable future scenarios. The study utilizes data pertaining to a sixty-year period (1951–2010). The records of rainfall were obtained from the archives of India Meteorological Department (IMD) while those for wind were obtained from the web-repository of National Oceanic & Atmospheric Administration (NOAA) Earth System Research Laboratory, USA.

2. Gridded climate data

Conventionally, climatic conditions are recorded at discrete meteorological stations. To achieve a spatially continuous representation of climate over a region, the recorded data are usually interpolated using deterministic or probabilistic techniques to a set of uniformly distributed points forming a system of square grids (Hartkamp et al., 1999). The interpolated data corresponding to a point thus provides an average depiction of the climate pertaining to a grid. For regions with sparse distribution of meteorological stations or in cases where the availability of data is limited, the constitution of gridded data is carried out using calibrated records obtained from ships, satellites and other non conventional sources. Furthermore, the data retrieved from different sources facilitates the identification of outliers and also enables addressing the problem of missing values.

2.1. Rainfall and wind data

The gridded rainfall data used in this study were obtained from the archives of IMD. The data set comprises daily rainfall values for 357 square grids, each of $1^0 \times 1^0$ spatial resolution, covering the entire Indian mainland. The data spans over a period of 60 years (1951–2010) and is based on rainfall records of 2140 stations. Thus, a total of 21915 (365 days $\times$ 45 non-leap years + 366 days $\times$ 15 leap years) data points at each of the 357 grids forms the basis of the present study. The reader is directed to (Shepard, 1968; Pai et al., 2014; Rajeevan et al., 2005; Narula et al., 2017) for a detailed description of spatial distribution of stations and the genesis of this data.

The gridded wind data for the chosen area and period of study was obtained from the web archives of NOAA. The data set provided by NOAA has a global coverage at $2.5^0 \times 2.5^0$ spatial resolution and is generated through the reanalysis of observed and estimated values determined from physical models that impute missing values between stations and time steps (Kalnay et al., 1996; NOAA). The data essentially comprises of the daily values of wind vector components oriented along the four cardinal directions which can be used to compute the speed and direction of resultant wind (Narula et al., 2017). The Data set pertaining to the Indian mainland was extracted from the global set and thereafter re-gridded to a finer resolution $1^0 \times 1^0$ using bi-linear interpolation in order to match the scale of rainfall data. The re-gridding has been performed in openly available statistical software R (R Core Team, 2013).

3. Methodology

3.1. Calculation of driving rain indices

The driving rain index for a location can be calculated using the daily, monthly or annual records of wind and rainfall data. The accuracy with which the severity of driving rain conditions is represented by the index is known to depend on the time resolution of measured data and improve substantially at finer scales (Blocken and Carmeliet, 2007). However, the availability of meteorological data of daily, hourly or sub-hourly frequencies for most of the stations remain too limited to facilitate a reliable analysis. This study utilizes average daily gridded data to determine *daDRI*. The values of *maDRI* and *aaDRI* for individual grids have also been computed by generating monthly and annual records from daily data. The scheme of calculation has been adopted from earlier works reported in literature and is briefly described in the sequel (Pérez-Bella et al., 2012; Giarma and Aravantinos, 2014).

The *daDRI* for a grid can be calculated as

$$daDRI = (1/N)\sum_{i=1}^{k} W_{d_i} R_{d_i} \tag{1a}$$

Here, *daDRI* is in m^2/s, N is number of years and k is number of days in N years. W_{d_i} *(m/s)* and R_{d_i} *(m)* represent the average wind speed and total rainfall respectively on the *i-th* day. To determine *maDRI* for a grid, the indices for each month $m = 1,2,3,\ \ldots\ 12$, $mDRI^{(m)}$ are first calculated as the product of average monthly wind speed (W_m) and average total monthly rainfall determined using available records of daily average