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Diffuse fraction models in southern latitudes

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Summary

Diffuse radiation is the result of multiple interactions and depends on the local atmospheric details (such as water vapor and aerosol content). However, long term diffuse radiation data is comparatively scarce and most diffuse fraction models have been adjusted and tested using northern hemisphere (mostly U.S. and Europe) ground data. In this work, 37352 hours of irradiance data from the southern part of Latin America are used to evaluate the performance of eight diffuse fraction models. Models based on double exponential (Gompertz) functions perform significantly better than the rest.

Data

We use 37352 diurnal hours of global and diffuse hourly irradiation on horizontal plane. The data was taken at three sites, using different methods (Delta-T SPN1 pyranometer at AZ, pyranometers with shadow band at SA and pyranometer, shaded pyranometer and pirheliometer mounted on a SOLYS2 tracking system, at LU). See Ref. [3] for details on the Lujan site data.

Site	Code	LAT (deg)	LON (deg)	ALT (m)	Time Span start	Time Span end	daytime hours
Montevideo	**AZ**	-34.92	-56.17	58	01-03-2011	31-08-2013	9314
Salto	**SA**	-31.27	-57.89	41	12-06-1998	30-12-2003	21646
Luján	**LU**	-34.58	-59.05	20	01-01-2011	05-07-2012	6392
All sites							37352

Table 1: Details for ground data sations used in this work.

The data was filtered according to standard quality control procedures [9].

		hours that pass			% of hours discarded			
Filter	**Condition**	**AZ**	**SA**	**LU**	**AZ**	**SA**	**LU**	**All**
F0	$\cos\theta_z \geq 0$ & $I_h > 0$	9314	21646	6392	-	-	-	-
F1	$\cos\theta_z \geq 0.1219$	7597	18393	5732	18.4	15.0	10.3	15.1
F2	$0 < I_h \leq I_c$	7212	17515	5344	5.1	4.8	6.8	5.2
F3	$I_{d,c} < I_d < I_{d,oc}$	6488	16023	5023	10.0	8.5	6.0	8.4
F4	$f_d < 1.07$	6485	15989	4918	0.0	0.2	2.1	0.5
F5	complete pair (k_t, f_d)	6160	15253	4560	5.0	4.6	7.3	5.2
All		6160	15253	4560	33.9	29.5	28.7	30.4

Table 2: Filters applied to the data.

For details on the filtering procedures see Refs. [9, 3]

Nomenclature

θ_z, solar (zenital) incidence angle
I_h, I_d, measured hourly global and diffuse irradiation on a horizontal surface
$I_c, I_{d,c}$, corresponding clear-sky quantities (from SOLIS clear sky model [7])
$I_{d,oc}$, diffuse radiation for overcast sky (Page's model, [9])
$f_d = I_d/I_h$, diffuse fraction
$k_t = I_h/I_0$, hourly clearness index
$I_0 = I_{sc}\epsilon\cos\theta_z$, extraterrestrial hourly irradiation on a horizontal surface.

$\Rightarrow n = 25973$ hours with valid (k_t, f_d) records are obtained.

Diffuse fraction models

Eight diffuse fraction models, with one or more predictors are considered.

▷ Orgill and Hollands [5]

$$\textbf{(M1)} \qquad f_d = \begin{cases} 1.000 - 0.249\,k_t & k_t < 0.35 \\ 1.557 - 1.840\,k_t & 0.35 \leq k_t \leq 0.75 \\ 0.177 & k_t > 0.75. \end{cases}$$

▷ Erbs, Klein and Duffie [4]

$$\textbf{(M2)}\ f_d = \begin{cases} 1.0 - 0.09\,k_t & k_t \leq 0.22 \\ 0.9511 - 0.1604\,k_t + 4.388\,k_t^2 & \\ \qquad -16.638\,k_t^3 + 12.336\,k_t^4 & 0.22 < k_t \leq 0.80 \\ 0.165 & k_t > 0.80. \end{cases}$$

▷ Reindl, Beckman, Duffie [6]: simplified version with one predictor (M3)

$$\textbf{(M3)} \qquad f_d = \begin{cases} 1.020 - 0.248\,k_t \quad (f_d \leq 1.0) & 0 \leq k_t \leq 0.3 \\ 1.45 - 1.67\,k_t & 0.35 < k_t < 0.78 \\ 0.147 & k_t \geq 0.78. \end{cases}$$

▷ Reindl, Beckman, Duffie [6]: version with two predictors $(k_t, \sin\alpha)$ **(M4)**

$$f_d = \begin{cases} 1.020 - 0.254\,k_t + 0.0123\,\sin(\alpha) & (f_d \leq 1.0) & 0 \leq k_t \leq 0.3 \\ 1.400 - 1.749\,k_t + 0.177\,\sin(\alpha) & (f_d \leq 0.97, f_d \geq 0.1) & 0.3 < k_t < 0.78 \\ 0.486\,k_t - 0.182\,\sin(\alpha) & (f_d \geq 0.1) & k_t \geq 0.78. \end{cases}$$

where α is the solar altitude angle.

▷ Boland et al. [1, 2]: logistic function, version with one predictor

$$\textbf{(M5)} \qquad f_d = \frac{1}{1 + \exp\left(-5.0033 + 8.6025\,k_t\right)}$$

▷ Ruiz-Arias et al. [8]: double exponential (Gompertz) function, versions with one or two predictors

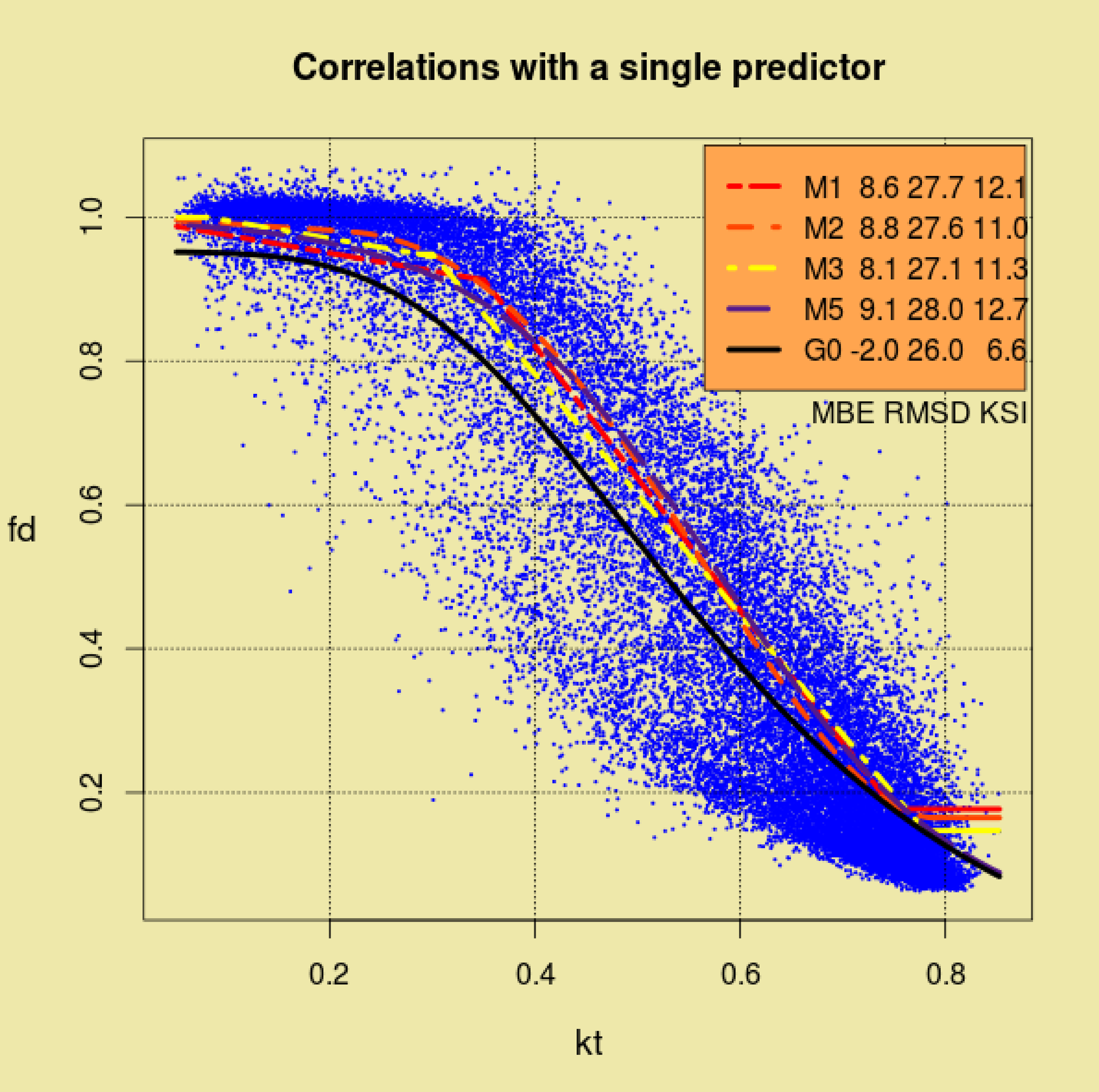
$$\begin{aligned} \textbf{(G0)} \quad f_d &= a_0 - a_1 \exp\left[-\exp\left(a_2 + a_3\,k_t\right)\right] \\ \textbf{(G1)} \quad f_d &= a_0 - a_1 \exp\left[-\exp\left(a_2 + a_3\,k_t + a_4\,m\right)\right] \\ \textbf{(G2)} \quad f_d &= a_0 - a_1 \exp\left[-\exp\left(a_2 + a_3\,k_t + a_4\,m + a_5\,k_t^2 + a_6\,m^2\right)\right]. \end{aligned}$$

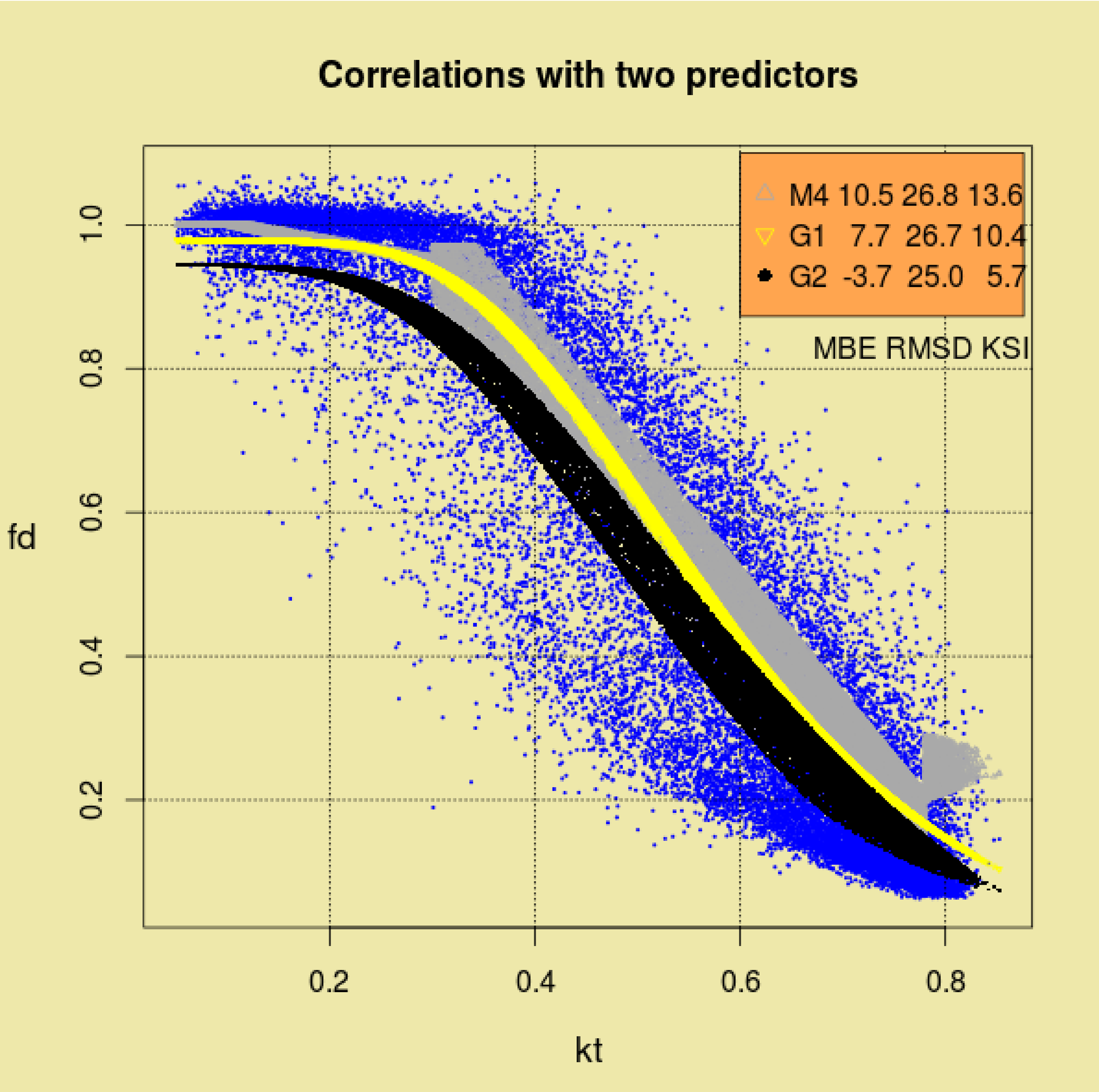
where m is the relative air mass.
Coefficients from [8] (21 sites, 20-30 years, high quality data) are

Model	a_0	a_1	a_2	a_3	a_4	a_5	a_6
G0	0.952	1.041	2.300	-4.702	-	-	-
G1	0979	1.017	2.880	-5.589	-0.110	-	-
G2	0.944	1.538	2.808	-5.759	-0.125	2.276	0.013

Table 3: Coefficients for models G0, G1, G2 from Ref. [8].
Based on good quality data for 21 sites in the Northern hemisphere.

Results



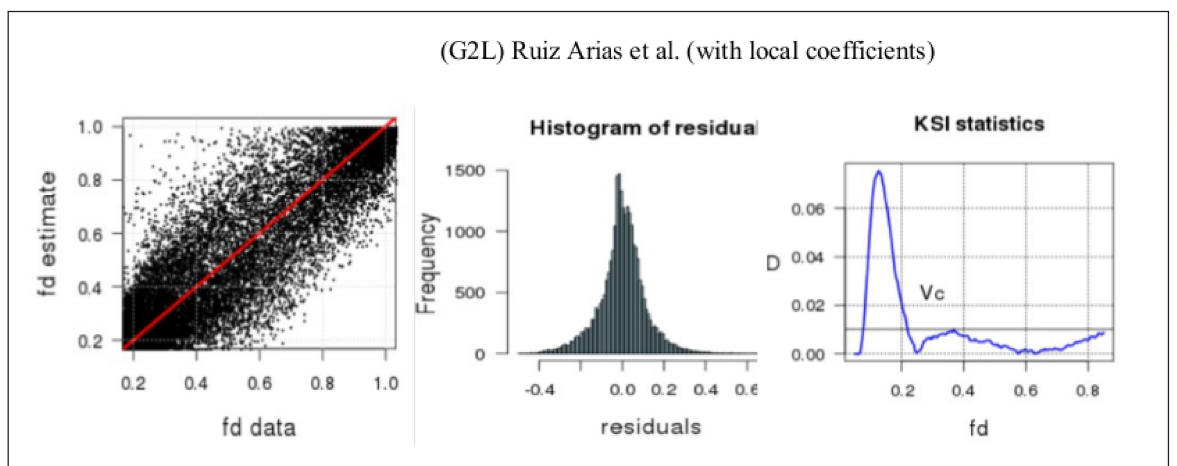


Locally adjusted models

We used a **ten-fold stratified random sampling technique** to adjust the coefficients of the G0,G1,G2 models [8] to the local data. The stratification was made according to k_t, randomly choosing data points within three stratum defined by $k_t < 0.3$, $0.3 \leq k_t \leq 0.6$ and $k_t > 0.6$. The whole data set was then divided randomly in two subsets: one with 90% of the data (sampled randomly within each stratum) was used for training the coefficients of the chosen model and the other 10% of the sampled data was reserved for testing the model's performance. The coefficients of models are adjusted by standard non-linear regression techniques and the model is tested calculating the relevant statistics. The procedure is repeated 10 times (10-fold sampling) and the average value of each coefficient is then taken as the fitted value (see Table below).

Model	a_0	a_1	a_2	a_3	a_4	a_5	a_6
G0	0.996	1.101	2.481	-5.076	-	-	-
G1	0.992	1.097	3.107	-5.634	-0.133	-	-
G2	0.996	1.012	2.839	-3.182	-0.322	-3.066	0.024

Table 4: Locally adjusted coefficients for models G0, G1, G2.



Model G1L: with locally adjusted coefficients (Table 4).

This is the best model for our target territory (Uruguay).
It can still be improved at low f_d values (clear days).

Statistics

For $i = 1, 2, \ldots n$ data points (k_t, f_d), let $\hat{f}_d$ be the modelled diffuse fraction We use the Mean Bias Error and the Root Mean Square Deviation,

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left[\hat{f}_d(i) - f_d(i)\right], \qquad RMSD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\hat{f}_d(i) - f_d(i)\right]^2}$$

both expressed as % of the measurements average, $\bar{f}_d$. We also consider the absolute difference between the Cumulative Distribution Functions of the measured (F) and modelled $(\hat{F})$ sets

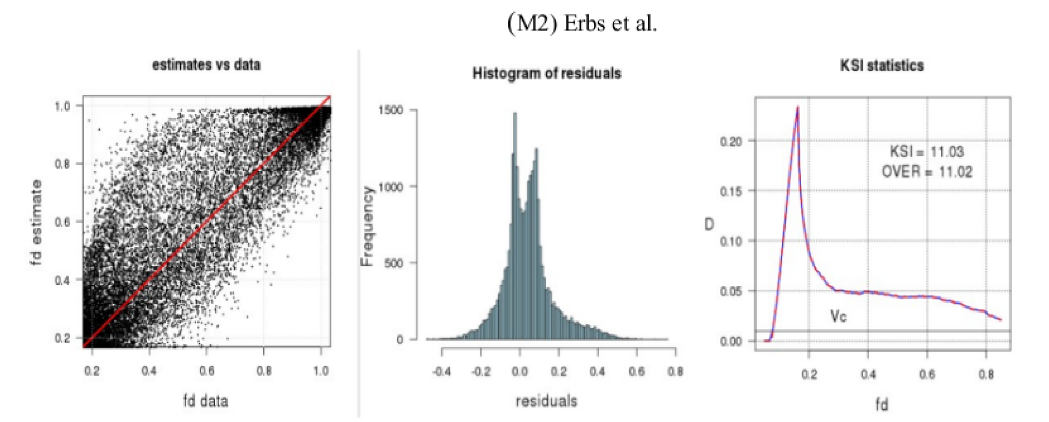
$$D(f_d) = \left|F(f_d) - \hat{F}(f_d)\right|, \qquad O(f_d) = \begin{cases} D(f_d) - V_c & \text{for} \quad D(f_d) > V_c \\ 0 & \text{for} \quad D(f_d) \leq V_c \end{cases}$$

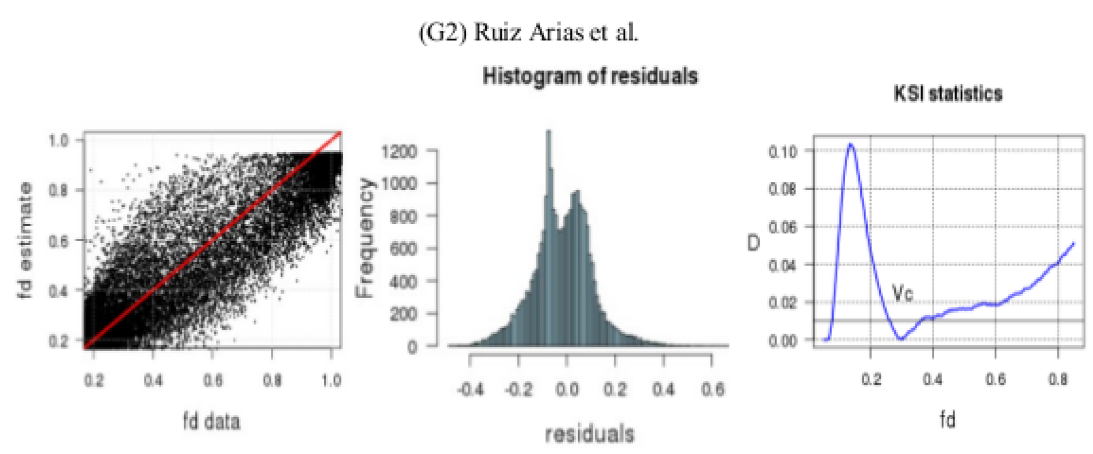
where $V_c = 1.63/\sqrt{n} \simeq 0.0062$. The Kolmogorov-Smirnov statistics (KSI) and the OVER parameter are

$$KSI = \sum_{i=1}^{n} D(f_d(i)), \quad OVER = \sum_{i=1}^{n} O(f_d(i)),$$

Model	rMBE (%)	rRMSD (%)	KSI	OVER
M1	8.6	27.7	12.1	12.1
M2	8.8	27.6	11.0	11.0
M3	8.1	27.1	11.3	11.1
M4	9.1	28.0	12.7	12.7
M5	10.5	26.8	13.6	13.4
G0	-2.0	26.0	6.6	6.3
G1	7.7	26.7	10.4	10.3
G2	-3.7	25.0	5.7	5.6
G0L (local fit)	-0.4	25.5	2.4	1.9
G1L (local fit)	-0.2	23.5	2.6	1.6
G2L (local fit)	0.0	23.3	2.4	1.6

Table 5: Statistics for all models considered in this work.





Conclusions

- Even among single-predictor models, the Gompertz models represent a significant improvement over previously existing models, as measured by the KSI statistics which is reduced from 11.0 (Erbs) to 6.3
- Local fitting of parameters improves substantially the model performance. Even though the Gompertz models where fitted using an extensive and high quality database, a local fitting of the parameters reduces the KSI from 6.3 to 2.4 for G0 and from 5.7 to 2.4 for G2.
- The improvement from G1 to G2 is marginal so the effect of quadratic dependence on the predictors k_t and m is not too important: from G1L to G2L, KSI reduces from 2.6 to 2.4 (OVER is unaffected).
- The best diffuse fraction model for Uruguay and neighboring areas, is G2L with locally adjusted parameters. This conclusion has a local character.

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