Research Article

Assessment of monthly global solar irradiation estimates using air temperature in different climates of the state of Rio de Janeiro, Southeastern Brazil

Allana Oliveira Lima[1] · Gustavo Bastos Lyra[2] · José Leonaldo de Souza[3] · Guilherme Bastos Lyra[4] · José Francisco de Oliveira-Júnior[3] · Anderson Amorim Rocha Santos[1]

Abstract

The number of weather stations that measure solar global irradiance (I_g) is scarce, and when it is available, it does not present long-time series, without gaps and high quality. When I_g is unavailable, it is possible to estimate its integral over time—solar global irradiation (H_g)—using empirical methods. However, for a better performance these methods need to be fitted to the local climatic conditions. The aim of this study was to assess the Hargreaves–Samani (HS) and Bristow–Campbell (BC) methods to estimate monthly average daily H_g in the state of Rio de Janeiro, Southeastern Brazil, and to propose a simple approach to determine the empirical coefficients in function of the climate. The methods are based on maximum and minimum air temperature and on extraterrestrial solar irradiation. Series of air temperature extremes and H_g from 15 automatic weather stations between 2000 until 2013 were used. The methods were evaluated by the statistical indexes: determination coefficient (r^2) of the linear regression between observed and estimated monthly H_g, root mean square error (RMSE), Willmott's index (d) and performance index (c). The methods (BC—$r^2 > 0.60$, $d > 0.85$ and RMSE < 2.99 MJ m^{-2} d^{-1} and HS—$r^2 > 0.55$, $d > 0.75$ and RMSE < 3.85 MJ m^{-2} d^{-1}) had satisfactory performance in the estimation of monthly H_g for the state of Rio de Janeiro, when their coefficients were fitted to local climatic conditions. The BC presented performance classified as "optimal" ($c > 0.85$) in approximately 80% of the stations analyzed, while for Hargreaves–Samani, only 55% of the stations were classified as "optimal." The highest HS coefficients (k_r) occurred in Semiarid (0.246 ± 0,023) and Dry Sub-humid (0.181 ± 0.011) climates and were associated with coastal regions (< 20 km), while the stations in Humid (0.146 ± 0.008), Sub-humid (0.1524 ± 0.003) and Dry Sub-humid (0.162 ± 0.011) climates located in interior regions presented the lowest k_r. Thus, it is possible to determine the k_r coefficient based only on the climatic classification of the site and distance of the coastal environment. In general, the highest atmospheric transmittance (β_0—BC method) was observed in Semiarid and Dry Sub-humid climate regions. β_1 and β_2 coefficients did not present a distribution pattern with the local climatology and with the proximity of large water bodies. The methods presented a better performance in Dry Sub-humid and Semiarid climates, due to the lower variability of cloudiness and greater thermal amplitude.

Keywords Solar radiation · Statistical models · Linear and nonlinear regression

✉ Gustavo Bastos Lyra, gblyra@ufrrj.br | [1]Departamento de Engenharia Agrícola e do Meio Ambiente, Escola de Engenharia, Universidade Federal Fluminense, 24.210-240 Niterói, Rio de Janeiro, Brazil. [2]Departamento de Ciências Ambientais, Instituto de Florestas, Universidade Federal Rural do Rio de Janeiro, Cidade Universitária, Rod BR 465, km 7, CEP 23890-000 Seropédica, Rio de Janeiro, Brazil. [3]Instituto de Ciências Atmosféricas, Universidade Federal de Alagoas, Campus A.C. Simões, BR 104-Norte, km 97, Tabuleiro dos Martins, 57.072-970 Maceió, Alagoas, Brazil. [4]Centro de Ciências Agrárias, Universidade Federal de Alagoas, Campus Delza Gítai, BR 104, km 85, s/n, 57.100-000 Rio Largo, Alagoas, Brazil.

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List of symbols

a	Intercept of linear regression
b	Slope of linear regression
c	Performance index
CV	Coefficient of variation
d	Willmott's index of agreement
d_r	Correction of the Earth–Sun distance
I_g	Global solar irradiance (W m^{-2})
H_0	Null hypothesis
H_1	Alternative hypothesis
H_g^h	Hourly global solar irradiation (kJ m^{-2} h^{-1})
H_g^d	Daily global solar irradiation (MJ m^{-2} d^{-1})
H_{go}^d	Daily global solar irradiation for clear sky (MJ m^{-2} d^{-1})
H_g	Monthly average daily global solar irradiation (MJ m^{-2} d^{-1})
H_o	Extraterrestrial solar irradiation (MJ m^{-2} d^{-1})
INMET	Instituto Nacional de Meteorologia
J	Day of the year or Julian day (1–365)
n	Sunshine duration in hours (h)
N	Maximum sunshine duration in hours (h)
k	Number of observations
k_r	Empirical coefficient of Hargreaves–Samani method
K_T	Atmospheric transmittance coefficient
K_{To}	Maximum atmospheric transmittance coefficient for clear sky
r	Pearson correlation coefficient
r^2	Determination coefficient
RH	Relative air humidity (%)
RMSE	Root mean square error
t_x	Maximum air temperature (°C)
t_n	Minimum air temperature (°C)
t_{ar}	Air temperature (°C)
z	Altitude (m)
φ	Latitude (rad)
β_0, β_1 and β_2	Empirical coefficients of Bristow–Campbell method
δ	Solar declination (rad)
ω_s	Sunset angle (rad)

1 Introduction

Solar radiation is a primary source of energy for several physical, chemical and biological processes that occur on Earth, being a factor which conditions air and soil temperature, and the photosynthesis and evapotranspiration processes (ET) [1, 2]. Radiation also represents an important meteorological variable in studies of the water needs of irrigated crops, modeling of growth and plant yield, climate changes, in the parameterizations of mesoscale and general circulation models (GCM), among others [3, 4].

It should be noted that due to the current high energy demand, the increase in the use and the cost of fossil fuels and society's major concern regarding environmental conservation have encouraged research and development of alternative sources of energy. Solar radiation is an alternative source of energy with low emission of greenhouse gases (GHG) or even local atmospheric pollutants, and it represents improvements in a country's energy efficiency and imposition of costs on GHG emitters [5] and can also be directly used for environment, water heating and the electricity generation.

Thus, quantifying solar radiation is essential for the physical and economic dimensioning of photovoltaic and thermal energy generating systems [3, 6] and for environmental studies, also allowing modeling meteorological and climatic conditions. It should be observed that solar radiation varies according to latitude, atmospheric conditions (e.g., cloudiness, air humidity, aerosols) and Sun positioning throughout the day and year, making it essential knowing its space–time variation [3, 5].

The global solar irradiance (I_g) expresses the incident power (Watts = J/s) per surface unit (m^2) at various wavelengths, which is measured or recorded by instruments, for example, pyranometers and actinographs, the former being more appropriate [3, 7]. Despite the importance of observations of this meteorological element, in many countries, as in Brazil, there are few weather stations that measure I_g [8]. In stations that perform irradiance measurements, there is lack of long continuous series of quality, which compromises the determination of the global solar irradiation—H_g (integral of the solar irradiance in a given scale of time, hour, day, month or year) in a given place and period.

For sites with no I_g measurements, H_g values can be estimated by means of empirical methods, which differ according to the degree of complexity and to the input variables. Empirical methods can be classified into four types based on: (1) sunshine duration; (2) cloudiness; (3) air temperature; and (4) other meteorological elements [5]. The input variables most used in these methods are: extraterrestrial solar irradiation—H_o, insolation—n (sunshine duration in hours), air temperature—t_{ar}, cloudiness, relative air humidity—RH, altitude—z, latitude—φ, and the day number of the year—J (Julian day), which can be used individually or in combination with each other [3, 9–11].

The method proposed by Hargreaves and Samani [12] stands out for its simplicity and for providing precise and accurate estimates of H_g [4, 13–15]. It estimates H_g based only on air temperature extremes (maximum and minimum) and H_o. In addition, the Hargreaves–Samani method is indicated by FAO (Food and Agriculture Organization) for estimating H_g

[16]. The method proposed by Bristow and Campbell [9] for the estimation of H_g is also practical and accessible, and similar to Hargreaves–Samani method, the Bristow–Campbell is based only on the thermal amplitude and H_o, but its empirical coefficients provide maximum atmospheric transmittance values expected for a clear sky day (β_0) and the control of the rate at which β_0 varies with thermal amplitude, represented by its β_1 and β_2 coefficients.

However, for a good performance of the methods, it is necessary that the empirical coefficients represent the local conditions [14, 15, 17, 18]. Hagreaves [17] comments that k_r varies only with the proximity of large bodies of water or extensive continental areas and suggests for regions of coast (< 20 km of large bodies of water) $k_r = 0.19$ and, in the case of interior, $k_r = 0.16$ [17, 18]. Allen et al. [19] and Annandale et al. [18] considered that in addition to these factors, associated with the phenomenon of oceanity/continentality, the altitude also influenced the values of k_r and, thus, proposed corrections for the values of Hargreaves as a function of the atmospheric pressure [17] or altitude [20]. Samani [21] for some localities of the USA observed the relation between k_r and air temperature and proposed an empirical relation for adjustment of k_r.

The original values of the coefficients proposed by Bristow–Campbell [9] were $\beta_0 = 0.7$, $\beta_1 = 0.01$ (winter) and 0.04 (summer) and $\beta_2 = 2.4$. The authors also observed that β_1 had relation with the monthly thermal amplitude, suggested an equation to fit this coefficient. Weiss et al. [22] and Abraha and Savage [23] suggested using constant β_0 (0.75) and, in the case of β_1, replaced either by a function of the thermal amplitude [23] or by H_o [22].

The above corrections for the coefficients did not necessarily result in improved accuracy and precision of H_g estimates by the Hargreaves–Samani and Bristow–Campbell methods in other regions [4, 15, 24], or by considering only one factor climatic conditions (e.g., oceanity/continentality, altitude, air temperature and thermal amplitude) or corrections are valid only for the place where they were proposed. Therefore, the aim of the present study was to fit and to assess the empirical coefficients of the Hargreaves–Samani [12] and Bristow–Campbell [9] methods for the estimation of monthly average daily global solar irradiation in the state of Rio de Janeiro, Brazil, and to propose a simple approach to determine their empirical coefficients in function of the climate.

2 Materials and methods

2.1 Study area and series of solar irradiation

The state of Rio de Janeiro has an area of 43,766.6 km^2, and it is located in Southeastern (SE) Brazil. The state has territorial limits to the north (N), with the state of Minas Gerais; to the south (S) and to the east (E), with the Atlantic Ocean; to the west (W), with the state of São Paulo; and to the northeast (NE), with the state of Espírito Santo (Fig. 1).

In the present study, air temperature (maximum and minimum daily) and hourly global solar irradiation series were obtained in Automatic Weather Stations (AWS) from the National Institute of Meteorology (Instituto Nacional de Meteorologia—INMET) at the following address: (http://www.inmet.gov.br/portal/index.php?r=estacoes/estacoesautomaticas), located between coordinates 40°57′59″ and 44°53′18″W and 20°45′54″ and 23°21′57″S.

The daily global solar irradiation (H_g^d, MJ m^{-2} d^{-1}) was obtained by integrating the hourly solar irradiation (H_g^h, kJ m^{-2}) over the daylight time using a trapezoidal integration method [25]:

$$H_g^d = \sum_{k=1}^{n} 1/2\left(t_{k+1} - t_{k-1}\right) H_g^h\left(t_k\right) \tag{1}$$

where $H_g^h(t_k)$ is the hourly solar irradiation at time t_k; t_0 and t_{n+1} are sunrise and sunset times, respectively. We assumed that $I_h(t_0) = I_h(t_{n+1}) = 0$.

For each month of the series, it was calculated the monthly average daily global solar irradiation (H_g, MJ m^{-2} d^{-1}). H_g was used to fit and to assess the Hargreaves–Samani and Bristow–Campbell methods.

The stations were preselected based on the size of their series (> 5 years) and period of measurement (2000–2013). Based on these criteria, 15 stations were selected, distributed throughout the state of Rio de Janeiro (Table 1).

2.2 Data quality control

The quality of weather data used in this study was based on a set of validation rules and analysis with the objective of identifying errors and failures in the meteorological series used in the methods to estimate H_g. A three-step quality control was used: (1) basic validation, (2) temporal validation and (3) spatial validation, as described by Allen [13, 26] and Baba et al. [27].

For basic validation, we identify inconsistent data, which can be attributed to errors in readings, calibration problems or defects in measuring instruments. In this step, the physical limits of data were validated, checking whether the daily observations of H_g^d, maximum (t_x, °C) and minimum air temperature (t_n, °C) were physically inconsistent.

In the case of H_g^d, the methodology proposed by Allen [13, 26] to define the physical limit was adopted, where H_g^d on a clear sky day (H_{go}^d) establishes an upper limit for H_g^d. Therefore, if $H_g^d > H_{go}^d$, the observation was considered spurious and

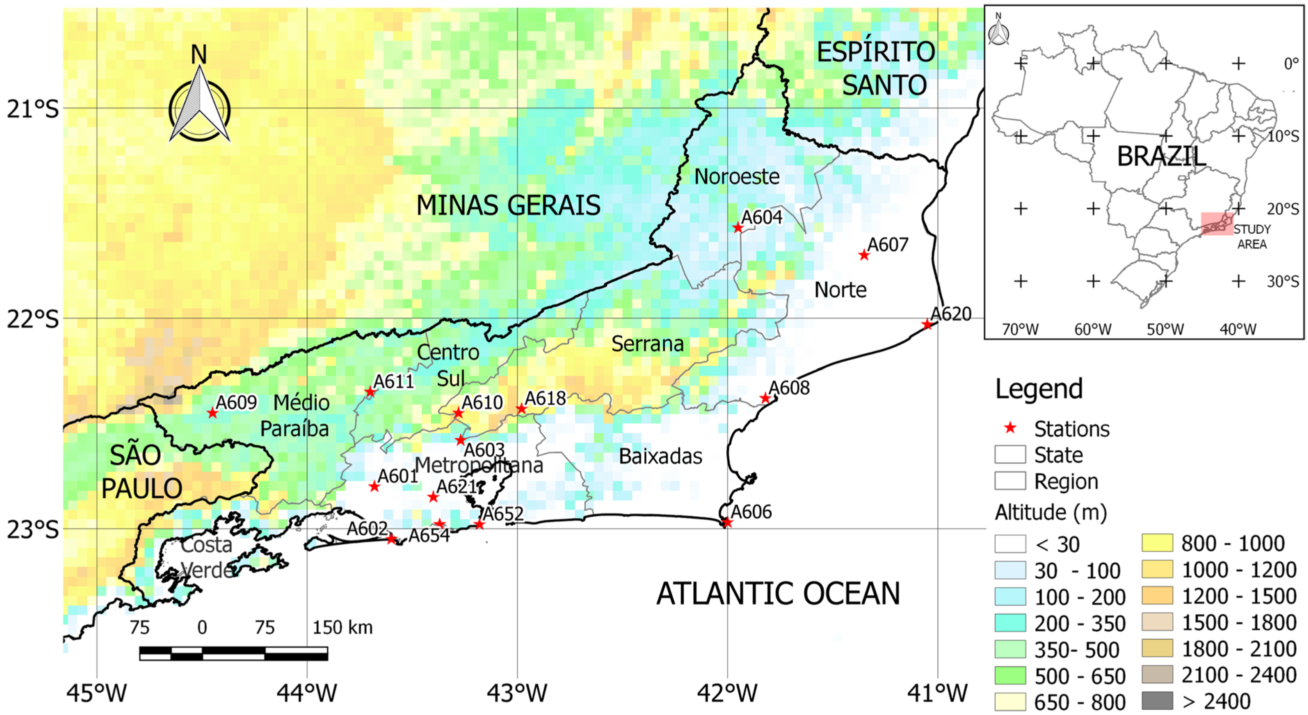

Fig. 1 Automatic Weather Stations—AWS used in the study, with their identifiers (ID) and hypsometry (*m*) of the state of Rio de Janeiro

Table 1 Automatic Weather Stations—AWS selected in the state of Rio de Janeiro with their respective identifiers (ID), municipality, region (coast or interior), climatic classification and geographical coordinates (latitude, longitude and altitude)

ID	Automatic weather stations	Lat. (°)	Long. (°)	Alt. (m)	Series	Gaps (%)
A601	Seropédica	−22.80	−43.68	34	2000–2013	16
A602	Marambaia	−23.05	−43.60	10	2004–2013	22
A603	Duque de Caxias	−22.58	−43.27	33	2002–2013	25
A604	Cambuci	−21.57	−41.95	35	2003–2013	25
A606	Arraial do Cabo	−22.97	−42.00	4	2006–2013	4
A607	Campos	−21.70	−41.35	25	2006–2013	4
A608	Macaé	−22.38	−41.82	32	2006–2013	5
A609	Resende	−22.45	−44.45	440	2006–2012	9
A610	Petrópolis	−22.45	−43.28	1777	2006–2013	8
A611	Valença	−22.35	−43.70	367	2006–2013	6
A618	Teresópolis	−22.43	−42.98	980	2006–2013	1
A620	Campos dos Goytacazes	−22.03	−41.05	8	2008–2013	0
A621	Vila Militar	−22.85	−43.40	45	2007–2013	14
A652	Copacabana	−22.98	−43.18	45	2007–2013	20
A654	Jacarepaguá	−22.98	−43.37	19	2007–2013	6

removed from the series, being disregarded from the fit and test of methods. It was considered that in clear sky situations, the atmospheric transmittance coefficient, known as clearness index ($K_T = R_s/R_a$), tends to a maximum value (K_{To}), where the insolation ratio is also maximum ($n/N = 1$). According to Borges [1], this analysis has as the main objective to verify and to correct the existence of continuous errors in the time series. K_T is normally used to classify the state of the sky (cloudy—$K_T \leq 0.3$, partially cloudy—$0.3 < K_T < 0.7$ and clear sky—$K_T \geq 0.7$) [22]. In the present analysis, K_{To} represents the maximum value of K_T and defines the physical limit to H_g^d (Eq. 2) [13, 18, 26].

H_{go}^d values were calculated by the relation proposed by Allen [26]:

$$H_{go}^d = K_{To} H_o \tag{2}$$

where H_o (MJ m^{-2} d^{-1}) is the extraterrestrial solar irradiation; H_{go}^{d} (MJ m^{-2} d^{-1}) is the global solar radiation on a clear sky day; and K_{To} represents the maximum atmospheric transmittance coefficient for clear sky condition.

For the K_{To} calculation, Eq. 3 was used, which is based only on the altitude of the site [18, 28]:

$$K_{To} = 0.75 + 2 \times 10^{-5} z \tag{3}$$

where z (m) is the altitude of the meteorological station.

As for the temporal validation, the history of the data series of stations was observed, and it was verified if the information was consistent for a certain period, as long as the climate of each region follows a pattern. For example, the highest air temperatures during the year are observed in the summer, while the smallest ones occur in winter, and this premise allows identifying possible errors.

The last step of the data quality analysis was performed after fitting and assessing the proposed methods. It was defined that all stations that presented r^2 between observed and estimated H_g^d values lower than 0.7 would be submitted to this analysis. It was necessary to identify the nearest stations, limited as those located within a radius of less than 150 km from the station under analysis. Stations also had to present data series in a coincident period of time. After the definition of neighboring stations, statistical parameters such determination coefficient (r^2), intercept (a) and slope (b) of the linear regression ($Y = a + bX$) were used to determine the correlation for variables air temperature and solar global irradiation.

The linear regression model (LRM) was used to calculate the estimates of each station and 95% confidence interval tests to determine which values presented significant statistical differences in relation to neighboring stations. Therefore, data that were outside the confidence interval were analyzed and removed when considered spurious for such location and time of year. This measure sought to obtain a homogeneous data series, eliminating possible errors.

After the quality data process, the monthly averages daily solar global irradiation were obtained. Only months with more than 2/3 of valid days were used.

2.3 Empirical methods to estimate solar irradiation

The Hargreaves–Samani [12] and Bristow–Campbell [9] methods were assessed to estimate solar irradiation in the state of Rio de Janeiro.

Hargreaves and Samani [12] proposed a method to estimate H_g as a function of H_o and the air temperature extremes expressed by the following equation:

$$H_g = k_r H_o \left(t_x - t_n\right)^{0.5} \tag{4}$$

where t_x and t_n (°C) are the maximum and minimum air temperature, respectively, and k_r is a dimensionless empirical coefficient.

Meteorological series of selected stations were divided into two parts: About 70% of data were used to fit the coefficient of the empirical method and approximately 30% of data were used in tests.

In this work, k_r was fitted to the climatic conditions of each station of the study region by means of LRM forced to pass at the origin ($Y = bX$), which is related to observed data (Y), that is, the monthly averages of H_g, and values were estimated by the Hargreaves–Samani method [$X = H_o (t_x - t_n)^{0.5}$], based on monthly data of t_x and t_n, so that b is the k_r coefficient of the method. The least square method (LSM) was used to determine b (k_r).

Bristow and Campbell [9] suggested an empirical method to estimate H_g as a function of H_o and the difference between the maximum and minimum temperatures (ΔT, °C)—thermal amplitude, represented by the following relation:

$$H_g = \beta_0 \left[1 - \exp\left(-\beta_1 \Delta T_2^{\beta_2}\right)\right] H_o \tag{5}$$

where β_0, β_1 and β_2 coefficients are empirical, but have physical meaning; ΔT (°C) is the thermal amplitude ($= t_x - t_n$).

Although coefficients are empirical, β_0 represents the expected atmospheric transmittance for a clear sky day, which depends, among others, on altitude and local air pollution, while β_1 and β_2 coefficients control the rate at which β_0 varies with the thermal amplitude. Coefficients can be differentiated, for example, in humid environments and arid zones [9].

For the fit of the Bristow–Campbell method, β_0 was considered the maximum value of the monthly atmospheric transmittance, which on the daily scale would represent a clear sky day. For this, the monthly data of the selected stations, in which the ratio between observed H_g and H_o was calculated, the maximum value obtained for each station represented the β_0 coefficient. The other coefficients of the method were fitted using the solver tool of the Excel® software. In the fit, the sum of the squares of residuals was minimized by the variation of coefficients of the Bristow–Campbell method by iteration (GRG—generalized nonlinear reduced gradient) with the aid of the solver. The initial values of coefficients were close to the originally ones proposed by Bristow–Campbell [9] ($\beta_1 = 0.05$ and $\beta_2 = 2.0$).

For the Hargreaves–Samani (Eq. 4) and Bristow–Campbell (Eq. 5) methods to be applied, H_o was determined according to the method proposed by FAO in its Irrigation and Drainage Bulletin No. 56 (FAO-56) [16], which is based on local latitude and Julian day (day of the year):

$$H_o = 37.59 d_r \left[\omega_s \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) \sin(\omega_s) \right] \quad (6)$$

where d_r (dimensionless) is the correction of the Earth–Sun distance; φ (radians) is the local latitude, having negative value for the Southern Hemisphere; ω_s (radians) is the time angle between sunrise and sunset; and δ (radians) is the solar declination.

The correction of the Earth–Sun distance (d_r), solar declination (δ) and sunset angle (ω_s) values was calculated by the following relations [16]:

$$d_r = 1 + 0.033 \cos\left(\frac{2\pi}{365} J\right) \quad (7)$$

$$\delta = 0.4093 \sin\left(\frac{2\pi}{365} J - 1.39\right) \quad (8)$$

$$\omega_s = \arccos(-\tan(\varphi)\tan(\delta)) \quad (9)$$

where J (days) is the order number of the day of the year or Julian day, between 1 (January 1) and 365 (December 31).

2.4 Statistical analysis

To test the proposed methods, the linear regression analysis was used ($Y = a + bX$) between the observed H_g values (X) in the weather stations and estimated H_g (Y) by the methods evaluated with the fitted empirical coefficients. If there is a significant linear relationship between the independent variable X (H_g observed) and the dependent variable Y (H_g estimated), the slope (b) will not be equal to zero. In the case of intercept (a), when it was applied to evaluate the performance of models, it was expected that the intercept would be equal to zero and the slope equal to 1 ($Y = X$). Thus, the following statistical hypotheses were tested, H_0: $a = 0$ and H_1: $a \neq 0$, H_0: $b = 0$ and H_1: $b \neq 0$, using Student's t test ($p < 0.05$).

The precision of estimates was evaluated by the determination coefficient (r^2) of the linear regression [29, 30].

$$r^2 = \frac{\sum_{i=1}^{k} (P_i - O)^2}{\sum_{i=1}^{k} (O_i - O)^2} \quad (10)$$

where P_i is the value estimated by the method; O_i is the observed value; O is the average of observed values; and k is the number of observations. r^2 varies from 0 to 1, where 0 indicates null precision and 1 represents ideal precision.

The following statistical indexes were also used to evaluate the accuracy of the method estimates: root mean square error (RMSE, MJ m^{-2} d^{-1}) (Eq. 11) and Willmott's index of agreement, d (Eq. 12) [29, 30]:

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{k} (P_i - O_i)^2}{k} \right]^{0.5} \quad (11)$$

$$d = 1 - \left[\frac{\sum_{i=1}^{k} (P_i - O_i)^2}{\left(\sum_{i=1}^{k} \left(|P_i - O| - |O_i - O| \right)^2 \right)} \right] \quad (12)$$

RMSE allows quantifying the error amplitude, and it is also considered a measure of accuracy. The value is always positive and can range from 0 to ∞. The d index defines the accuracy or agreement of estimates in relation to the observed values [29, 30]. This index can vary from 0 to 1, with 0 (zero) indicating that there is no agreement in estimates and 1 (one) representing perfect agreement.

The reliability or performance index (c) proposed by Camargo and Sentelhas [31] is obtained by the product between the precision index (Pearson correlation coefficient, r) and the index of agreement (d). The performance of the methods can be interpreted using the criteria suggested by Camargo and Sentelhas [31] presented in Table 2.

3 Results

3.1 Hargreaves–Samani method

The values of the fitted k_r coefficient ranged from 0.134 (Duque de Caxias—ID 603, interior) to 0.262 (Arraial do Cabo—ID 606, coast), with the average of 0.173 (±0.035) and coefficient of variation (CV, %) of 20.3% (Table 3). The pattern of higher k_r values in the coastal regions and lower k_r values in interior regions was observed. It should be noted that the predisposition of weather stations, with a larger number of stations near the Atlantic Ocean and the two Bays, Sepetiba and Guanabara, favored the higher k_r values. Analogous to this study, Hargreaves [17] and Lyra et al. [15] also observed the highest k_r values in stations located on the coast of Alagoas.

Regarding the climatic classification of the weather stations analyzed in the present study, it was observed that, in general, the highest k_r values occurred in Semiarid (0.246 ± 0.023) and Dry Sub-humid (0.181 ± 0.011) (Table 4)

Table 2 Criterion of performance interpretation of the method using the Camargo e Sentelhas—c index

c index	Performance
> 0.85	Excellent
0.76–0.85	Very good
0.66–0.75	Good
0.61–0.65	Reasonable
0.51–0.60	Poor
0.41–0.50	Very poor
≤ 0.40	Extremely poor

Table 3 Fitted k_r empirical coefficient for the Hargreaves–Samani method and β_0, β_1 and β_2 coefficients for the Bristow–Campbell method

ID	Hargreaves–Samani	Bristow–Campbell		
	k_r	β_0	β_1	β_2
601	0.154 (±0.001)	0.609	0.014	2.099
602	0.182 (±0.002)	0.623	0.125	1.277
603	0.134 (±0.002)	0.588	0.007	2.233
604	0.155 (±0.002)	0.667	0.032	1.603
606	0.262 (±0.004)	0.659	0.884	0.456
607	0.169 (±0.002)	0.652	0.007	2.441
608	0.168 (±0.002)	0.639	0.014	2.172
609	0.144 (±0.002)	0.591	0.009	2.221
610	0.172 (±0.004)	0.680	0.115	1.167
611	0.152 (±0.002)	0.627	0.029	1.707
618	0.145 (±0.003)	0.625	0.007	2.381
620	0.229 (±0.004)	0.684	0.065	1.851
621	0.150 (±0.002)	0.597	0.034	1.689
652	0.194 (±0.004)	0.614	0.843	0.347
654	0.178 (±0.002)	0.613	0.046	1.759

Table 4 Thornthwaite climate classification and interior or coastal region for the automatic weather stations

ID	Automatic weather stations	Region[a]	Climate classification[b]
A601	Seropédica	Interior	C2rA′
A602	Marambaia	Coastal	C1dA′
A603	Duque de Caxias	Interior	B1rA′
A604	Cambuci	Interior	C1sA′
A606	Arraial do Cabo	Coastal	DdA′
A607	Campos	Coastal	C1sA′
A608	Macaé	Coastal	C1dA′
A609	Resende	Interior	B2rB′4
A610	Petrópolis	Interior	B1rB′2
A611	Valença	Interior	B2rA′
A618	Teresópolis	Interior	B4rB′4
A620	Campos dos Goytacazes	Coastal	DdA′
A621	Vila Militar	Interior	C2rA′
A652	Copacabana	Coastal	C1dA′
A654	Jacarepaguá	Coastal	C1dA′

[a]Interior or coastal by Hargreaves (1994) necessary to define the coefficient of the Hargreaves and Samani (1985) method

[b]Thornthwaite's climate classification: *D* Semiarid, *C1* Dry Sub-humid, *C2* Sub-humid, *B1*, *B2*, *B3* and *B4* Humid, *r* small or no water deficiency in winter, *d* small or no water excess in summer, *A′* megathermal, *B′2* and *B′4* mesothermal

climates and were associated with coastal regions, while the majority of stations with the lowest k_r values presented Humid (0.146 ± 0.008), Sub-humid (0.152 ± 0.003) and Dry Sub-humid (0.162 ± 0.011) climate classification and were located in interior regions (Table 5), i.e., they have a strong climate dependence.

The r^2 coefficient of the regression between observed and estimated H_g ranged from 0.55 (Petrópolis—A610) to 0.91 (Marambaia—ID602). It is noteworthy that, from the 15 analyzed stations, only two presented r^2 lower than 0.7 (Petrópolis and Teresópolis—A618); therefore, in most stations, the Hargreaves–Samani method presented accuracy greater than 80% in relation to H_g observations (Table 6). The stations with less precision were located in the Serrana region (A610 and A618) of the state (interior) and the highest altitude 950 m. This result indicates that the precision was close to those observed by Lyra et al. [15], which report r^2 between 0.62 and 0.87 for the state of Alagoas.

Regarding the d index, it was observed that most stations (14 stations) had higher values than 0.85; only Petrópolis station had a lower d index (0.75). Again, Petrópolis station obtained a statistical index below the other stations. Based on this result, it could be stated that H_g estimated by Hargreaves–Samani shows agreement above 85% of data observed in most stations in the state of Rio de Janeiro.

RMSE normalized by the average monthly global solar irradiation ranged from 8.5% (Campos dos Goytacazes—ID620) to 22.5% (Petropólis), representing an absolute variation of 1.47–3.85 MJ m^{-2} d^{-1}, respectively. The stations with lower d index and higher RMSE were predominantly of interior classification and humid climate (Table 4). These values were lower than those obtained by Liu et al. [32] for China; when considering the confidence interval, RMSE ranged from 3.85 to 4.51 MJ m^{-2} d^{-1}.

In all stations, the precision (r^2) was bigger than the accuracy (d), which indicated that the fits were satisfactory and minimized the systematic errors [29, 30].

The coefficient *c* results were above 0.7 for most stations, except for Petrópolis station, which presented performance classified as *Poor* (0.55). Eight stations presented *Excellent* performance, which represents about 55% of the stations evaluated, and six presented *Good–Very Good* performances. The lower performances (*poor*, *good and very good*) of the H_g estimates by Hargreaves–Samani method alternated in interior/coast stations and from semiarid to humid climates. However, the *Excellent* performance was observed in Sub-humid and Semiarid stations, with the exception of Duque de Caxias station (Humid).

3.2 Bristow–Campbell method

Regarding the fit of the empirical coefficients of the Bristow–Campbell method, β_0 ranged from 0.588 to 0.684, with the average of 0.631 (±0.001). In general, the highest β_0 values were observed in stations located in Semiarid

Table 5 Climate classification and Hargreaves–Samani coefficient—average, standard deviation (SD) and coefficient of variation (CV, %)

Climate	Thornthwaite classification	Interior			Coast		
		Mean	SD	CV (%)	Mean	SD	CV (%)
Humid	*B4*, *B2*, *B1*	0.1455	0.0076	5.2%	–	–	–
Sub-humid	*C2*	0.1524	0.0028	1.8%	–	–	–
	C1 (dry)	0.1622	0.0105	6.5%	0.1805	0.0110	6.1%
Semiarid	*D*	–	–	–	0.2459	0.0233	9.5%
All		0.1507	0.0097	6.4%	0.2023	0.0363	17.9%

Table 6 Determination coefficient (r^2), intercept (*a*) and slope of the linear regression (*b*), Willmott's index (*d*), root mean square error (RMSE, MJ m^{-2} d^{-1}) for the Hargreaves–Samani method

ID	r^2	*a*	*b*	*c*	*d*	RMSE		*c* index
						(MJ m^{-2} d^{-1})	%	
601	0.86	0.82	0.99	0.88	0.87	1.47	9.1	Excellent
602	0.91	1.74	0.86	0.92	0.87	1.60	9.3	Excellent
603	0.87	1.83	0.85	0.90	0.87	3.85	16.7	Excellent
604	0.84	5.18	0.70	0.86	0.94	2.23	12.3	Excellent
606	0.70	2.34	0.84	0.76	0.91	2.48	13.7	Very good
607	0.86	3.12	0.82	0.89	0.96	1.50	8.5	Excellent
608	0.82	3.50	0.77	0.85	0.94	1.77	10.1	Very good
609	0.81	−0.08	0.98	0.85	0.94	1.59	9.2	Very good
610	0.55	0.33	0.84	0.56	0.75	3.12	22.5	Poor
611	0.80	3.56	0.75	0.82	0.92	2.06	11.6	Very good
618	0.67	2.17	0.83	0.74	0.90	1.94	13.3	Good
620	0.85	3.88	0.79	0.88	0.95	1.80	9.1	Excellent
621	0.84	2.54	0.83	0.88	0.95	1.47	8.7	Excellent
652	0.80	2.08	0.82	0.82	0.92	2.53	15.0	Very good
654	0.87	1.97	0.87	0.90	0.96	1.55	9.1	Excellent

and Dry Sub-humid climate regions, except for Petrópolis station, which was classified as Humid climate and presented the second highest β_0 value (0.680) (Table 3).

Considering the values of the β_1 coefficient, a variation from 0.007 to 0.884 was obtained. The values of the β_2 coefficient fitted for the state of Rio de Janeiro ranged from 0.344 to 2.441. The β_1 and β_2 coefficients did not present distribution pattern with the local climatology, with the proximity of large water bodies, and were also not influenced by the thermal amplitude of the analyzed areas. However, these coefficients presented an inversely proportional relation between them.

The r^2 coefficient ranged from 0.6 (Petrópolis) to 0.93 (Duque de Caxias, Teresópolis and Campos dos Goytacazes), and only Petropólis, Arraial do Cabo and Copacabana—ID 652 station had the r^2 value lower than 0.75. From the analyzed stations, ten stations presented r^2 higher than 0.85; therefore, in most of the stations, the Bristow–Campbell method was tested which had more than 85% accuracy of estimates in relation to H_g observations (Table 7). Regarding the d index, it was observed that from the 15 analyzed stations, 13 presented values higher than 0.9 and only Petrópolis and Copacabana stations had lower *d* index (0.9). Based on this result, it could be concluded that H_g estimated by the Bristow–Campbell method presented agreement above 90% in relation to the observed data. Analogous with the precision, the accuracy of Petropólis, Arraial do Cabo and Copacabana (A652) stations was the lowest among stations. The accuracy of the H_g estimated by Bristow–Campbell was greater than its precision.

This result indicated that the accuracy was analogous to values obtained by Almorox et al. [6] for Madrid in Spain, which ranged from 0.871 to 0.892, and they were higher than those presented by Moreno et al. [33] also for Spain, with the value of 0.71; Silva et al. [3] for Minas Gerais in Brazil who presented the value of approximately 0.72; and Tanaka [34] who found values between 0.576 and 0.798 for the state of Mato Grosso in Brazil.

The RMSE values normalized by the mean solar irradiation ranged from 6.0 to 17.4%, representing an absolute variation from 1.08 to 2.99 MJ m^{-2} d^{-1}. These values were lower than those obtained by Liu et al. [20] for China;

Table 7 Determination coefficient (r^2), intercept (*a*) and slope of the linear regression (*b*), Willmott's index (*d*), root mean square error (RMSE, MJ m^{-2} d^{-1}) for the Bristow–Campbell method

ID	r^2	*a*	*b*	*c*	*d*	RMSE		*c* index
						(MJ m^{-2} d^{-1})	%	
A601	0.90	− 0.13	1.05	0.91	0.96	1.41	8.6	Excellent
A602	0.90	2.06	0.84	0.91	0.96	1.68	9.8	Excellent
A603	0.93	− 0.38	0.99	0.94	0.98	1.14	7.6	Excellent
A604	0.86	4.11	0.75	0.88	0.95	2.05	11.5	Excellent
A606	0.73	2.48	0.84	0.78	0.92	2.31	12.6	Very good
A607	0.93	1.65	0.92	0.95	0.98	1.05	5.9	Excellent
A608	0.86	2.40	0.84	0.89	0.96	1.50	8.5	Excellent
A609	0.83	− 1.90	1.10	0.86	0.95	1.60	9.1	Excellent
A610	0.60	− 1.02	1.04	0.66	0.85	2.45	15.7	Good
A611	0.84	2.68	0.81	0.86	0.94	1.76	9.8	Excellent
A618	0.93	− 3.26	1.19	0.93	0.97	1.28	8.7	Excellent
A620	0.88	3.69	0.81	0.91	0.96	1.58	7.9	Excellent
A621	0.88	2.28	0.86	0.90	0.96	1.28	7.4	Excellent
A652	0.74	4.25	0.68	0.75	0.87	3.00	17.5	Good
A654	0.87	1.65	0.89	0.90	0.97	1.48	8.7	Excellent

considering the confidence interval, RMSE ranged from 3.85 to 4.51 MJ m^{-2} d^{-1}.

The coefficient *c* results were higher than 0.85 for most stations, except for Arraial do Cabo station with *Very Good* performance (0.78) and Petrópolis (0.67) and Copacabana (0.75) with *Good* performance. Twelve stations presented *Excellent* performance, representing 80% of the stations evaluated, and three showed *Good*–*Very Good* performance. The stations with better performance ($c > 0.90$) were classified predominantly as Sub-humid and Semi-arid climates and only Teresópolis and Duque de Caxias presented Humid climate.

The precision and accuracy of the H_g estimates of the Bristow–Campbell method stood out in most stations over that of Hargreaves–Samani. Only in the stations of Marambaia (ID—A602) and Copacabana, there were better performances of the estimates with the method of Hargreaves–Samani than with the method of Bristow–Campbell. These stations are located in the coast region of the Metropolitana region of the Rio de Janeiro State.

Figures 2, 3 and 4 show the dispersion and time series between monthly H_g estimated values and those observed in weather stations. Three stations were selected to show the different precision and accuracy characteristics of the data studied and seasonal behavior (summer/winter). Two stations (Petrópolis and Teresópolis) were located in mountains region and showed poor performance of the estimates, and another one (Duque de Caxias) located in middle altitudes, between the costal lowland and mountains, had better precision and accuracy.

Figure 2b and c shows the linear regression of Teresopólis station, referring, respectively, to the Hargreaves–Samani and Bristow–Campbell methods, in which the Bristow–Campbell result was observed to be more accurate than Hargreaves–Samani result, with less dispersion of data. Figure 3b and c shows (Duque de Caxias) that the linear regression found for both methods tested tends to underestimate H_g during the period of the highest H_g monthly values (Figs. 2a and 3a), i.e., H_g estimates in the summer tend to be underestimated; however, it was observed that the methods presented satisfactory accuracy and precision for this location, with data close to each other and to line 1:1 of the graph, while in Fig. 4b and c, Petrópolis station, it was observed that the Hargreaves–Samani method resulted in lower precision and accuracy compared to the other stations and the Bristow–Campbell method presented unsatisfactory precision and, however, significant accuracy. In this station, the behavior was to underestimate H_g during winter and spring, when the lowest H_g values are observed, mainly with the Bristow–Campbell method.

4 Discussion

The values of the k_r coefficient fitted in the present study were higher than those found by Jerszurki and Souza [8], who observed variation between 0.11 and 0.12 in the state of Paraná, Brazil, and close to interval observed by Silva et al. [3], which obtained k_r between 0.166 and 0.186, with the average of 0.176 (± 0.008) in the northwestern (NW) region of Minas Gerais, Brazil, and those found by Lyra et al. [15] for Alagoas, Brazil, which ranged from 0.168 to 0.231. Hargreaves [17] recommended two values for k_r, 0.16 for regions considered interior and 0.19 for coastal regions. The interior region would be characterized as

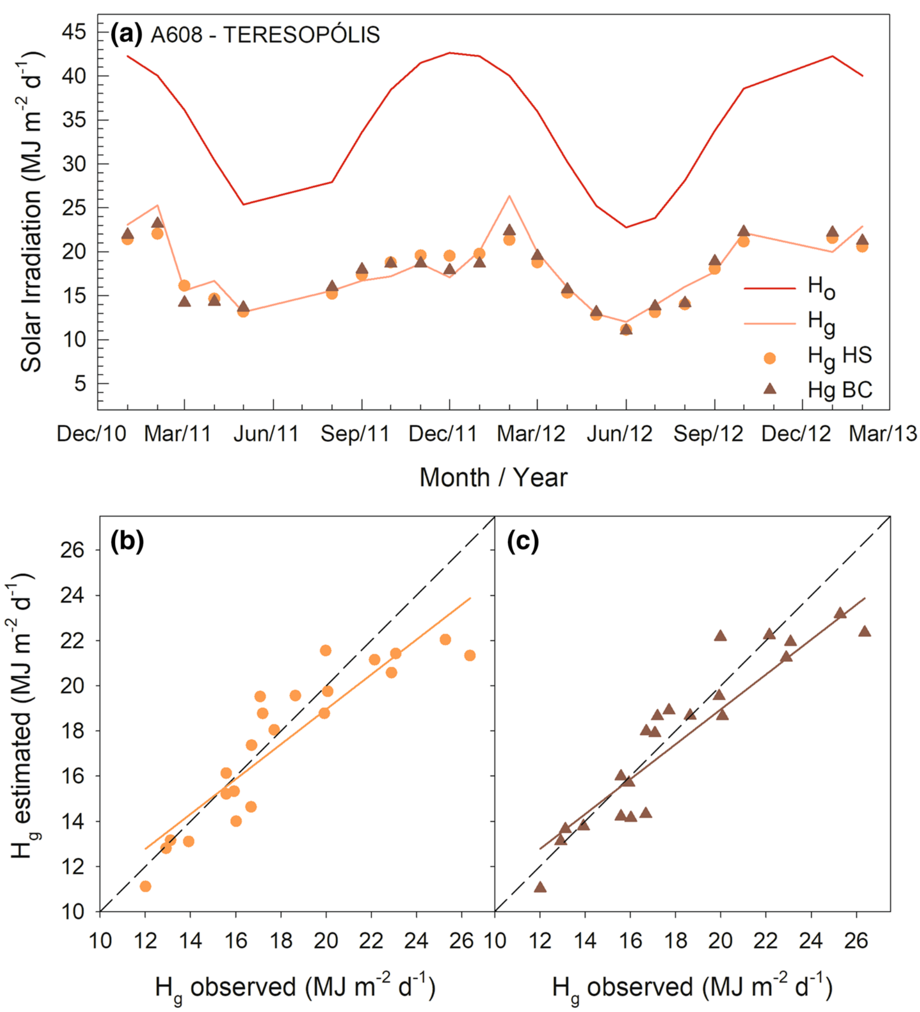

Fig. 2 Monthly extraterrestrial solar irradiation (H_o) (**a**), solar global irradiation estimated by the Hargreaves–Samani—H_{g_HS} (**a**, **b**) and Bristow–Campbell H_{g_BC} (**a**, **c**) methods *versus* observed solar irradiation (H_g) (**a**, **b**, **c**) of ID 618—Teresópolis station

the place where land mass dominates the climate and air masses are not strongly influenced by large water bodies (e.g., ocean, lakes), while the coastal region would be the region whose climate patterns are dominated by the proximity to large water bodies.

It could be inferred that the distance from large water bodies is a determining factor for the k_r coefficient of the Hargreaves–Samani method. The proximity of the Atlantic Ocean interferes in the atmospheric processes of the study region, since the advection of water vapor, due to atmospheric circulation, is greater along the coastal environment in relation to places inside the continent (interior) [15]. Thus, localities in the coast (interior) present higher (lower) air humidity, which results in higher (lower) specific air heat and thus lower (greater) thermal amplitude, since more (less) energy is needed to heat the same mass of humid air in relation to dry air.

Associated with local circulation (sea/land breezes circulations, bays and lacustrines), which induces the advection of moisture to the coast, the presence of the ocean favors the reduction in the thermal amplitude due to the high specific heat of the water [15]. The air temperatures of the coastal regions show lower annual and diurnal thermal amplitude in relation to inland regions, due maritime/continentality effect. Therefore, for near (distant) places in the coastal environment, k_t coefficient should be larger (smaller) to maintain the identity expressed by the Hargreaves–Samani method (Eq. 4) between thermal amplitude and solar irradiation.

The values of the β_0 coefficient of the Bristow–Campbell method for the state of Rio de Janeiro were lower than that indicated by Meza and Varas [35], which is 0.7. In addition, the lowest values obtained were also lower than those found by Liu et al. [32], $0.613 \le \beta_0 \le 0.836$, and by Silva et al. [3], $0.658 \le \beta_0 \le 0.843$. Santos et al. [14] observed that the lowest coefficient values were in periods of higher total rainfall and theoretically low temperature (autumn/winter), while the highest values were observed in periods of lower total rainfall and higher temperature (spring/summer). Thus, a correlation can be made with the values

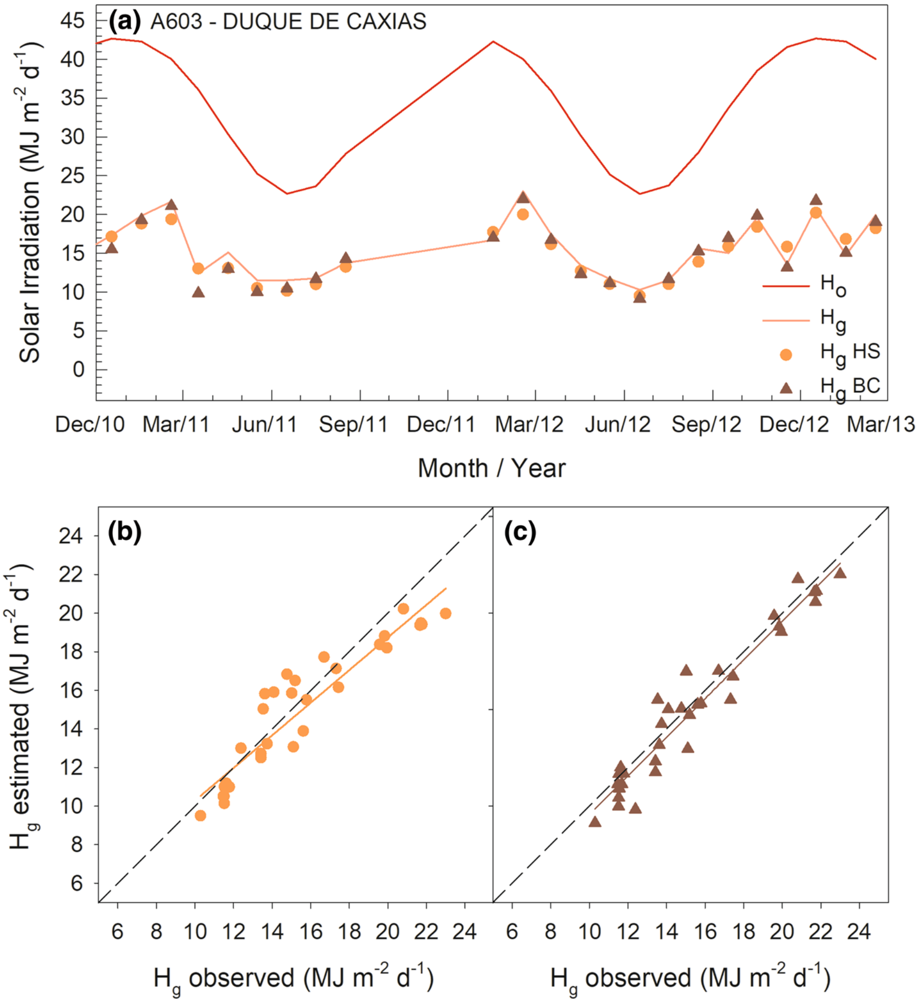

Fig. 3 Monthly extraterrestrial solar irradiation (H_o) (**a**), solar global irradiation estimated by the Hargreaves–Samani—H_{g_HS} (**a**, **b**) and Bristow–Campbell H_{g_BC} (**a**, **c**) methods *versus* observed solar irradiation (H_g) (**a**, **b**, **c**) of ID 603—Duque de Caxias

obtained for the state of Rio de Janeiro, where the highest values were observed in areas with little or no water surplus (Sub-humid and Semiarid climate).

The amplitude of β_1 is higher than the range of values recommended by Meza and Varas [35], ranging from 0.004 to 0.010; values obtained by Almorox et al. [6], ranging from 0.001 to 0.039; values obtained by Moreno et al. [33], ranging between 0.029 and 0.030; and values obtained by Silva et al. [3], ranging from 0.009 to 0.027.

The empirical coefficients of Hargreaves–Samani and Bristow–Campbell methods when fitted for the climatic conditions of the state of Rio de Janeiro presented similar pattern, where in general the highest k_r, β_0 and β_1 values were observed in Semiarid and Dry Sub-humid locations, while for β_2, the lowest values were found in these types of climate.

According to Besharat et al. [5], the air temperature amplitude (ΔT) can influence the fit and the performance of the methods, and higher ΔT values generally result in a better accuracy in the fit, since models based on the air temperature are more appropriate for areas with greater air temperature amplitude. It was observed in the study area that the less accurate results of fit and test, especially those of the Bristow–Campbell method, were observed in stations with lower ΔT.

The lowest performing stations were located in the mountain range (Teresópolis and Petrópolis), facing the Atlantic Ocean. These regions present the highest rainfall totals in the state of Rio de Janeiro, due to the combined effect of continentality and large-scale meteorological systems (Frontal Systems and South Atlantic Convergence Zone—SACZ) [36, 37]. Associated with these totals of rainfall, the high variability in the cloudiness of this region induces the low performance of the methods based on the thermal amplitude [15]. In Dry Sub-humid and Semiarid climate, due to lower cloudiness and greater thermal amplitude, the methods presented better results.

Lyra et al. [15] and Allen [13] also identified better performances, with a decrease in the dispersion of the estimates, in the station characterized by lower total rainfall, due to associated cloudiness. In addition to the cloudiness associated with these weather systems, the lower thermal

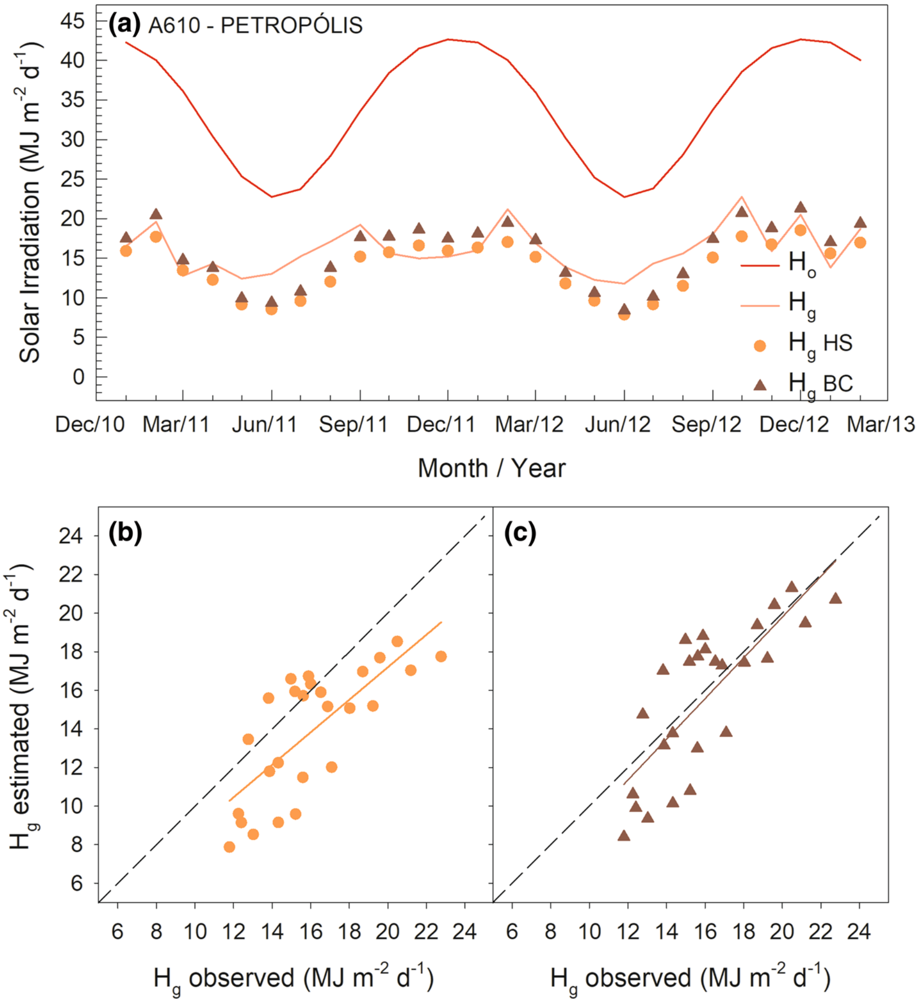

Fig. 4 Monthly extraterrestrial solar irradiation (H_o) (**a**), solar global irradiation estimated by the Hargreaves–Samani—H_{g_HS} (**a**, **b**) and Bristow–Campbell H_{g_BC} (**a**, **c**) methods *versus* observed solar irradiation (H_g) (**a**, **b**, **c**) of ID 610—Petrópolis

amplitude of these stations results in the large dispersion of the estimates [21]; thus, their relationship is far from linear [13].

However, it is important to emphasize that the Hargreaves–Samani method is simple and has only one empirical coefficient, so the results obtained using this method are satisfactory for the climatic conditions of the study area. Almorox et al. [6] tested eight models of solar radiation estimation for seven meteorological stations in Madrid, Spain, and concluded that due to its simplicity, the Hargreaves–Samani method not only easily determined the coefficient compared to other models, but also showed satisfactory result in the general ranking, in which r^2 and RMSE were considered. It is important to point out that due to the simplicity of the method by Hargreaves–Samani, it becomes more practical to be applied in different regions.

Even with statistically lower results, the Hargreaves–Samani method is considered more practical to be applied in different locations because it requires only one empirical coefficient, whereas the Bristow and Campbell method requires three coefficients.

5 Conclusions

Hargreaves–Samani and Bristow–Campbell models presented precision and accurate estimates of monthly average daily total solar irradiation in the state of Rio de Janeiro when their coefficients are previously fitted to local climatic conditions.

The coefficients of the Hargreaves–Samani and Bristow–Campbell methods are dependent on climatic conditions, influenced by the continentality effect, altitude, thermal amplitude and other regional factors. The highest k_r, β_0 and β_1 values were observed in Semiarid and Dry Sub-humid climate, while for β_2, the lowest values were found in these types of climate.

The coefficient of Hargreaves–Samani can be determinate based only on Thornthwaite local climate classification.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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