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Assessment of a Global-to-Direct empirical model for the long-term characterization of Direct Normal Insolation

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Abstract

The statistical characterization of the solar resource (direct normal solar radiation) is a key point in the initial phases of a solar thermal electricity (STE) plant project. Ideally, this characterization should be based on long time series (at least 8 years) of on-site measured data of Direct Normal Insolation (DNI) and other meteorological parameters. Unfortunately, there are very few places around the world where such time series are available, so alternative methods have to be used. Most of them rely on the application of global-to-direct conversion models to long time series of Global Horizontal Insolation (GHI), measured or derived from satellite images, to estimate the long-term resource. Usually, a meteorological station including sensors for the measurement of DNI is installed at the selected project site at the beginning of the project. The data collected during the measurement campaign, which normally extends between a few months and 2 years, are used to adjust the conversion models and to correct the estimates. In this paper, a simple empirical model that relates monthly clearness index and monthly direct normal fraction is used to estimate monthly and annual long-term DNI from statistically representative monthly values of GHI. This model is adjusted with GHI and DNI data collected during measurement campaigns of different durations. We show that the accuracy of the proposed model is under ±5% and that this accuracy improves sharply with the duration of the test campaign. For this purpose, we have used 13 years of high quality DNI and GHI data from the radiometric station of the Group of Thermodynamics and Renewable Energies (GTER) of the University of Seville, Spain. The results suggest that, this simple empirical model is a good alternative to the present methodologies when short DNI measurement campaign but long-term GHI values are available.

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1. Introduction

The characterization of the direct normal solar radiation is one of the key points in the initial phases of a solar thermal electricity (STE) plant project. Direct normal insolation (DNI) series, which statistically represent the solar resource for the plant site, are commonly used to analyze the financial feasibility of STE projects. These data sets involve an uncertainty that depends, among other factors, on the number of the DNI years measured on site, the quality of these measurements and the methodology used for estimating them. For the purpose of reducing the uncertainty, a DNI measurement campaign starts up on the chosen site at the beginning of the project [1].

DNI databases covering a period long enough to apply the conventional methodologies [2] are not very common. In consequence, the need to characterize this variable has stimulated the development of alternative methodologies adapted to the available information with uncertainties associated [3,4]. Most of these methodologies are based on global horizontal insolation data; either measured at nearby stations or estimated from satellite images, corrected with short DNI measurement campaign on site.

Studies show that GHI datasets estimated from satellite images could supply a reasonable result for long-term estimates in monthly and annual frequency, and even more if that datasets were corrected with measurements on site [5]. Nevertheless, that is not the case of DNI datasets estimated from satellite images. A cross comparison of a few of them in Europe showed that within 90% of the study area the annual uncertainty of DNI may go up to 17% [6]. Other validation studies based on ground measurements reveal a number of problems in geographical areas where significant disagreement exist between the tested datasets. Unfortunately, some of these geographical areas are within those with a very high potential in terms of DNI. Overall annual differences within ±10% and monthly differences of more than 30 % have been reported for Europe. Regarding North Africa, the differences reach significant values in some areas higher than 100% [7].

The possibility of estimating a statistically representative DNI set using only on-site measurements and an empirical simple model developed from these recorded data is explored in this work. The basic assumption for this methodology is that enough information to characterize the GHI from the site [8] and a minimum period of a year of DNI measurements on site are available. To quantify the quality of the results, 13 complete and quality-controlled years of GHI and DNI measurements from the radiometric station of the Group of Thermodynamics and Renewable Energies sited in Seville are used.

As a result of this study, the annual and the monthly errors –defined as the difference between the reference series, obtained as the average from the 13-year DNI measurements and the estimates obtained when applying this methodology- are shown, with different measurement campaigns of direct normal radiation from 1 to 12 years.

Nomenclature

$H_{g0,m}$	*monthly horizontal global radiation*
$H_{0,m}$	*monthly horizontal extraterrestrial radiation*
$H_{n,m}$	*monthly normal extraterrestrial radiation*
$H_{bn,m}$	*monthly direct normal radiation*
k_t	*monthly clearness index*
k_{bn}	*monthly direct normal fraction*

2. Background

2.1. Data collection and processing

The radiometric station of the Group of Thermodynamics and Renewable Energies (GTER) of the University of Seville, sited at the Engineering School of Seville, has recorded radiometric and meteorological measures since 1984. During its lifetime, the radiometric station has been relocated and the sensors upgraded several times. During the period 2000-2012 the station was sited in 37.40º N, 6.01ºE and collected accurate and high resolution DNI and GHI data in 5 seconds intervals, with a secondary standard pyranometer and a first class pyrheliometer, according to ISO specifications.

The data collected during the period 2000-2012 have been checked, corrected, and validated through a procedure developed by GTER, resulting in a high quality time series of DNI, GHI and other meteorological parameters that constitutes the basis for the present work.

The quality control and correction process is briefly described below:

- Quality control: The preliminary step includes a daily visual inspection of the graphical representations, the centered of days if necessary, the location of gaps at the records and, finally, the classification of days depending on the cloudiness level [9,10].

- Classification of days: In this section the days are classified as shown in figure 1. This classification has been done attending to the validity of data, location of errors and kind of days.

VALID DAYS	CORRECTABLE DAYS	DISCARED DAYS
Valid measurements from sunrise to sunset of GHI and DNI.	**CASE 1**: Correct measurements of GHI and DNI with a gap lower or equal than one hour close to the sunset/sunrise. **CASE 2**: Correct and completed measurements of GHI. Wrong/Not existing measurements of DNI. **CASE 3**: Correct measurements of GHI with a gap lower or equal than one hour close to the sunset/sunrise. Wrong/Not existing measurements of DNI. **CASE 4**: Correct and completed measurements of DNI. Wrong/Not existing measurements of GHI	1. File not created. 2. Wrong measurements of GHI and DNI. 3. Gap higher than one hour close to the sunrise/sunset at GHI and DNI measurements. 4. Gap higher than thirty minutes.

Fig 1. Classification of days.

- Correction: At this point the correction methods are developed for each case. There are two main groups of days that need to be modified; discarded and correctable. Correctable days are those that complement the database using mainly radiation models [11] and theoretical relationships widely recognized [12]. Regarding to discarded days, depending on which radiometric component is the anomaly detected, nearby databases or DNI models developed for the site are used.

From the total recorded days during the period 2000-2012, only 8% were classified as discarded days and 18% as correctable days. The rest of the days, a 74 % were recorded without any anomalies.

2.2. Correlation between clearness index and direct normal fraction

The aim of this work is to assess the uncertainty of a simple empirical model that relates monthly GHI values with monthly DNI values and allows the estimation of long-term monthly DNI data from long term GHI data under the following assumptions:

- Enough information to characterize the GHI from the site.
- A minimum period of a year of DNI measurements on site is available.

The model chosen for this purpose is based in an empirical relation between the monthly clearness index, k_t (1) and the direct normal fraction k_{bn} defined in (2). The clearness index is well documented in literature and widely used to characterize solar radiation in different timescales. However the direct normal fraction is not so used, being in most cases the diffuse fraction the chosen index.

$$k_t = \frac{H_{g0,m}}{H_{0,m}} \tag{1}$$

$$k_{bn} = \frac{H_{bn,m}}{H_{n,m}} \tag{2}$$

As first step, the whole selected period (2000-12) of both variables recorded by GTER station is considered to evaluate with the best scenario the type of regression model properly for the study. Among the regression tested models, linear and second order polynomial fits provide a reasonable result. Increasing the complexity of the model does not result in a significant improvement.

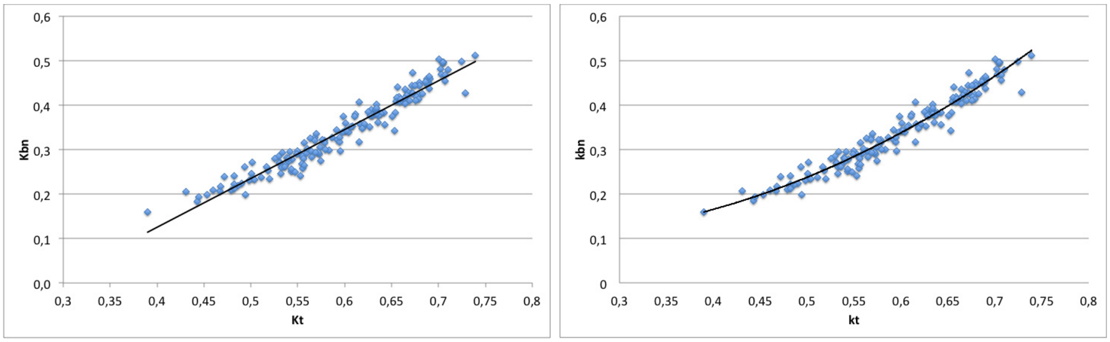

Fig 2. Linear (a) and second order polynomial (b) fits from kt and kbn values.

The estimated equation for the linear fit is:

$$k_{bn} = 1.0983 \cdot k_t - 0.3141 \tag{3}$$

The estimated equation for the polynomial fit is:

$$k_{bn} = 1.3771 \cdot k_t^2 - 0.5153 \cdot k_t + 0.151 \tag{4}$$

Although, the linear fit is less satisfactory for the extreme values, both regressions provide reasonable results. The polynomial coefficient of correlation R^2 is 0.95, very similar to the linear coefficient correlation 0.94. In order to analyze the possible effect in the monthly uncertainty for the different seasons, both fits will be used for this study.

3. Methodology

When a solar resource assessment study is addressed, the on-site measurement campaign rarely exceeds two years. Consequently, an alternative methodology has to be use to estimate a representative DNI dataset, and quantify the uncertainty from the methodology is not an easy task because a reference result is not available. In this study, the monthly average GHI and DNI measures from the 2000-12 period are considered the long term representative values and they are used as a reference to evaluate the uncertainty of the models when shorter periods of DNI measurements are available. To cover a representative number of possible cases and, at the same time, habitual scenarios, periods of records have been selected based on the criteria described bellow:

- Periods include consecutive months.
- The number of selected months is multiple of 12: from 1 year to 12 years.
- All the possible combinations are assessed for every period. The table 1 shows several examples of the analyzed cases.

Once selected the period of measurements (input data to the model), the linear and polynomial k_t-k_{bn} models are adjusted from DNI and GHI measurements. Subsequently and using the fitted models, the long-term monthly DNI values are estimated from the monthly average GHI measurements of the complete time series (2000-2012). The relative error between the long-term monthly estimated DNI values and the monthly average DNI measurements from the whole period is considered the uncertainty of the models.

These steps are repeated for every period and every previously described case. Several examples of the number of cases for each analyzed period are shown in the following table.

Table 1. Periods of DNI measurements used to quantify the uncertainty of the model.

	1 year	2 years	3 years	…	10 years	11 years	12 years
Case 1	Ene00-Dic00	Ene00-Dic01	Ene00-Dic02	…	Ene00-Dic09	Ene00-Dic10	Ene00-Dic11
Case 2	Feb00-Ene01	Feb00-Ene02	Feb00-Ene03	…	Feb00-Ene10	Feb00-Ene11	Feb00-Ene12
…	…	…	…	…	…	…	…
Case n	Ene12-Dic12	Ene11-Dic12	Ene10-Dic12	…	Ene03-Dic12	Ene02-Dic12	Ene01-Dic12
n	145	133	121	…	37	25	13

4. Results and discussion

The relative error of the long-term estimated DNI years from the methodology with respect to the average DNI year from the whole period of measurements are compared in this section. As already stated above, this parameter is assumed as the uncertainty of the models.

4.1. Annual uncertainty:

The annual DNI uncertainty values for each period analyzed by means of the linear and the polynomial model are represented in the figures 2 and 3. For both regression models, the maximum annual uncertainty is reached for one year of DNI measurements and clearly decreases when the measurement period increases until 9 years. For campaigns between 9 and 13 years the uncertainty trend changes very slightly, but always keeping a value inside ± 1%. This fact is a consequence of the monthly errors obtained. These ones, as show the tables 2 and 3, always decrease when the period of years increases but with different sign, causing these changes of trend in the annual errors.

As shown the figure 3, the annual uncertainty when fitting the linear model from one year of DNI measurements reaches values between -6 % and 5% and this interval slightly decreases with the polynomial model presenting values between 3.4% and -5%, as shown the figure 4. In this case, the polynomial model provide more accurate results, but when the measurement campaign is longer than one year both type of regressions present similar results. For periods equal to or higher than 3 years, both models show an uncertainty equal or lower than 3%. These results indicate the possibility of an annual long-term DNI estimation on this site with a k_t-k_{bn} model, with an acceptable uncertainty when a short period of DNI measurements is available and very low uncertainty when this period is higher than two years.

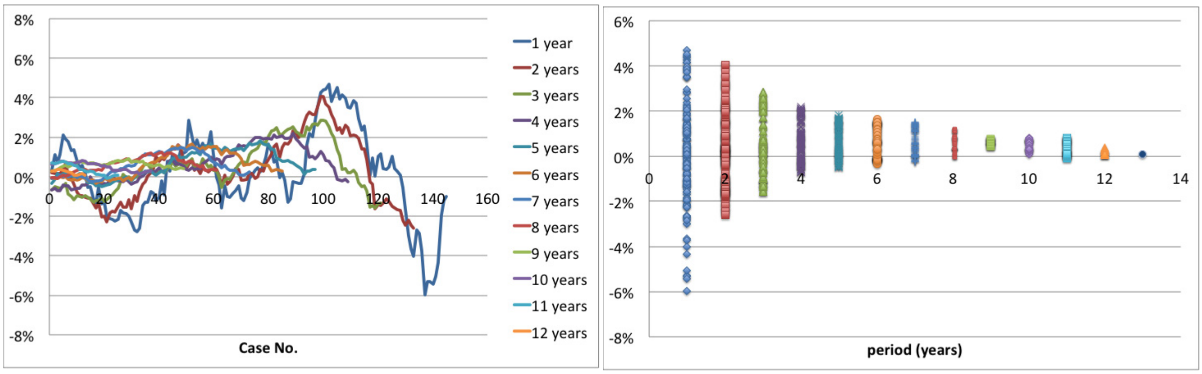

Fig 3. Relative errors between annual long-term DNI estimated values by means of the linear model and annual average DNI measurements against the number of cases studied (a) and for each analyzed period (b).

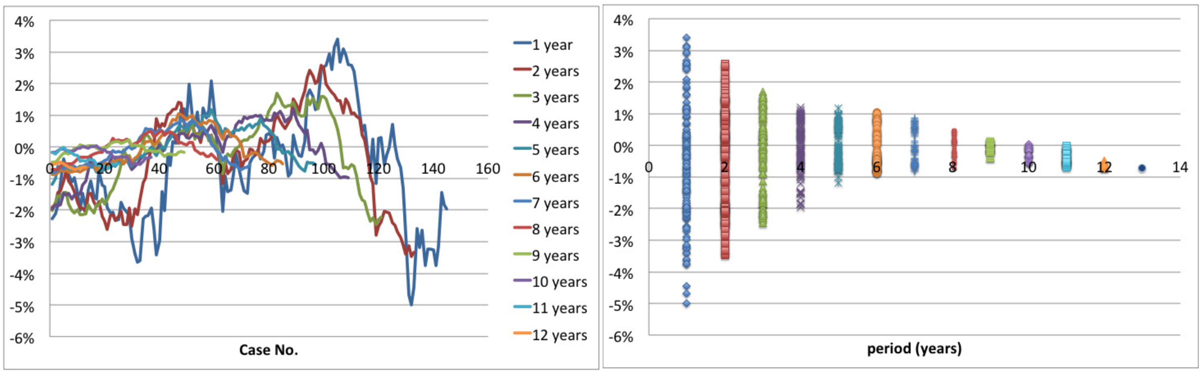

Fig 4. Relative errors between annual long-term DNI estimated values by means of the polynomial model and annual average DNI measurements against the number of cases studied (a) and for each analyzed period (b).

4.2. Monthly uncertainty

In the tables 2 and 3, the maximum and minimum monthly and annual relative errors obtained for each period and each month with linear and polynomial model are shown. The maximum monthly relative errors for both models correspond to December (18.3 % with the linear model and 21.6 % with the polynomial model) but as shown in figure 5, these values only appear in a few of the 145 cases. Discounting December and considering the relative errors as the uncertainty models, the polynomial model provides reasonable results with an uncertainty lower than 10 % with only one year of measurements and this uncertainty decreases when the recorded period increases. Periods of 3 years and longer provide uncertainties lower than 6 % in the highest radiation months with this regression model.

In a first impression, the polynomial model presents the best monthly results, mainly when the campaign is composed of one year of DNI measurements, but a more detailed analysis show that the lineal model provides lower errors in January, October and November when periods are longer. Nevertheless, both models show similar behavior in months with highest DNI or summer months. This fact suggests a dependence of the type of model with the type of climate. Figures 6 (a) and (b) illustrate this fact.

Table 2. Relative errors between annual and monthly long-term DNI estimated with the linear model and measured for each months and analyzed period.

Period (years)		Anual	Jan.	Feb.	Mar.	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
1	Min.	**-6,0%**	-12,8%	-7,2%	-4,2%	-4,4%	-1,4%	-3,7%	-8,4%	-5,4%	-3,0%	-9,7%	-12,3%	-18,3%
	Max.	**4,7%**	2,2%	5,7%	9,6%	7,5%	8,4%	5,8%	2,5%	5,2%	7,1%	4,3%	3,6%	0,4%
2	Min.	**-2,6%**	-6,1%	-2,0%	1,5%	0,0%	0,9%	-2,6%	-7,1%	-4,1%	-0,4%	-3,7%	-5,2%	-11,4%
	Max.	**4,1%**	0,5%	4,6%	8,3%	6,6%	8,1%	5,1%	0,9%	3,8%	6,6%	2,9%	1,8%	-1,8%
3	Min.	**-1,6%**	-5,6%	-0,9%	2,5%	1,1%	1,8%	-1,8%	-6,4%	-3,4%	0,5%	-2,8%	-4,6%	-10,0%
	Max.	**2,9%**	-0,5%	3,5%	7,2%	5,4%	6,8%	4,3%	0,3%	3,3%	5,3%	1,9%	0,8%	-2,9%
4	Min.	**-0,7%**	-4,9%	-0,2%	3,3%	1,9%	2,9%	-0,5%	-5,1%	-2,0%	1,6%	-2,0%	-4,1%	-9,5%
	Max.	**2,2%**	-1,5%	2,6%	6,2%	4,7%	6,2%	3,6%	-0,5%	2,5%	4,7%	0,9%	-0,3%	-3,5%
5	Min.	**-0,5%**	-4,7%	-0,4%	3,1%	1,8%	3,3%	0,0%	-4,4%	-1,4%	2,0%	-2,2%	-3,7%	-8,3%
	Max.	**1,8%**	-1,8%	2,3%	5,9%	4,3%	5,9%	3,5%	-0,6%	2,4%	4,4%	0,6%	-0,6%	-4,1%
6	Min.	**-0,3%**	-4,5%	-0,1%	3,4%	2,0%	3,6%	0,4%	-4,0%	-1,0%	2,2%	-1,9%	-3,5%	-8,5%
	Max.	**1,6%**	-2,3%	1,9%	5,5%	4,0%	5,7%	3,2%	-0,8%	2,1%	4,3%	0,2%	-1,1%	-4,9%
7	Min.	**-0,2%**	-4,7%	-0,2%	3,3%	2,0%	3,7%	0,5%	-3,8%	-0,8%	2,3%	-2,0%	-3,7%	-8,6%
	Max.	**1,5%**	-2,3%	1,9%	5,4%	3,9%	5,5%	2,7%	-1,5%	1,5%	4,1%	0,1%	-1,2%	-5,1%
8	Min.	**-0,1%**	-3,9%	0,4%	3,9%	2,4%	3,7%	0,8%	-3,5%	-0,6%	2,4%	-1,4%	-2,8%	-7,4%
	Max.	**1,2%**	-2,5%	1,7%	5,2%	3,7%	5,2%	2,3%	-1,8%	1,1%	3,8%	0,0%	-1,2%	-5,4%
9	Min.	**0,3%**	-3,6%	0,8%	4,3%	2,8%	4,2%	1,1%	-3,3%	-0,3%	2,8%	-1,0%	-2,5%	-7,0%
	Max.	**0,9%**	-2,6%	1,3%	4,8%	3,3%	4,9%	2,1%	-2,0%	0,9%	3,4%	-0,4%	-1,3%	-5,2%
10	Min.	**0,1%**	-3,4%	0,7%	4,2%	2,6%	3,9%	0,9%	-3,4%	-0,4%	2,5%	-1,0%	-2,1%	-6,5%
	Max.	**0,8%**	-2,5%	1,4%	5,0%	3,3%	4,7%	1,9%	-2,3%	0,6%	3,3%	-0,2%	-1,2%	-5,2%
11	Min.	**-0,1%**	-3,6%	0,4%	4,0%	2,4%	3,8%	0,8%	-3,5%	-0,5%	2,4%	-1,2%	-2,4%	-6,6%
	Max.	**0,8%**	-2,6%	1,4%	5,0%	3,3%	4,6%	1,6%	-2,7%	0,3%	3,3%	-0,2%	-1,3%	-5,3%
12	Min.	**0,1%**	-3,0%	0,8%	4,4%	2,6%	3,8%	0,6%	-3,8%	-0,8%	2,4%	-0,8%	-1,8%	-5,6%
	Max.	**0,4%**	-2,7%	1,0%	4,6%	2,9%	4,2%	1,2%	-3,2%	-0,2%	2,8%	-0,5%	-1,4%	-5,1%
13		**0,1%**	**-2,9%**	**0,8%**	**4,4%**	**2,7%**	**3,8%**	**0,7%**	**-3,8%**	**-0,8%**	**2,5%**	**-0,7%**	**-1,6%**	**-5,3%**

Table 3. Relative errors between annual and monthly long-term DNI estimated with the polynomial model and measured for each months and analyzed period.

Period (years)		Anual	Jan.	Feb.	Mar.	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
1	Min.	**-5,0%**	-9,6%	-5,9%	-2,3%	-4,3%	-3,7%	-5,0%	-7,9%	-5,6%	-5,0%	-6,7%	-8,9%	-21,6%
	Max.	**3,4%**	-0,6%	4,1%	7,2%	7,5%	9,4%	6,3%	5,3%	7,1%	7,9%	1,4%	1,2%	5,4%
2	Min.	**-3,5%**	-7,1%	-4,2%	-0,8%	-2,2%	-0,9%	-3,3%	-6,7%	-4,1%	-2,2%	-5,4%	-5,5%	-12,6%
	Max.	**2,6%**	-2,4%	1,4%	4,7%	4,1%	6,2%	5,1%	3,0%	5,2%	4,7%	-0,4%	-0,6%	-1,8%
3	Min.	**-2,5%**	-6,9%	-3,7%	-0,3%	-1,9%	0,2%	-2,1%	-5,8%	-3,1%	-1,3%	-5,1%	-5,4%	-7,3%
	Max.	**1,7%**	-3,2%	0,1%	3,7%	2,2%	4,6%	4,4%	2,8%	4,9%	3,0%	-1,3%	-1,7%	-2,4%
4	Min.	**-2,0%**	-6,5%	-3,4%	0,0%	-1,5%	0,6%	-0,6%	-4,2%	-1,5%	-0,9%	-4,8%	-5,0%	-6,7%
	Max.	**1,2%**	-3,4%	-0,6%	3,1%	1,6%	4,1%	3,9%	2,4%	4,4%	2,5%	-1,6%	-1,7%	-3,8%
5	Min.	**-1,2%**	-5,4%	-2,3%	1,2%	-0,4%	1,5%	0,2%	-3,0%	-0,4%	0,0%	-3,6%	-3,9%	-6,4%
	Max.	**1,2%**	-3,6%	-0,7%	2,9%	1,2%	3,7%	3,7%	2,1%	4,1%	2,1%	-1,9%	-2,0%	-4,0%
6	Min.	**-0,9%**	-5,5%	-2,2%	1,2%	-0,2%	1,9%	0,5%	-2,6%	0,0%	0,3%	-3,6%	-4,0%	-6,0%
	Max.	**1,0%**	-3,9%	-0,8%	2,8%	1,3%	3,9%	3,6%	1,8%	3,9%	2,2%	-2,1%	-2,3%	-3,7%
7	Min.	**-0,8%**	-5,6%	-2,3%	1,2%	-0,3%	1,9%	0,6%	-2,4%	0,1%	0,4%	-3,7%	-4,1%	-6,2%
	Max.	**0,9%**	-4,2%	-0,9%	2,6%	1,3%	3,7%	3,3%	1,2%	3,4%	2,1%	-2,4%	-2,6%	-4,5%
8	Min.	**-0,7%**	-5,6%	-2,4%	1,1%	-0,3%	2,0%	0,9%	-2,1%	0,4%	0,4%	-3,8%	-4,1%	-6,0%
	Max.	**0,5%**	-3,9%	-0,7%	2,8%	1,1%	3,4%	2,7%	0,6%	2,7%	1,8%	-2,0%	-2,4%	-4,7%
9	Min.	**-0,5%**	-5,3%	-2,1%	1,4%	-0,1%	2,2%	1,1%	-2,0%	0,6%	0,6%	-3,5%	-3,8%	-5,7%
	Max.	**0,2%**	-3,8%	-0,7%	2,9%	1,1%	3,1%	2,5%	0,4%	2,6%	1,5%	-2,0%	-2,3%	-4,4%
10	Min.	**-0,6%**	-5,2%	-1,9%	1,6%	0,1%	2,2%	0,9%	-2,1%	0,4%	0,7%	-3,3%	-3,7%	-5,7%
	Max.	**0,0%**	-4,0%	-0,9%	2,7%	0,9%	2,9%	2,3%	0,2%	2,4%	1,3%	-2,2%	-2,5%	-4,7%
11	Min.	**-0,7%**	-5,2%	-1,9%	1,6%	0,1%	2,2%	0,8%	-2,2%	0,3%	0,7%	-3,3%	-3,7%	-5,7%
	Max.	**0,0%**	-4,3%	-1,2%	2,4%	0,7%	2,8%	2,2%	0,1%	2,3%	1,2%	-2,5%	-2,8%	-5,0%
12	Min.	**-0,7%**	-5,2%	-1,9%	1,6%	0,0%	2,1%	0,8%	-2,0%	0,4%	0,6%	-3,3%	-3,6%	-5,6%
	Max.	**-0,5%**	-4,5%	-1,4%	2,1%	0,4%	2,3%	1,5%	-0,9%	1,4%	0,8%	-2,7%	-2,9%	-4,9%
13		**-0,7%**	**-4,6%**	**-1,5%**	**2,0%**	**0,3%**	**2,1%**	**0,7%**	**-2,1%**	**0,4%**	**0,6%**	**-2,8%**	**-3,1%**	**-5,1%**

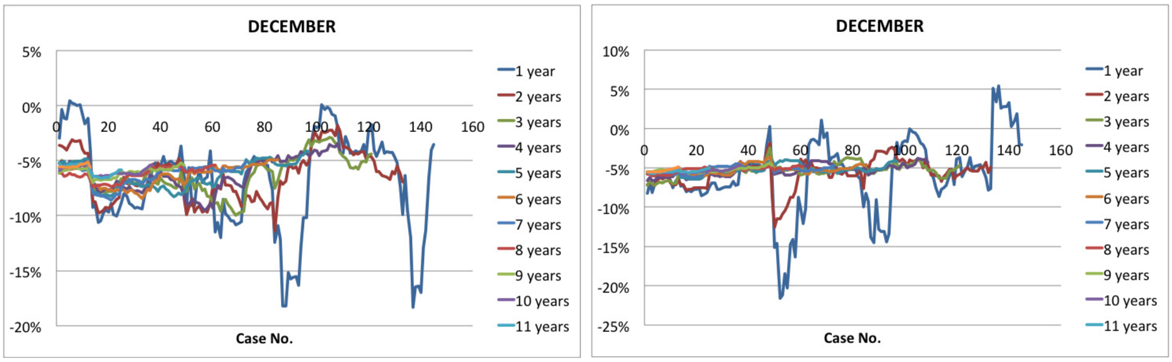

Fig 5. Relative errors between monthly long-term DNI estimated values with linear (a) and polynomial (b) model and average measured values from the whole database in December.

In figure 6 (a), the uncertainty is plotted against the duration, in years, of the measurement campaign for the months of January, May, June and July. For all months, the uncertainty decreases as the duration of the DNI measurement campaign increases. The monthly uncertainty values obtained with both models fitted from the 13 years of DNI measurements as a function of the monthly clearness index are shown in figure 6 (b). This figure suggests that the lineal model provides more accurate results in months with lower k_t values.

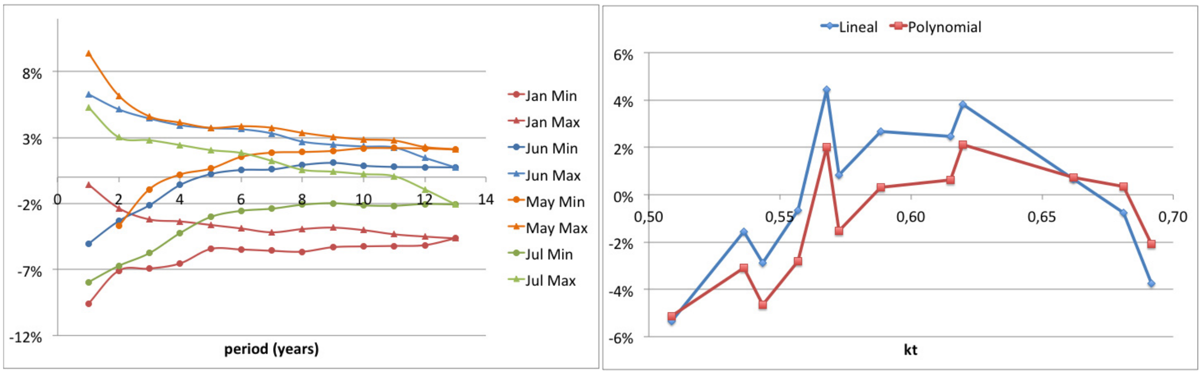

Fig 6. (a) Maximum and minimum monthly uncertainty obtained with the polynomial model in January, May, June and July from every period analyzed. (b) Monthly uncertainty obtained with the polynomial and the linear model fitted with the 13 years of DNI measurements against the monthly clearness index from the monthly average GHI measurements.

5. Conclusion

In this work, we have proposed and tested a simple empirical model to estimate monthly and annual long-term DNI representative values. The uncertainty of this model has been evaluated comparing the DNI values provided by the model, once adjusted with the data collected in measurement campaigns of different duration, with the average values of a 13-year time series recorded at the radiometric station of the Group of Thermodynamics and Renewable Energy, University of Seville. The results show an annual uncertainty lower than 5% when one year of DNI measurements is available and lower than 3% when the DNI campaign is equal or higher than 3 year from a second order polynomial model. Regarding to monthly results, the best type of regression model is not so clear, suggesting a different type of regression on base of the monthly k_t value. Nevertheless, both models present reasonable monthly uncertainties with values lower than 10 % for the highest radiation months from one year of DNI measurements and lower than 6% from three years of DNI measurements. The results obtained on the selected site suggest the use of this kind of model for long-term DNI estimations as a very good option when long DNI datasets of measurements are not available. The authors propose to extend this study to other locations where the required information is available.

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