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RESEARCH COLLABORATION IN SOLAR RADIOMETRY BETWEEN THE UNIVERSITY OF REUNION ISLAND AND THE UNIVERSITY OF KWAZULU-NATAL

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ABSTRACT

Since 2012, the Universities of KwaZulu-Natal and Reunion Island have collaborated on a joint programme of solar energy research. The initiative has two principle aims: the development of solar forecasting techniques and the expansion of solar monitoring capabilities from continental Africa into the southern Indian Ocean region. In this paper, we introduce the programme and review the progress made. A key activity is performance validation of a low-cost radiometric sensor, the Delta-T Devices SPN1, which has been operated at a UKZN ground station for comparison against reference sensors. The instrument potentially represents an opportunity to expand existing radiometric networks by reducing the cost of ground station facilities. A novel feature of the device is its use of seven thermopile sensors and a stationery shading mask which together enable the simultaneous measurement of global horizontal and diffuse horizontal irradiance. It is important that the instrument performance should first be assessed, however, so that its measurement uncertainty is known ahead of deployment. Data from the UKZN trial are included in the paper, along with a description of a meteorological classification system that may be used in solar forecasting systems. The system is based on the direct solar fraction, that is, the ratio of direct horizontal irradiance to global horizontal irradiance. A clustering methodology is described and sample data are provided to illustrate the ability of the method to segregate days into statistically significant bins.

INTRODUCTION

The island of Reunion is located in the southern Indian Ocean, east of Madagascar at a latitude of 21.1° South. As a department of France it has a population of over 850 000, a surface area of approximately 2 500 km^2 and a tropical climate heavily influenced by the trade winds. The topography is mountainous and volcanic in origin.

Over the past several years, Reunion has embarked on a programme to expand the deployment of renewable energy technologies, including wind and solar power systems. The island has a very good solar resource, however its weather patterns are influenced by several factors including seasonal variation in wind and the mountainous landscape that generates orographic rainfall patterns. The result is a diversity of climatic conditions over a small land area and resulting microclimate phenomena. This set of factors complicates the use of solar energy technologies such as photovoltaics (PV) and limits the use of renewable energy power sources to 30% of the island's installed capacity for grid-stability reasons (in 2012, more than 150 MW came from solar plants). As a result, the development of solar forecasting systems has become a priority to ensure the maximal use of renewable energy, even in the face of resource variability.

Two key requirements for a successful solar forecasting capability are 1) a spatially expansive network of ground-based sensors providing near-real-time radiometric data on which to base the prediction, and 2) an effective data processing technique that can model the stochastic nature of solar irradiance in the presence of cloud. This research programme aims to address both requirements by evaluating a low-cost sensor for possible use in a southern Indian Ocean regional network, including Reunion island, and in evaluating a novel processing technique developed by the LE²P laboratory for classifying solar data. The classification method is intended as a tool to enable more effective solar forecasting over short time periods.

KEY WORDS:
Diffuse and global solar radiation; subtropical weather; direct and diffuse fraction; total sky imager; Hierarchical Clustering; Principal Components Analysis.

NOMENCLATURE

DNI	direct normal irradiance (W/m^2)
GHI	global horizontal irradiance (W/m^2)
DHI	diffuse horizontal irradiance (W/m^2)
k_b	direct fraction
Z	solar zenith angle (°)
s_i^t	time series
i	day index
n	number of day

PERFORMANCE OF THE SPN1 RADIOMETER

Radiometric schemes seek to characterise sun strength through the measurement of solar irradiance in [W/m^2] at high temporal resolution, typically with 1-minute averages. Optimal schemes provide for the independent measurement of direct normal irradiance (DNI), global horizontal irradiance (GHI) and diffuse horizontal irradiance (DHI) using three separate sensors. Alternately, sub-optimal schemes can be configured to measure two of the three components and calculate the third from the well-known closure equation equating GHI with the sum of DHI and the vertical component of DNI. There is a cost-advantage to using sub-optimal schemes and more sensors may be deployed in the network, however the statistical uncertainty of the measurements rises. Higher uncertainties may be tolerable, but sensor behaviour must be well understood before any decision is made about deployment.

The SPN1 radiometer (Figure 1) uses an array of seven miniature thermopile sensors and a computer-designed shading mask to measure DHI and GHI. The mask ensures that at least one of the thermopiles is always fully exposed to GHI, and one is always fully shaded [1].

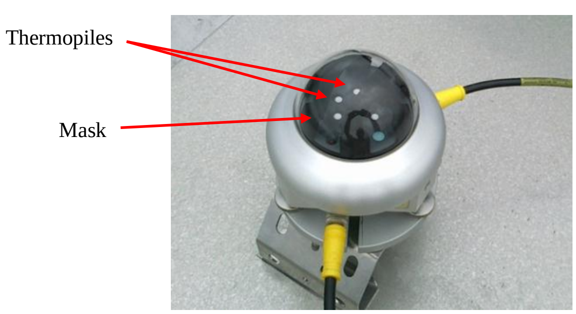

Figure 1 SPN1 sensor installed at the UKZN Howard College radiometric ground station

The spectral response of the SPN1 is 400-2700 nm with a measurement range of 0 to 2000 W/m², a measurement uncertainty of ±10 W/m² and a response time of 0.1 second [1]. It is compact, light-weight and easy to use with no moving parts and no external shading ring. Two analogue voltage outputs are provided for global and diffuse radiation, from which DNI can be calculated. Digital outputs are also provided. At present, the SPN1 retails for approximately 5 000 Euros, making it an attractive alternative to optimal measurement schemes that cost several times as much.

An SPN1 provided by the University of Reunion Island has been operating at UKZN's Howard College radiometric ground station since April 2013. Data from the sensor are compared against measurements from collocated Kipp & Zonen radiometers measuring DHI, GHI and DNI independently.

Figure 2 compares output from the UKZN SPN1 with reference values for clear-sky and partly cloudy conditions. To date, the SPN1 has been a reliable instrument with no outages and minimal maintenance required, other than cleaning. The uncertainty values are approximately 6.7% for GHI and 9.3% for DHI.

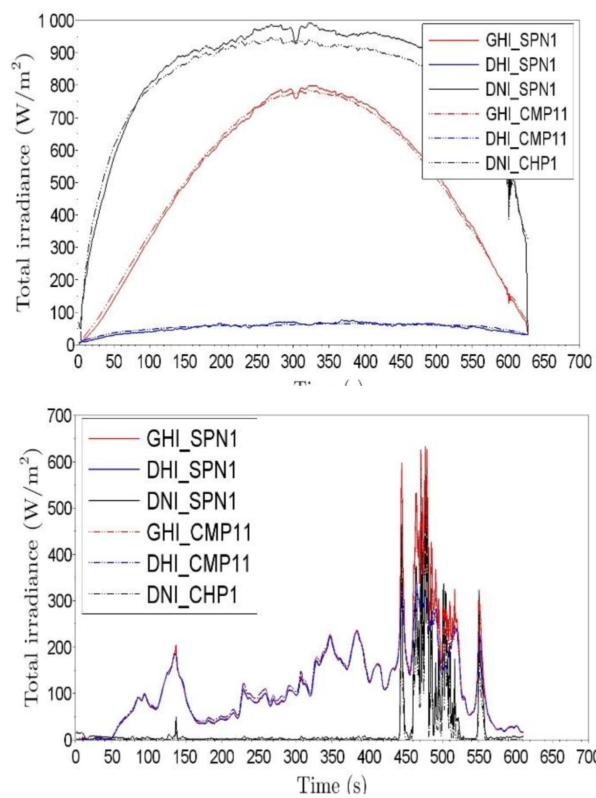

Figure 2 Comparison of GHI, DHI and DNI from the SPN1 sensor (solid) and collocated references instruments (dotted) for a clear sky day (top) and a partial cloudy day (bottom)

According to Delta-T Devices [1], an SPN1 is said to be calibrated when the standard deviation is less than 5% on the global irradiance and 10% on the diffuse irradiance, both limits given at 0.5%. We are then slightly off by 1.23% on the diffuse measurements. The control made on the readings consistency of the 7 thermopiles gives 95% (saying that for 95% of the time, the seven sensors read the same) which is above the limit given by the manufacturer (94%). The conclusion of this study is that our SPN1 is due for an indoor calibration as one of the two controls defined by Delta-T Devices has not passed. This is expected since the equipment was manufactured in 2009 and has never been recalibrated since.Data quality definitively depends on maintenance and calibration of the radiometer. We know that a major effort is to be made in that direction. Today, the collaboration between the LE^{2}P lab and Delta-T Devices should soon allow the lab to conduct its own outdoor calibration as per ISO norms (instead of sending all SPN1s back to UK every two years.

DATA ACCESSIBILITY AND NETWORK EXPANSION

The output from the SPN1 at UKZN is made available as 1-minute averages via the publicly accessible Southern African Universities Radiometric Network (SAURAN), at www.sauran.net. The website permits researchers working on this collaborative programme to access measurements easily and within a few hours of them having been generated.

A secondary aim of this collaboration is the development of measurement networks to gather data and refine forecasting techniques. Over the forthcoming year, the SAURAN network will be expanded from continental southern Africa into the southern Indian Ocean region with the addition of a station at Le Port, Reunion. Further expansion into the neighbouring “Vanilla Islands” surrounding Reunion is also under consideration.

In addition to the UKZN trial, the SPN1 is also being evaluated in parallel in Reunion. Since 2008, LE^{2}P has established the RCI_GS solar radiation network to provide GHI and DHI at 1-minute intervals. Each station includes meteorological capabilities in the form of a Vaisala WXT520 suite. This is a compact and light-weight instrument that measures temperature, humidity, barometric pressure, precipitation, and wind speed and direction. The measurement range and accuracy are respectively [-52 +60] ±0.3°C for temperature, [0 100] ±3% for humidity, [600 1100] ±1 hPa for pressure, cumulative accumulation with 0.01 mm for precipitation, [0 60] ± 0.3m/s for wind speed, [0 360] ±3° for wind direction.

The RCI_GS network consists of eleven ground-based stations covering mainly the coastal areas of Saint-André, Saint-Leu, Saint-Pierre, Le Port, Saint-Denis, Bras-Panon, Saint-Joseph, La Possession and Sainte-Rose. There are two additional sites further inland. Figure 3 provides a map of the network, and Figure 4 shows the installation of one of the stations near Saint-Denis, on the northern coast of the island. At present, the raw measurement data from the RCI_GS network are used exclusively by LE^{2}P for development of forecasting and mapping techniques, and, for the moment, are not publicly accessible. Processed data in the form of irradiance maps and predictions of solar radiation can be obtained from the LE^{2}P website at http://le2p-cc.org/RCIGS/ [2]. In time, the results from the evaluation trial of the UKZN SPN1 sensor and those being tested in Reunion, will be used to develop a strategy for expanding the measurement networks currently operating across the region. The intention of this collaboration is thus to explore efficient ways of measuring and processing solar data so as to promote the use of renewable energy in the southern African and southern Indian Ocean region.

Figure 2 Location of RCI_GS monitoring stations

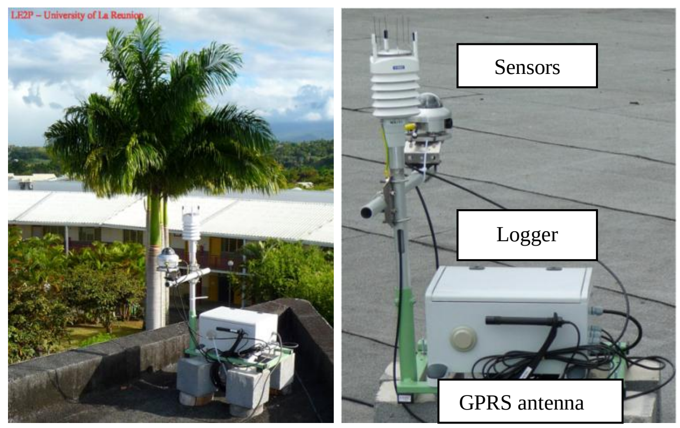

Figure 4 An RCI_GS station with SPN1 sensor, Vaisala meteorological suite, logger and communications hardware

SOLAR FORECASTING

As solar energy technologies increase in popularity, both with respect to PV and concentrating power systems (CSP), the need is also growing for accurate short-term forecasts of solar irradiance. This is important for ensuring electrical grid stability and managing plant operations. Sun strength is notoriously difficult to predict, however, as a result of stochastic variations that result in the presence of cloud.

To date, much of the work done in forecasting has focused on statistical techniques that capture the behaviour of the irradiance time series, rather than describing the underlying physics. These include auto-regression (AR), autoregressive moving averages (ARMA) and autoregressive integrated moving averages ARIMA. Other approaches include Artificial Neural Networks (ANNs), Numerical Weather Prediction (NWP), Satellite and Ground-based Imaging as well as Hybrid methods which are a combination of the above [3].

Each of the above methods has its own shortcomings. For example, NWP models are unable to precisely predict the position and extent of cloud fields. This is primarily due to their relatively coarse spatial resolution (1-20 km), therefore rendering these models inefficient in resolving micro-scale physics associated with cloud formation. However, NWP models have the advantage of producing forecasts over long time horizons (15-240 h) and can be more accurate than satellite based models for horizons greater than 4 hours [3].

To achieve higher spatial and temporal resolution, and to fill the gap between NWP and satellite models, ground-based imaging has been used. This provides a method to obtain sky cover and cloud shadows, and cross-correlation of consecutive sky images are used to produce cloud motion vectors and forecast cloud locations. Depending on cloud speed and height, a ground-based imager (such as a total sky imager) may be useful for providing forecasts in the 5-25 minute horizon [4].

The development of a Hybrid method was proposed by many researchers [5,6,7] to increase forecast accuracy by combining the strengths of more than one forecast methodology. The Durban area has a reasonable solar resource by comparison with much of Europe and exhibits good potential for the deployment of solar water heating and photovoltaic systems. It is relatively poor compared to the western parts of South Africa [8], however, due to its sub-tropical climate and associated levels of cloud coverage. The city experiences a variety of dynamic cloud systems that provide a good location for study, testing and development of solar forecasting. As part of this effort, the classification of Durban's solar micro-climate is important to the future development of effective forecasting techniques.

CLASSIFICATION USING DIRECT SOLAR FRACTION

In an effort to develop a solar forecasting capability, the University of Reunion Island has proposed the use of a classification methodology that describes the daily sky condition from the point of view of cloud cover [9]. The driving parameter for this approach is direct solar fraction, or k_b, where k_b = DNI.cos Z/GHI, and Z is the solar zenith angle.

The direct fraction k_b is used to identify different types of days depending on their level of solar irradiance among known situations: clear sky (Figure 5), cloudy, intermittent cloudy (Figure 6). To do so, different samples of daily sequences of k_b measured between 08:00 AM and 05:00 PM are analysed.

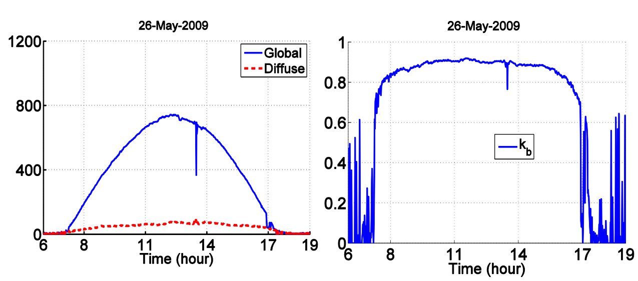

Figure 5 Clear sky day solar radiation on the left [W/m^2], and the k_b index on the right

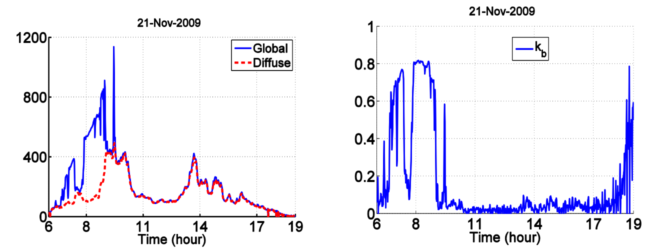

Figure 6 Intermittent cloudy day solar radiation on the left [W/m^2], and the k_b index on the right

A. Methodology

A time series s_i is a sequence of numbers representing the measurements of a given attribute at equal time intervals. Let $I = \{1, \dots, n\}$ and $T = \{1, \dots, p\}$. A set of time series $\{s_i | i \in I\}$ can be represented by the matrix

$$S = (s_i^t)_{i \in I, t \in T}$$

where s_i^t is the value of the attribute for the series s_i at the time t. In our case, a time series records the different measurements of k_b every minute during a day. Each series $s_i = (s_i^t)_{t \in T}$ is viewed as a vector of the Euclidian space $E = \mathbb{R}^p$, a weight $p_i = 1/n$ is associated to s_i, and the gravity centre of the set of series $N(I) = \{(s_i, p_i)_{i \in I}\}$ is denoted G.

The methodology used to cluster a set of time series consists in combining three data mining methods: Principal Component Analysis (PCA), Ward and K-means clustering methods. We used the package FactoMineR [10] that implements this strategy in the R platform.

1. Principal Component Analysis was used as a pre-process for hierarchical clustering method for reduction and denoising [11]. The first principal components are a set of new uncorrelated variables which extract the main information contained in the data. This issue is important to analyse Time series when measurements are done on a long period, and when the values are correlated. The partitioning obtained by the hierarchical clustering method performed on a set of selected pertinent principal components is more stable than the one obtained from the original data. The number of dimensions suggested by the strategy of FactoMineR retains 92% of the total variance.

2. To determine an optimal number of clusters, the Ward Hierarchical method [12] is applied on these PCA principal components. This organizes the set of days in a sequence of nested partitions forming a hierarchical tree. The total variance is $V = \sum_i p_i\, d^2(s_i, G)$. Then $P = \{C_k\}_{k \in K}$ is a partition of I, where p_{C_k} and G_k are respectively the weight and the gravity centre of the cluster C_k.

The within-cluster variance $W = \sum_{k \in K} \sum_{i \in C_k} p_i\, d^2(s_i, G_k)$ and the between-cluster variance $B = \sum_{C_k \in P} p_{C_k}\, d^2(G, G_k)$ characterise the homogeneity of the clusters of the partition P. The Huygens theorem allows one to decompose the total variance V as follows: $V = B + W$. At each step, the Ward method merges two clusters that minimise the reduction of the between-cluster variance. A good number of clusters can be picked out by analysing the between-cluster variance B

decreasing of the partitions of the hierarchical tree. This number K of clusters is suggested when the increase of B between $K-1$ and K clusters is much greater than the one between K and $K+1$ clusters.

3. When a number of clusters is selected, the quality of the partition P obtained by cutting the hierarchical tree is improved by applying a K-means algorithm. The quality of the partition P is measured by

$$Q(P) = B / V$$

representing the percentage of variance explained by the partition.

B. Cluster interpretation

For a class C_k, the Huygens theorem gives $V_k = B_k + W_k$ with $V_k = \sum_{s_i \in C_k} p_i d^2(s_i, G)$, $B_k = p_{C_k} d^2(G, G_k)$ and $W = \sum_{i \in C_k} p_i\, d^2(s_i, G_k)$. The quality of a class k is measured by $Q(C_k) = B_k / V_k\,\%$, which incorporates the variance of the class. A value close to 1 describes a homogeneous class.

To give meaning to clusters, we used data-mining tools developed by the University of Geneva for extracting interesting knowledge from sequence data. These tools are implemented in the TraMineR [13] library of the R platform. To apply these methods, numerical series must be converted into categorical data. We consider normalized series; each numerical value $s_i^t \in [0,1]$ of a series s_i is coded in a state or graduation $\hat{s}_i^t$ ranging from 1 to 10 according to its numerical value. Now, a series $\widehat{s_i}$ is a vector of the space $F = [\![1, 10]\!]^p$. Then let $\hat{s}^t = (\hat{s}_i^t)_{i \in I}$ the transverse state of the series at the time t. Each cluster will be described by the transverse distribution of states for each time t. The capabilities of TraMineR allow us to plot the state distribution for each class.

C. Results

In this subsection, we present the results obtained by application of the clustering strategy to Reunion Island data. Figure 7 suggests a partition of the data into 5 classes with a quality of 64%. Table 1 gives the description of each class. Except the class 3, we can see that the weight of each class is similar. We notice that the variance explained is important for the extremes class (1 and 5). It means that these classes are the more homogeneous and the least ones are class 3 and 4.

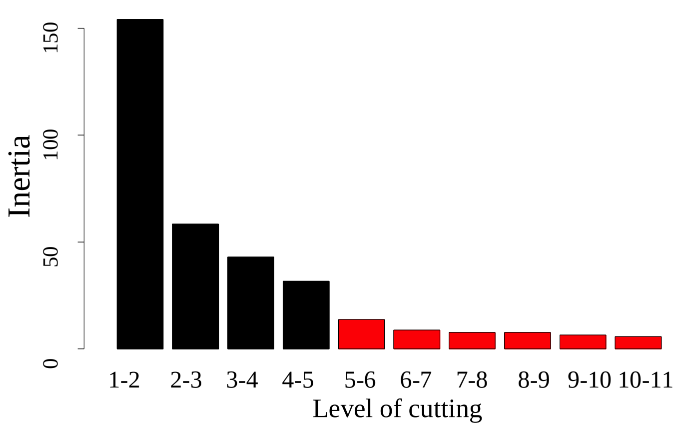

Figure 7 Bar plot of the gain in between cluster variance

Table 1 Cluster description.

Class	*Nb. Obs.*	*Freq.*	*Variance explained*
1	178	18.6 %	79.9 %
2	191	20.0 %	59.2 %
3	130	13.6 %	39.5 %
4	223	23.2 %	47.6 %
5	237	24.7 %	78.2 %

Figure 8 gives the distribution of k_b levels on all days and allows the determination of the significance of each class. Moreover, this representation allows us to look through all days of each class and evaluate the dispersion within the classes. We notice the homogeneity of each class and low frequencies of average levels in graduation for classes 1, 2, 4 and 5. In class 3, the presence of all levels of graduations of k_b suggests a strong variability in days.

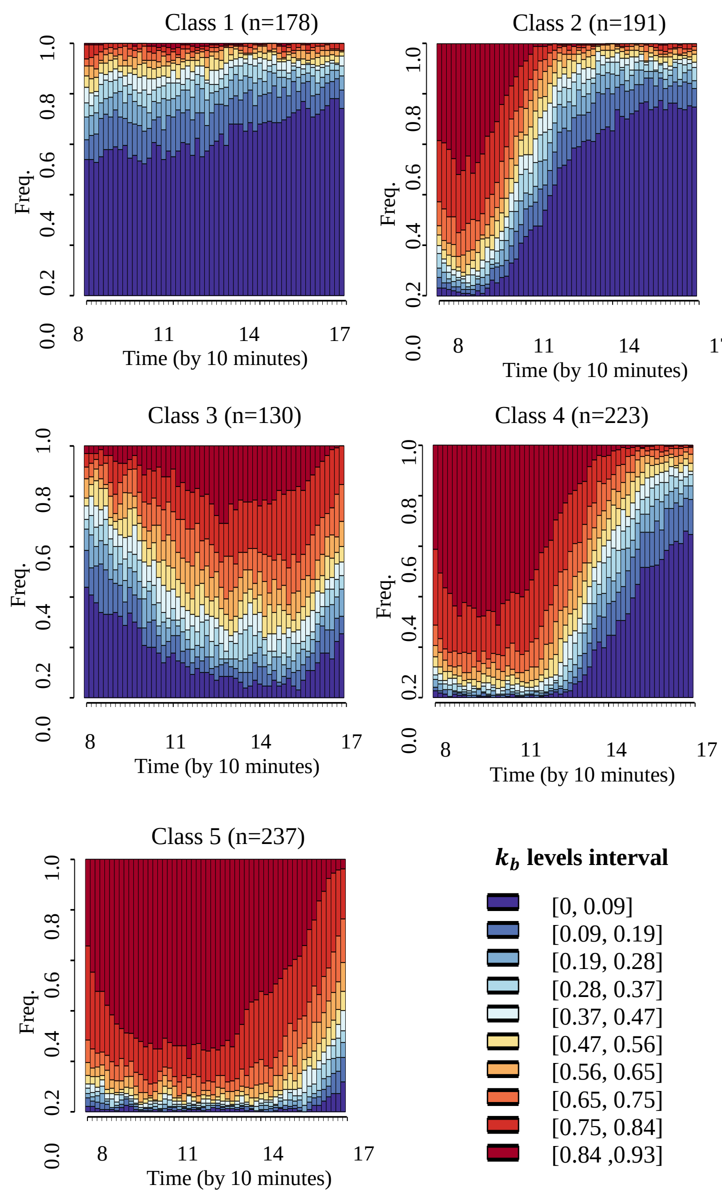

Figure 8 Transverse distribution of all states of k_b

Class 1 corresponds to a very low level of sunshine all day. This class presents dominant local phenomena which include, on one hand, the weak trade winds accompanied by a flow of moisture leading to significant effects of orographic clouds, and, on the other hand, the land breeze phenomenon induced by thermal contrasts.

Class 2 has a sunny beginning until mid-morning around 09:00 - 09:30 AM and a cloudy afternoon. Diffuse radiation is dominant in the afternoon while the direct component is more important in the morning.

Class 3 corresponds to a day with a variable weather with a high variability of the direct fraction: improvement in the late morning and moderate cloud cover in the afternoon.

The behaviour of Class 4 is similar to that of Class 2, but with a stronger sunny regime during all morning until early afternoon. DHI predominates later in Class 4 than in Class 2.

Class 5 days correspond to a regime of good weather throughout the day. Intermittent clouds passing over the station do not have a systematic character since direct radiation dominates in this class.

The significance of this work lies in its ability to classify weather patterns and therefore to predict coming cloud cover based on which class the day falls into. This might constitute one of the preliminary steps in a general forecasting methodology. In addition to classifying the day, additional steps would then be tailored to the type of weather patterns expected to predominate.

CONCLUSION

A collaborative programme of research in solar radiometry has been established between the University of KwaZulu-Natal and the University of Reunion Island. This focuses on the development of sun strength measurement stations and techniques for forecasting solar energy over short term periods. The programme is currently evaluating the performance of a low-cost sensor which may enable the expansion of monitoring networks by providing a less expensive radiometric capacity with reasonably low measurement uncertainties. In addition, a classification system based on the direct solar fraction, k_b, and developed by the University of Reunion Island has been demonstrated. This will be tested with Durban-based data and will serve as the one of the tools employed to predict short-term variations in sun strength, based on prevailing conditions at future test locations.

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