EMPIRICAL MODELS FOR ESTIMATION OF DIFFUSE SOLAR RADIATION IN A TROPICAL, MOUNTAINOUS AND HUMID PLACE (XALAPA, MEXICO)

Adalberto TEJEDA-MARTÍNEZ* and J. Ernesto LÓPEZ-VELÁZQUEZ**,
**Grupo de Climatología Aplicada, Universidad Veracruzana, Xalapa, México*
***Instituto de Ingeniería de la Universidad Autónoma de Baja California, México*
atejeda@uv.mx, ernesto.lopez16@uabc.edu.mx

RESUMEN

Para estimar la radiación difusa horizontal en un sitio de clima tropical y montañoso, se presenta una selección de polinomios empíricos. Para generarlos se usaron datos registrados cada 10 minutos entre julio 2011 y junio 2012. Las variables independientes son el índice *Kt* (cociente de radiación solar global entre extraterrestre) y el *Kd* (cociente de radiación difusa entre radiación global). Las temperaturas máximas y mínimas y la precipitación diarias, se usaron como discriminantes en agrupaciones de casos para mejorar la bondad de ajuste de los modelos. Los polinomios tienen validez mensual, trimestral, semestral o anual, y no son aplicables a condiciones de cielo completamente nublado o completamente despejado.

Palabras clave: radiación difusa, clima tropical de montaña, regresión polinomial.

ABSTRACT

In order to estimate the horizontal component of diffuse solar radiation in a tropical, mountainous, and humid place, a selection of empirical polynomial models is presented which was obtained by statistical regression. The data of global and diffuse irradiance were captured every 10-min from July 2011 to June 2012. The independent variables are the clearness index (*Kt*, the ratio of global radiation over extraterrestrial radiation), and the diffuse fraction (*Kd,* the ratio of diffuse radiation over global radiation). Daily temperatures as well as rainfall were used to cluster cases and thus improve the goodness of fit of the empirical models. The models have a monthly, quarterly, semi-annual or annual validity, but are mostly not applicable to cloudy or clear sky conditions.

Key words: diffuse irradiation, mountainous tropical climate, polynomial regression.

1. INTRODUCTION

Global radiation is the algebraic sum of the dispersed radiation by gases, water droplets and particles of the atmosphere (diffuse radiation) plus direct (from the Sun, not dispersed) solar radiation. Knowing the value of these three variables is useful for research and engineering applications, especially in solar energy harnessing projects. However, the measurements of them are scarce in the world and, in fact, in Mexico.

In the city of Xalapa, Mexico (19° 33' 35,70"N, 96° 55' 44,95"W, 1464 m above mean sea level), there is a solarimetric station which has been recording global radiation and diffuse radiation, in addition to other variables such as air temperature, air humidity and wind, since the beginning of 2011. The climate and vegetation of Xalapa are those of mountainous sites in tropical latitudes, and the humidity is high because it is transported by wet winds and hydro-meteorological systems that frequently come from the Gulf of Mexico and higher latitudes: trade winds in summer, cold fronts in winter, and sea breezes almost whole year (Fig. 1). The annual average temperature is 19°C, with peaks in spring that exceed the 30°C and with minimum temperature in winter which is slightly above 0°C; the annual rainfall average is 1500 mm, of which 75% is concentrated in the May-October period; out of 170 rainy days in a year, 40% of them correspond to the semester November-April. The annual averages of relative humidity and cloud cover are 70% and 60%, respectively (SMN, 2013).

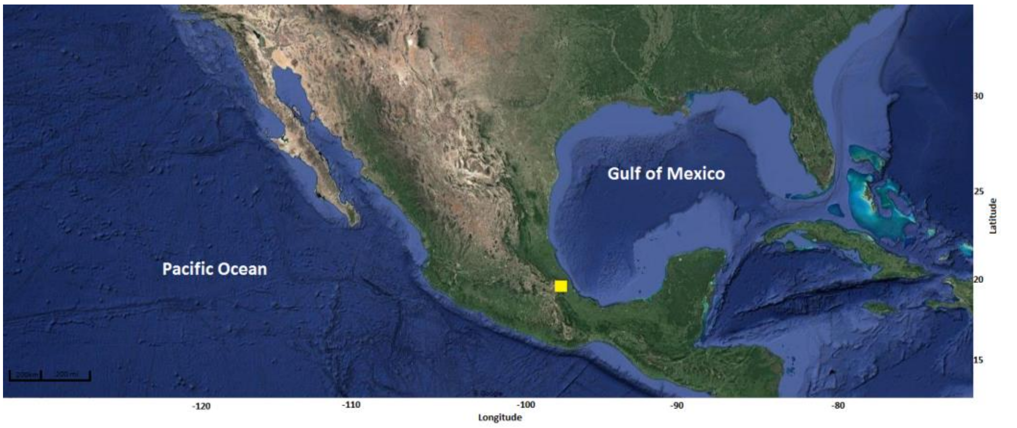

Fig.1. Location of Xalapa city (modified after Google Earth, visited on May 2018).

This communication proposes the usage of empirical statistical polynomials models developed from the data measured in Xalapa solarimetric station, to estimate the diffuse solar radiation. These models are based on the pioneering research by Liu and Jordan (1960) and on adaptations and improvements that have been made in the last fifty years (for example the work of Li *et al.*, 2011).

2. BACKGROUND

The interest in the use of renewable energy sources has led to specific studies similar to the present, such as in Algeria (Chikh *et al.*, 2012), Egypt (Trabea, 1999; El-Sebaii and Trabea, 2003), Saudi Arabia (El-Sebaii *et al.*, 2010), Libya (Said *et al.*, 1998), Turkey (Ulgen and Hepbasli, 2009), Brazil (Oliveira *et al.*, 2002; Furlan *et al.*, 2012), China (Jiang, 2009; Li *et al.*, 2011), India (Pandey and Katiyar, 2009; Singh *et al.*, 2013), and Greece (Paliatsos *et al.*, 2003). Bartolini *et al.* (2013) have done research for most of the countries in Europe, on basis on 44 specific studies. Their regression models started off from a first analysis that included 28 predictors, which the clearness index, solar altitude, air temperature and relative humidity were the most significant. However, in the case of Xalapa, neither the solar altitude nor the moisture are significant, possibly because Xalapa is a very humid place all year round, located inside the tropical latitudinal belt where solar trajectory does not have an important seasonal variation.

Another group of studies are those which resort to different techniques than regression models. Boland *et al.* (2008) have modeled the diffuse radiation using a logistic function; they showed that the models generated for Europe are unsuitable for Australia, by resorting to the elimination of clear (sunny) or cloudy cases, in order to improve the goodness of fit.

Mellit *et al.* (2010) applied the technique of neural networks, for the estimation of diffuse, global and the direct radiation at Jeddah, Saudi Arabia, using the air temperature, the relative humidity, and insolation hours as input data.

Another matter of interest is the comparison or evaluation of models, for example Torres *et al.* (2010) estimated 17 models for the hourly diffuse radiation, 12 polynomial models, two logistic function models and three models considering the diffuse radiation values one day before and one day after, for the city of Pamplona, Spain. The general conclusion is that although polynomials are simpler, they have similar quality to the others.

Following the original idea of Liu and Jordan (1960), various authors have proposed numerous empirical equations for the estimation of diffuse solar radiation; three examples are described in Table 1.

Spitters *et al.* (1986) found that the coefficients of the linear regression between daily diffuse radiation and global radiation showed very similar coefficients for different parts of the Netherlands; instead Gopinathan and Soler (1995) concluded that when the monthly values of global and diffuse radiation were used (for forty towns in the latitudinal range of 35 °S and 60 °N), the regression coefficients substantially varied according to geographic location.

Reindl *et al.* (1990) introduced new modeling variables in order to estimate the diffuse radiation as well as the clearness index *Kt*, such as the mean of the sine of the solar altitude, the ambient temperature and the relative humidity, all on a monthly basis.

Authors (year)	Lowest range	Middle range	Highest range
Orgill and Hollands (1977)	$Kt<0.35$	$0.35 \leq Kt \leq 0.75$	$Kt> 0.75$
Erbs *et al.* (1982)	$Kt < 0.22$	$0.22 \leq Kt \leq 0.80$	$Kt > 0.80$
Reindl *et al.* (1990)	$Kt \leq 0.30$	$0.30 < Kt \leq 0.78$	$Kt > 0.78$

Table 1. Comparisons of the Kt ranges for polynomial models.

In the case of Xalapa the divisions of *Kt* intervals did not contribute to improving the goodness of fit in the polynomial models. Instead, it was necessary to eliminate the cases of very cloudy or very clear skies in order to increase the good of fitness of the models. A similar approach has been followed by Boland *et al.* (2008) and by Chickh *et al.* (2012).

3. INSTRUMENTS AND DATA

The data were taken from the solarimetric station from the city of Xalapa, Veracruz (Mexico) covering the period July 2011 to June 2012 (Table 2). The station collects the data with a Campbell CR1000 data logger; measures solar radiation, temperature and wind; the records are 10-min averages from a 2-seconds sampling interval. So, the total of daytime database is about 25 thousand rows, that were reduced to 17,860 after the erroneous data were eliminated when the values of diffuse or global radiation were not registered or when $Kt<0$, or $Kd<0$, or $Kt>1$, or $Kd>1$.

INSTRUMENT	VARIABLE	RANGE
Piranometer Kipp & Zonen model CMP11	Global solar radiation (W.m^{-2})	0 to 2800 W.m^{-2}
Piranometer Kipp & Zonen model CMP11 with shadow ring model CM121B	Diffuse solar radiation (W.m^{-2})	0 to 2800 W.m^{-2}
Thermo Hygrometer model HMP45ACF1450051	Temperature (°C) and relative humidity (%)	-50°C to 50°C and 0% to 100% RH
Pluviometer model 7852 Davis, added to the automatic weather station DAVIS Vantage PRO2	Rainfall (mm)	Daily rainfall (0.0 mm to 999.8 mm) total rainfall (0.0 mm to 9999 mm)

Table 2. Main characteristics of measurement instruments in Xalapa solarimetric station (Kipp and Zonen, 2013).

To get the *Kt* index, the hourly extraterrestrial irradiation (Q_{ext}) was calculated by using the equation (Hernández *et al.*, 1991):

$$Q_{ext} = Io\,[1+0{,}033\cos(0{,}984\eta)][\mathrm{sen}\phi\ \mathrm{sen}\,\delta + \cos\phi\cos\delta\ \cos\omega] \quad \text{(1a)},$$

and for mean daily extraterrestrial radiation (Q_{ext24h}):

$$Q_{ext24h} = (Io/\pi)\,[1+0{,}033\cos(0{,}984\eta)]\,[\cos\phi\cos\delta\,\mathrm{sen}\,\omega_1 + \omega_1\,\mathrm{sen}\,\phi\,\mathrm{sen}\,\delta] \quad \text{(1b)},$$

where Io is the solar constant (1367 W.m^{-2}), ϕ is the latitude, δ is the solar declination, ω is the hour angle measured as negative before noon and positive after noon, ω_1 is the hour angle at sunrise, measured in radians, and η takes the values of 1 on January 1st to 365 -or 366- on December 31st.

4. METHODS

The calculations were performed with R-project version 3.3.0 (R-core Team, 2016), and two types of models were generated to estimate the *Kt* ratio according to *Kd*: one type with 10-min data and the other one with daily accumulated data. Additionally, some adaptations of the criteria proposed by Orgill and Hollands (1977) and Chickh *et al.* (2012) were applied to eliminate the cases of extremely cloudy situations (see Fig. 2). The degree of the polynomials was obtained by increasing the degree, step-by-step until getting the best possible coefficient of determination (R^2) between measured and estimated data (Tables 3 to 6).

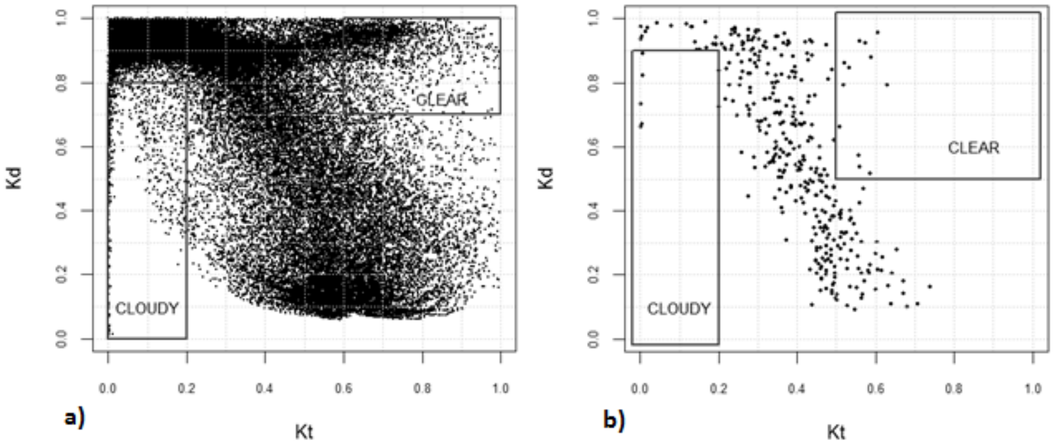

Fig. 2. Dispersion of Kt against Kd from: a) ***10-min data*** *showing cloudy (Kd ≤ 0.8 and Kt ≤ 0.2) and clear-sky (Kd ≥ 0.7 and Kt ≥ 0.6) conditions; b)* ***daily data*** *for cloudy (Kd ≤ 0,9 and Kt ≤ 0,2) and clear-sky (Kd ≥ 0,5 and Kt ≥ 0,5) conditions. Xalapa July 2011-June 2012.*

The inclusion of predictors such as precipitation and temperature came from the proposal of Li *et al.* (2011). For models based on monthly precipitation, the weighted mean of diffuse radiation was calculated:

$$Qdif = \left[\frac{n^{0}(\mathbf{\Pi}_0) + n^{1}(\mathbf{\Pi}_1) + n^{10}(\mathbf{\Pi}_{10})}{n}\right] Qg \qquad (2),$$

where *Qdif* is the diffuse radiation and *Qg* the global radiation (both at $\mathrm{MJm^{-2}}$-day), n is the total number of days in the month, n^0 the number of days without precipitation, n^1 is the number of days per month with rainfall lower or equal to 10 mm, n^{10} is the number of days with precipitation greater than 10 mm, and the respective polynomials are $\mathbf{\Pi}_0, \mathbf{\Pi}_1$ and $\mathbf{\Pi}_{10}$. In order to apply the Eq. 2 to extended periods out July 2011 – June 2012, n^{0}, n^{1} and n^{10} were obtained from the climatic period 1982-2010 (National Weather Service, Xalapa's database of CliCom, Mexico, 2010; SMN, 2013).

Another option was also explored. The daily data of *Kt* and *Kd* was grouped according to three intervals of the daily maximum temperature (*Tmax*) of approximately the same length: $Tmax < 20$ °C (n^{max1} cases), 20°C ≤ $Tmax < 26$°C (n^{max2} cases) and $Tmax \geq 26$ °C (n^{max3} cases). The respective polynomials are β_1, β_2, and β_3, and the weighted mean equation is:

$$Qdif = \left[\frac{n^{max1}(\beta_1) + n^{max2}(\beta_2) + n^{max3}(\beta_3)}{n}\right] Qg \qquad (3)$$

In the case of the minimum temperature, a similar procedure was applied, considering the minimum temperature (*Tmin*) to be defined by the intervals $Tmin < 12$°C (n^{min1}

cases), 12°C$\leq$ *Tmin* < 17°C (n^{min2} cases) and *Tmin* $\geq$ 17 °C (n^{min3}cases), with their respective polynomials δ_1, δ_2 and δ_3:

$$Qdif = \left[\frac{n^{min1}(\delta_1) + n^{min2}(\delta_2) + n^{min3}(\delta_3)}{n}\right] Qg \tag{4}$$

5. RESULTS

The accuracy of the models was established with the mean bias error (MBE, dimensionless), the root mean square error (ESR) and the coefficient of determination (square of the correlation coefficient of Pearson, R^2). See Figs. 3 and 4, and Tables 3 to 6.

Period	a_0	a_1	a_2	a_3	a_4	a_5	Size of sample	R^2 (estimated vs measured)	ESR (W.m^{-2})	MBE
March*	0,95	-0,83	6,21	-18,94	13,89	0	2011	0,74	76	-0,020
April*	0,89	0,57	-3,2	1,92	0	0	1509	0,61	94	0,023
May*	0,87	0,89	-3,72	2,15	0	0	1593	0,76	68	0,017
June*	0,89	0,58	-2,94	1,17	0	0	1660	0,82	58	0,021
July*	0,92	1,27	-9,95	30,17	-41,56	19,66	1418	0,92	45	0,004
August*	0,93	0,86	-4,81	2,56	0	0	1648	0,73	71	0,022
September*	0,94	0,85	-4,35	2,83	0	0	1452	0,60	92	0,031

Table 3. Coefficients of the polynomial models [$Qdif = (a_0 + a_1 Kt + a_2 Kt^2 + a_3 Kt^3 + a_4 Kt^4 + a_5 Kt^5)\, Qg$*] only for* $R^2 \geq 0,6$*, for each month with 10-min data. The data analysis excludes *cases with* $Kd \leq 0,8$ *and* $Kt \leq 0,2$ *or* $Kd \geq 0,7$ *and* $Kt \geq 0,6$*.*

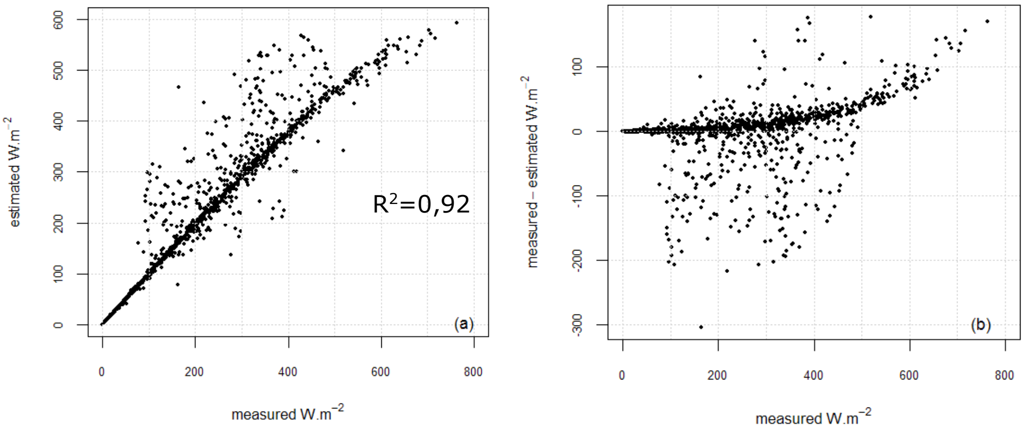

Fig. 3. (a): Comparison of estimated and measured values of diffuse radiation by the best polynomial model [Qdif = (19,66 – 41,56 Kt+ 30,17 Kt^2 – 9,95 Kt^3+ 1,27 Kt^4+0,92 Kt^5) Qg], valid for July from 10-min data, excluding cases where Kd $\leq$ 0,8 and Kt$\leq$0,2 Kt or Kd $\geq$ 0,7 and Kt $\geq$ 0,6. (b): Behavior of the residuals.

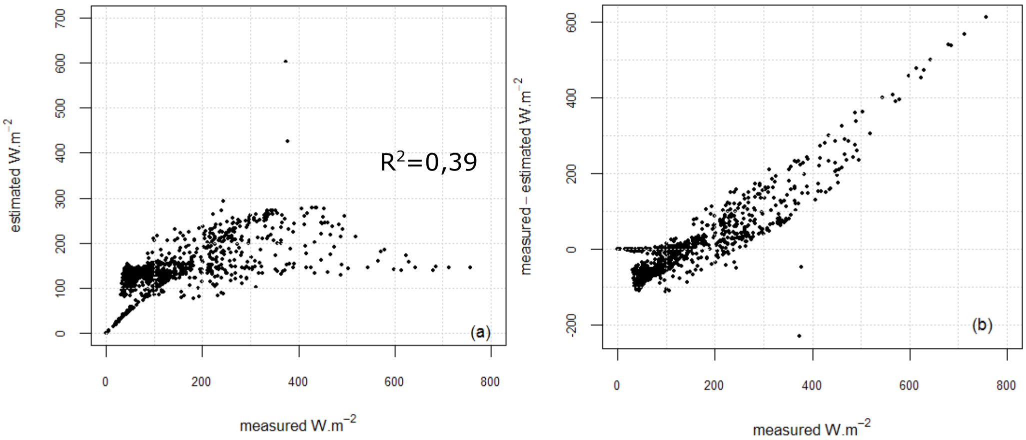

Fig. 4. (a): Comparison of estimated and measured values of diffuse radiation by the worst polynomial model [Qdif = (12,46 – 12,9 Kt+ 2,08 Kt^2 +0,89 Kt^3) Qg], valid for November from 10-min data, excluding cases where Kd $\leq$ 0,8 and Kt $\leq$ 0,2 Kt or Kd $\geq$ 0,7 and Kt $\geq$ 0,6. (b): Behavior of the residuals.

The two polynomials for the six-month periods are of third degree (Table 5), very similar in terms of coefficients and goodness of fit; for both it was necessary to remove cloudy and clear cases, and it was resorted to the clustering of minimum temperature days.

Period	a_0	a_1	a_2	a_3	a_4	Size of sample	R^2 (estimated vs measured)	ESR ($MJ.m^{-2}.day^{-1}$)	MBE
January**	0,92	1,04	-5,13	0	0	30	0,83	0,75	0,052
February **	0,96	1,14	-4,48	0	0	27	0,79	1,29	0,068
July Tmin	0,73	2,90	-11,82	9,21	0	20	0,88	1,30	-0,181
September, Tmin	0,67	3,27	-12,42	9,53	0	28	0,60	1,49	-0,048
October**	1,71	-3,85	2,12	0	0	31	0,66	0,97	-0,009
November**	-6,17	54,76	-138,54	108,88	0	28	0,76	0,83	0,018
December**	0,99	-0,20	-2,91	0.00	0	31	0,63	1,01	0,029

*Table 4. Polynomial models [Qdif = ($a_0 + a_1 Kt + a_2 Kt^2 + a_3 Kt^3 + a_4 Kt^4$) Qg] only for $R^2 \geq 0,6$. Cumulative daily data excluding cases ** with $Kd \leq 0,9$ and $Kt \leq 0,2$ or $Kd \geq 0,5$ and $Kt \geq 0,5$; Tmin means clustering in basis on daily minimum temperatures.*

Period	a_0	a_1	a_2	a_3	Size of sample	R^2 (estimated vs measured)	ESR ($MJ.m^{-2}. day^{-1}$)	MBE
November to April** and Tmin	0,82	2,50	-11,95	9,98	169	0,66	1,75	0,052
May to October** and Tmin	0,66	3,30	-12,46	9,56	156	0,62	1,39	-0,015

*Table 5. Polynomial models [Qdif = ($a_0 + a_1 Kt + a_2 Kt^2 + a_3 Kt^3$) Qg], for six-month periods. Cumulative daily data excluding cases ** with $Kd \leq 0,9$ and $Kt \leq 0,2$ or $Kd \geq 0,5$ and $Kt \geq 0,5$; Tmin means clustering in basis on daily minimum temperatures.*

Period	a_0	a_1	a_2	a_3	a_4	Size of sample	R^2 (estimated vs measured)	ESR ($MJ.m^{-2}. day^{-1}$)	MBE
** and Tmin	0,74	2,90	-12,21	9,77	0	324	0,65	1,6779	0,018
** and Tmax	-0,06	8,53	-24,45	17,77	0,59	323	0,65	1,6581	0,012
** and Precip	1,04	-0,40	2,64	-19,96	21,65	323	0,62	1,7754	0,044
** and all data	0,89	2,02	-10,64	8,82	0,00	329	0,62	1,7788	-0,004

Table 6. Polynomial models [$Qdif = (a_0 + a_1 Kt + a_2 Kt^2 + a_3 Kt^3 + a_4 Kt^4)Qg$*] for average annual values. Tmin, Tmax and Precip refer to clustering in basis on daily data of minimum/maximum temperatures or precipitation.*

6. CONCLUDING REMARKS

The original linear regression model proposed by Liu and Jordan (1960), is not enough to estimate diffuse radiation on a horizontal plane in a tropical, humid, and mountainous site as Xalapa. Instead, polynomial regressions (of second, third or even fourth degree) explain more than 50% of the variability of diffuse radiation in basis on the behavior of the ratio between global and extraterrestrial radiation. Monthly, semi-annual or annual models are based on daily data accumulated. Daily precipitation, minimum and maximum temperatures were used as discrimination criteria to improve the models. Although acceptable statistical values were obtained in the generated polynomial models, due to the lack of measured data it was not possible to evaluate them in other localities with similar climatic conditions. However, in order to test the 10-minute polynomials (Table. 3), and without performing an exhaustive filtering and treatment of potential erroneous *Qg* data, measurements from 2016 were simulated, and it was observed that most of the models reasonably estimated the *Qdif* with ESR values from 77 to 182 $W.m^{-2}$ and R^2 from 0.4 to 0.60. This result highlights the importance of pre-processing data and the limitations of the proposed models during cloudy periods.

Tables 4 to 6 indicate that the ESR values are very similar among the different models, so in this case they do not constitute a practical qualification criterion. Moreover, the MBE in 60% of the models indicates that they are prone for over-estimation and 40% for underestimation.

The validity of the models presented here excludes mostly cloudy or clear sky conditions that comprise 7% of the cases. The application of these models could be tested for an eventual extrapolation to other humid mountainous climatic areas, facing the Gulf of Mexico coast.

Finally, it must be recognized that in some models the obtained goodness-of-fit and accuracy are not high. This indicates that other related predictors could be incorporated with the dispersion and dissemination physics of solar radiation in the atmosphere, e.g., cloud cover information, cloud types, and atmospheric turbidity among others; unfortunately these variables are not routinely measured in Mexico and have not been utilized in previous studies under similar climatic conditions.

The residual graphs in the figures 3(b) and 4(b), shows that the presented models are not the optimal regression expressions, and yet it is not totally clear what parameter needs to be introduced for an improvement. However, it must be considered that these goodness-of-fits in the models are sufficient and useful to obtain information on the magnitude of the anticipated diffuse radiation for harnessing solar energy or basically descriptions of ecosystems.

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