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

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RESUMEN
Para estimar la radiación difusa horizontal en un sitio de clima tropical y montañoso, se presenta una selección de polinomios empiricos. Para generarlos se usaron datos registrados cada 10 minutos entre julio 2011 y junio 2012. Las variables independientes son el índice $K_t$ (cociente de radiación solar global entre extraterrestre) y el $K_d$ (cociente de radiación difusa entre radiación global). Las temperaturas máximas y mínimas y la precipitación diaria, 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 ($K_t$, the ratio of global radiation over extraterrestrial radiation), and the diffuse fraction ($K_d$, 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).

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 $K_t$, such as the mean of the sine of the solar altitude, the ambient temperature and the relative humidity, all on a monthly basis.

<table>
<thead>
<tr>
<th>Authors (year)</th>
<th>Lowest range</th>
<th>Middle range</th>
<th>Highest range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orgill and Hollands (1977)</td>
<td>$K_t &lt; 0.35$</td>
<td>$0.35 \leq K_t \leq 0.75$</td>
<td>$K_t &gt; 0.75$</td>
</tr>
<tr>
<td>Erbs et al. (1982)</td>
<td>$K_t &lt; 0.22$</td>
<td>$0.22 \leq K_t &lt; 0.80$</td>
<td>$K_t &gt; 0.80$</td>
</tr>
<tr>
<td>Reindl et al. (1990)</td>
<td>$K_t &lt; 0.30$</td>
<td>$0.30 &lt; K_t \leq 0.78$</td>
<td>$K_t &gt; 0.78$</td>
</tr>
</tbody>
</table>

Table 1. Comparisons of the $K_t$ ranges for polynomial models.

In the case of Xalapa the divisions of $K_t$ 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 $Kd>1$.

<table>
<thead>
<tr>
<th>INSTRUMENT</th>
<th>VARIABLE</th>
<th>RANGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Piranometer Kipp &amp; Zonen model CMP11</td>
<td>Global solar radiation (W.m²)</td>
<td>0 to 2800 W.m²</td>
</tr>
<tr>
<td>Piranometer Kipp &amp; Zonen model CMP11 with shadow ring model CM121B</td>
<td>Diffuse solar radiation (W.m²)</td>
<td>0 to 2800 W.m²</td>
</tr>
<tr>
<td>Thermo Hygrometer model HMP45ACF1450051</td>
<td>Temperature (°C) and relative humidity (%)</td>
<td>-50°C to 50°C and 0% to 100% RH</td>
</tr>
<tr>
<td>Pluviometer model 7852 Davis, added to the automatic weather station DAVIS Vantage PRO2</td>
<td>Rainfall (mm)</td>
<td>Daily rainfall (0.0 mm to 999.8 mm) total rainfall (0.0 mm to 9999 mm)</td>
</tr>
</tbody>
</table>

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):

$$Q_{ext} = Io \left[1+0,033 \cos (0,984 \eta)]\right] \frac{\sin \phi \ \sin \delta + \cos \phi \cos \delta \ \cos \omega}{\cos \delta}$$  \hspace{1cm} (1a),

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

$$Q_{ext24h} = \frac{1+0,033 \cos (0,984 \eta)}{Io} \left[\cos \phi \cos \delta \ \sin \omega \right] \left[\cos \phi \cos \delta \ \sin \omega + \sin \phi \ \sin \delta \right]$$  \hspace{1cm} (1b),

where $Io$ is the solar constant (1367 W.m²), $\phi$ is the latitude, $\delta$ is the solar declination, $\omega$ is the hour angle measured as negative before noon and positive after noon, $\omega_{H}$ is the hour angle at sunrise, measured in radians, and $\eta$ 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).
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:

$$Q_{dif} = \left[ \frac{n^0(\Pi_0) + n^1(\Pi_1) + n^{10}(\Pi_{10})}{n} \right] Q_g$$  \hfill (2)

where $Q_{dif}$ is the diffuse radiation and $Q_g$ the global radiation (both at 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 $\Pi_0$, $\Pi_1$ and $\Pi_{10}$. 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 $K_t$ and $K_d$ was grouped according to three intervals of the daily maximum temperature ($T_{max}$) of approximately the same length: $T_{max} < 20$ °C ($n^{max1}$ cases), $20^\circ C \leq T_{max} < 26^\circ C$ ($n^{max2}$ cases) and $T_{max} \geq 26$ °C ($n^{max3}$ cases). The respective polynomials are $\beta_1$, $\beta_2$, and $\beta_3$, and the weighted mean equation is:

$$Q_{dif} = \left[ \frac{n^{max1}(\beta_1) + n^{max2}(\beta_2) + n^{max3}(\beta_3)}{n} \right] Q_g$$  \hfill (3)

In the case of the minimum temperature, a similar procedure was applied, considering the minimum temperature ($T_{min}$) to be defined by the intervals $T_{min} < 12^\circ C$ ($n^{min1}$...
cases), $12^\circ C < Tmin < 17^\circ C$ ($n_{min}^2$ cases) and $Tmin \geq 17^\circ C$ ($n_{min}^3$ cases), with their respective polynomials $\delta_1$, $\delta_2$ and $\delta_3$:

$$Q_{dif} = \left[ \frac{n_{min}^1(\delta_1) + n_{min}^2(\delta_2) + n_{min}^3(\delta_3)}{n} \right] Q_g$$

(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.

<table>
<thead>
<tr>
<th>Period</th>
<th>$a_0$</th>
<th>$a_1$</th>
<th>$a_2$</th>
<th>$a_3$</th>
<th>$a_4$</th>
<th>$a_5$</th>
<th>Size of sample</th>
<th>$R^2$ (estimated vs measured)</th>
<th>ESR (W.m$^{-2}$)</th>
<th>MBE</th>
</tr>
</thead>
<tbody>
<tr>
<td>March*</td>
<td>0.95</td>
<td>0.83</td>
<td>6.2</td>
<td>18.9</td>
<td>13.8</td>
<td>0</td>
<td>2011</td>
<td>0.74</td>
<td>76</td>
<td>-0.020</td>
</tr>
<tr>
<td>April*</td>
<td>0.89</td>
<td>0.57</td>
<td>-3.2</td>
<td>1.92</td>
<td>0</td>
<td>0</td>
<td>1509</td>
<td>0.61</td>
<td>94</td>
<td>0.023</td>
</tr>
<tr>
<td>May*</td>
<td>0.87</td>
<td>0.89</td>
<td>3.7</td>
<td>2.15</td>
<td>0</td>
<td>0</td>
<td>1593</td>
<td>0.76</td>
<td>68</td>
<td>0.017</td>
</tr>
<tr>
<td>June*</td>
<td>0.89</td>
<td>0.58</td>
<td>-2.9</td>
<td>1.17</td>
<td>0</td>
<td>0</td>
<td>1660</td>
<td>0.82</td>
<td>58</td>
<td>0.021</td>
</tr>
<tr>
<td>July*</td>
<td>0.92</td>
<td>1.27</td>
<td>9.9</td>
<td>30.1</td>
<td>41.5</td>
<td>19.6</td>
<td>1418</td>
<td>0.92</td>
<td>45</td>
<td>0.004</td>
</tr>
<tr>
<td>August*</td>
<td>0.93</td>
<td>0.86</td>
<td>-4.8</td>
<td>2.56</td>
<td>0</td>
<td>0</td>
<td>1648</td>
<td>0.73</td>
<td>71</td>
<td>0.022</td>
</tr>
<tr>
<td>September*</td>
<td>0.94</td>
<td>0.85</td>
<td>-4.3</td>
<td>2.83</td>
<td>0</td>
<td>0</td>
<td>1452</td>
<td>0.60</td>
<td>92</td>
<td>0.031</td>
</tr>
</tbody>
</table>

Table 3. Coefficients of the polynomial models $[Q_{dif} = (a_0 + a_1 Kt + a_2 Kt^2 + a_3 Kt^3 + a_4 Kt^4 + a_5 Kt^5) Q_g]$ only for $R^2 \geq 0.6$, for each month with 10-min data. The data analysis excludes *cases with $Kd < 0.8$ and $Kt < 0.2$ or $Kd > 0.7$ and $Kt > 0.6$. 

Empirical models for estimation of diffuse solar ra...
Fig. 3. (a): Comparison of estimated and measured values of diffuse radiation by the best polynomial model \[ Q_{\text{dif}} = (19.66 - 41.56 \, K_t + 30.17 \, K_t^2 - 9.95 \, K_t^3 + 1.27 \, K_t^4 + 0.92 \, K_t^5) \, Q_g \], valid for July from 10-min data, excluding cases where \( K_d < 0.8 \) and \( K_t < 0.2 \) or \( K_d > 0.7 \) and \( K_t > 0.6 \). (b): Behavior of the residuals.

Fig. 4. (a): Comparison of estimated and measured values of diffuse radiation by the worst polynomial model \[ Q_{\text{dif}} = (12.46 - 12.9 \, K_t + 2.08 \, K_t^2 + 0.89 \, K_t^3) \, Q_g \], valid for November from 10-min data, excluding cases where \( K_d < 0.8 \) and \( K_t < 0.2 \) or \( K_d > 0.7 \) and \( K_t > 0.6 \). (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.
<table>
<thead>
<tr>
<th>Period</th>
<th>$a_0$</th>
<th>$a_1$</th>
<th>$a_2$</th>
<th>$a_3$</th>
<th>$a_4$</th>
<th>Size of sample</th>
<th>$R^2$ (estimated vs measured)</th>
<th>ESR (MJ.m$^{-2}$.day$^{-1}$)</th>
<th>MBE</th>
</tr>
</thead>
<tbody>
<tr>
<td>January**</td>
<td>0.9</td>
<td>1.04</td>
<td>-5.13</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>0.83</td>
<td>0.75</td>
<td>0.052</td>
</tr>
<tr>
<td>February**</td>
<td>0.9</td>
<td>1.14</td>
<td>-4.48</td>
<td>0</td>
<td>0</td>
<td>27</td>
<td>0.79</td>
<td>1.29</td>
<td>0.068</td>
</tr>
<tr>
<td>July Tmin</td>
<td>0.7</td>
<td>2.90</td>
<td>-11.82</td>
<td>9.21</td>
<td>0</td>
<td>20</td>
<td>0.88</td>
<td>1.30</td>
<td>0.18</td>
</tr>
<tr>
<td>September, Tmin</td>
<td>0.6</td>
<td>3.27</td>
<td>-12.42</td>
<td>9.53</td>
<td>0</td>
<td>28</td>
<td>0.60</td>
<td>1.49</td>
<td>0.048</td>
</tr>
<tr>
<td>October**</td>
<td>1.7</td>
<td>-3.85</td>
<td>2.12</td>
<td>0</td>
<td>0</td>
<td>31</td>
<td>0.66</td>
<td>0.97</td>
<td>0.009</td>
</tr>
<tr>
<td>November*</td>
<td>6.1</td>
<td>54.7</td>
<td>138.5</td>
<td>108.8</td>
<td>0</td>
<td>28</td>
<td>0.76</td>
<td>0.83</td>
<td>0.018</td>
</tr>
<tr>
<td>December*</td>
<td>0.9</td>
<td>-0.20</td>
<td>-2.91</td>
<td>0.00</td>
<td>0</td>
<td>31</td>
<td>0.63</td>
<td>1.01</td>
<td>0.029</td>
</tr>
</tbody>
</table>

*Table 4. Polynomial models $[\text{Qdif} = (a_0 + a_1 Kt + a_2 Kt^2 + a_3 Kt^3 + a_4 Kt^4) Qg]$ 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.

<table>
<thead>
<tr>
<th>Period</th>
<th>$a_0$</th>
<th>$a_1$</th>
<th>$a_2$</th>
<th>$a_3$</th>
<th>$a_4$</th>
<th>Size of sample</th>
<th>$R^2$ (estimated vs measured)</th>
<th>ESR (MJ.m$^{-2}$.day$^{-1}$)</th>
<th>MBE</th>
</tr>
</thead>
<tbody>
<tr>
<td>November to April** and Tmin</td>
<td>0.82</td>
<td>2.50</td>
<td>-11.95</td>
<td>9.98</td>
<td>169</td>
<td>0.66</td>
<td>1.75</td>
<td>0.052</td>
<td></td>
</tr>
<tr>
<td>May to October** and Tmin</td>
<td>0.66</td>
<td>3.30</td>
<td>-12.46</td>
<td>9.56</td>
<td>156</td>
<td>0.62</td>
<td>1.39</td>
<td>0.015</td>
<td></td>
</tr>
</tbody>
</table>

*Table 5. Polynomial models $[\text{Qdif} = (a_0 + a_1 Kt + a_2 Kt^2 + a_3 Kt^3) Qg]$, 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.
**Table 6. Polynomial models \[Q_{dif} = (a_0 + a_1 Kt + a_2 Kt^2 + a_3 Kt^3 + a_4 Kt^4)Qg\] for average annual values. Tmin, Tmax and Precip refer to clustering in basis on daily data of minimum/maximum temperatures or precipitation.**

<table>
<thead>
<tr>
<th>Period</th>
<th>(a_0)</th>
<th>(a_1)</th>
<th>(a_2)</th>
<th>(a_3)</th>
<th>(a_4)</th>
<th>Size of sample</th>
<th>(R^2) (estimated vs measured)</th>
<th>ESR (MJ.m(^{-2}).day(^{-1}))</th>
<th>MBE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>and Tmin</strong></td>
<td>0.74</td>
<td>2.90</td>
<td>-</td>
<td>12.21</td>
<td>9.77</td>
<td>0</td>
<td>324</td>
<td>0.65</td>
<td>1.6779</td>
</tr>
<tr>
<td><strong>and Tmax</strong></td>
<td>-0.06</td>
<td>8.53</td>
<td>-</td>
<td>24.45</td>
<td>17.77</td>
<td>0.59</td>
<td>323</td>
<td>0.65</td>
<td>1.6581</td>
</tr>
<tr>
<td><strong>and Precip</strong></td>
<td>1.04</td>
<td>-</td>
<td>2.64</td>
<td>19.96</td>
<td>21.65</td>
<td>0.62</td>
<td>323</td>
<td>0.62</td>
<td>1.7754</td>
</tr>
<tr>
<td><strong>and all data</strong></td>
<td>0.89</td>
<td>2.02</td>
<td>-</td>
<td>10.64</td>
<td>8.82</td>
<td>0.00</td>
<td>329</td>
<td>0.62</td>
<td>1.7788</td>
</tr>
</tbody>
</table>

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 \(Q_{dif}\) 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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