Modeling Earth Systems and Environment (2021) 7:603–622
https://doi.org/10.1007/s40808-020-00956-x

ORIGINAL ARTICLE

Performance and estimation of solar radiation models in state of Minas Gerais, Brazil

Angélica Carvalho Cunha[1] · Luís Roberto Almeida Gabriel Filho[2] · Adriana Aki Tanaka[3] · Fernando Ferrari Putti[2]

Received: 26 May 2020 / Accepted: 25 August 2020 / Published online: 16 September 2020

Abstract
Solar radiation is one of the most important meteorological variables, as it is directly related to evaporation. Based on this variable, it is possible to develop models for estimating meteorological elements. However, when there is lack of data, estimates can be made using mathematical models. The objective of this paper was to perform the calibration and statistical performance evaluation of fifteen simplified models of global solar radiation estimation based on air temperature for 51 cities in the state of Minas Gerais, Brazil. The data were provided by the National Meteorological Institute using Automatic Meteorological Stations (EMA's) located in the cities studied. The performance indexes used were the Coefficient of Determination for Linear Regression (R^2), Root-Mean-Square Error and Mean Relative Error, and the Willmott d Index. Through the results obtained, it is possible to observe that the model with the best performance for the state of Minas Gerais was that of Donatelli and Campbell, because, based on the statistical analysis and ordering of the indexes, that is, the use of the position values (V_p) of the indicatives statistics to classify and define the best method for estimating global radiation, this model was the one that obtained the lowest V_p value.

Keywords Global solar radiation · Simplified models · Donatelli and Campbell

Introduction

Agriculture plays a strategic role in Brazilian economic development. In addition to the economy, it has also contributed to the reduction of poverty and inequality in Brazil (Berchin et al. 2019). The Brazilian agricultural sector is characterized by modernity and dynamism (Garcia and Vieira Filho 2014; Meyer and Silva 2019; Meyer and Braga 2019).

The state of Minas Gerais is described as having a vast climatic diversity (Antunes 1986; Dubreuil et al. 2019), with four main characteristics: humid tropical savanna (Aw), dry climate with summer rains (BSw), rainy temperate (Cwa) and subtropical altitude (Cwb), according to the Köppen climate classification (Souza et al. 2006).

Minas Gerais is a state that has significant importance in Brazil's agricultural economy. In 2017, agribusiness accounted for 33.54% of the state's GDP and had a 13.59% share of the Brazil's GDP. The predominant culture in Minas Gerais is coffee, in a way that Minas Gerais is the Brazilian state with the highest coffee production, responsible for 54.27% of the produced coffee in the country (CEPEA 2019; FAEMG 2019).

Several aspects, such as climate, relief and hydrographic basins, are predominant in the composition of the varied biodiversity of the state of Minas Gerais (Oliveira et al. 2017). The state's vegetation can be described in three main biomes: Atlantic Forest, Cerrado and Caatinga (IEF 2018).

The predominant biome is the Cerrado, appearing in about 50% of the State, mainly in the basins of the São Francisco and Jequitinhonha rivers (Callisto et al. 2016). In the Cerrado, the dry and rainy seasons are well defined (Scherrer et al. 2016). The vegetation consists of grasses, shrubs and trees. The second largest biome in Minas is the Atlantic

✉ Fernando Ferrari Putti
fernando.putti@unesp.br

[1] School of Agronomy, José Rosário Vellano University (Unifenas), Rodovia MG 179, Km 0, Alfenas, MG 37132-440, Brazil

[2] School of Sciences and Engineering, São Paulo State University (UNESP), Rua Domingos da Costa Lopes 780, Tupã, SP 17602-496, Brazil

[3] School of Agronomy, Rural Federal University of Pernambuco (UFRPE), Rua Manuel de Medeiros, 98-402, Recife, PE 52171-900, Brazil

Forest, with a dense vegetation and permanently green forest, due to great periods of rainfall (Szabó et al. 2018). The trees have large, smooth leaves. The Campo de Altitude, or rock biome, is characterized by a lower proportion of vegetation cover with a wide variety of species, with herbaceous vegetation predominating, where shrubs are scarce and trees are rare and isolated (Silveira et al. 2016). They are found at the highest points of the mountains of Mantiqueira, Espinhaço and Canastra (Silva et al. 2018). Mata Seca (Dry Forest) is present in the north of the state, in the São Francisco river valley (Rodriguez et al. 2017). The plant formations of this biome are characterized by the appearance of spiny plants, dry branches and few leaves in the dry season. In the rainy season, the forest flourishes intensely, providing great foliage (IEF 2018).

Solar radiation is all electromagnetic radiation derived from the Sun that reflects the planet (Querino et al. 2011). Solar radiation is the driving force for many physical–chemical and biological actions that take place in the Earth-Atmosphere system (Brusseau et al. 2019). It is considered an important meteorological variable used in the analysis of water requirement of irrigated crops, modeling of plant growth and production, climate change, among others (Borges et al. 2010; Jahani et al. 2017).

The difficulty in measuring solar radiation, mainly due to the cost of sensors, maintenance and the technical difficulty of installation in remote locations (Das et al. 2015; Yang et al. 2006), causes the need for modeling to estimate solar radiation. Thus, several researchers have developed models to determine radiation, being based on artificial intelligence (Mohammadi et al. 2015; Shamshirband et al. 2016). The importance of determining solar radiation is extremely important, since it is a source of energy for plants.

However, there are locations where the collection of solar radiation data is not performed. In these cases, the estimated values can be obtained by means of mathematical models, which differ from each other by the degree of complexity and by the input variables (Borges et al. 2010). The first published model to estimate solar radiation was made by Angströn (1924). This model is based on heat stroke (hours of sunlight), to estimate the incident solar radiation (Borges et al. 2010; Buriol et al. 2012).

For Tanaka et al. (2016), the most popular and employed temperature-based models are the models by Hargreaves (1981) and Bristow and Campbell (1984), since they require few meteorological variables to estimate solar radiation, thus being characterized by simplicity.

An Automatic Meteorological Station (EMA) collects, every minute, meteorological data (temperature, humidity, atmospheric pressure, precipitation, wind direction and speed, and solar radiation) that represent the place where it is located. Every hour, these data are received and made available to be transmitted, via satellite or cell phone, to the National Meteorological Institute (INMET's) headquarters in Brasília (capital of Brazil). All data received are validated, through a quality control and stored in a database (INMET 2018).

In view of this relevant scenario of agribusiness in the state of Minas Gerais, it is noted that it is extremely important to have knowledge of the conditions that can influence agricultural production. Based on the problem raised, in which several regions of the state of Minas Gerais do not present data, and studies that indicate the simplified model that presents the best performance, the present work aimed to perform the calibration of fifteen simplified models for estimating solar radiation and, subsequently, evaluate their statistical performance for 51 cities in the state of Minas Gerais.

Materials and methods

Study area

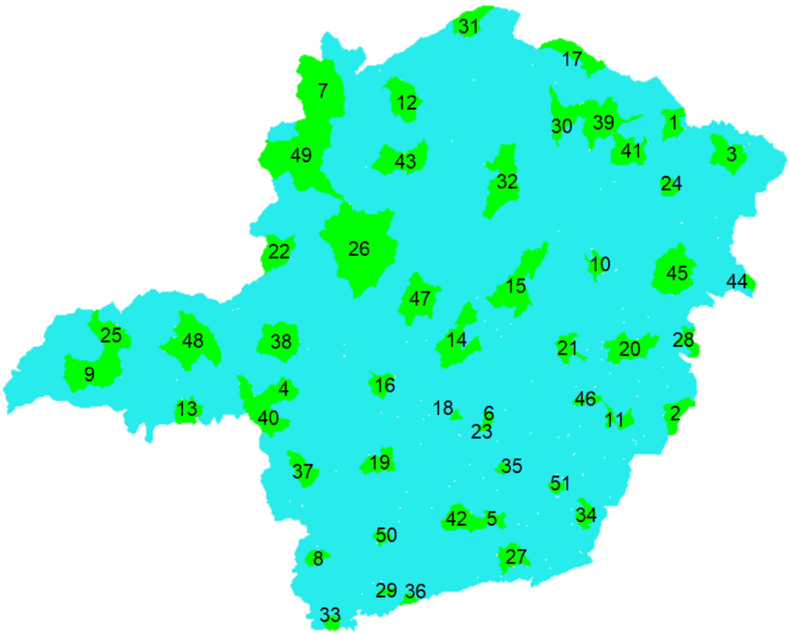
Figure 1 shows the location of the 51 cities where the automatic stations are located in the state of Minas Gerais, which were used in the study. It is observed that all regions of the state were able to be contemplated.

Data acquisition and information about EMA's

The data used in this work were obtained from the network of Automatic Meteorological Stations (EMA's) of the National Institute of Meteorology (INMET), located in 51 cities in the state of Minas Gerais, Brazil (Table 1). This network is composed by 68 EMA's in the whole of the state. However, some EMAs had failures and lack of data, characterized by equipment failures, maintenance periods, or were built recently and so, had little data. Therefore, 17 EMA's were disregarded in the analyses.

The data period was different from city to city, since the EMA's started operations at different times, and also, due to technical problems, there were periods when data collection did not occur, thus causing different amounts of data between the cities studied. Table 1 shows the amount of data used in the study, the period of data collection, the amount of data collected and the percentage of null data. The data actually used in the analyzes are lower than the totals collected, since there was a loss of data caused through collection system failures, instrument failures, data capture problems, among others.

The climatic stations in which the data were collected are standardized, being free from natural and building obstruction, with a minimum area of 14X18 meters, fenced and grassed. The vegetation within that radius is grassy, always kept around 5 cm. This area is closed with a fence



Location of the cities

1. Águas Vermelhas
2. Aimorés
3. Almenara
4. Araxá
5. Barbacena
6. Belo Horizonte - Pampulha
7. Buritis
8. Caldas
9. Campina Verde
10. Capelinha
11. Caratinga
12. Chapada Gaúcha
13. Conceição das Alagoas
14. Curvelo
15. Diamantina
16. Dores do Indaiá
17. Espinosa
18. Florestal
19. Formiga
20. Governador Valadares
21. Guanhães
22. Guarda-Mor
23. Ibirité (Rola Moça)
24. Itaobim
25. Ituiutaba
26. João Pinheiro
27. Juiz de Fora
28. Mantena
29. Maria da Fé
30. Mocambinho
31. Montalvânia
32. Montes Claros
33. Monte Verde
34. Muriaé
35. Ouro Branco
36. Passa Quatro
37. Passos
38. Patrocínio
39. Rio Pardo de Minas
40. Sacramento
41. Salinas
42. São João del Rei
43. São Romão
44. Serra dos Aimorés
45. Teófilo Otoni
46. Timóteo
47. Três Marias
48. Uberlândia
49. Unaí
50. Varginha
51. Viçosa

Fig. 1 Location of the cities studied in the state of Minas Gerais. Source: INPE (2019)

to prevent the entry of animals. Since the EMA's are composed of a data collection subsystem, through sensors that measure environmental variables; control subsystem and local storage in data-logger; power subsystem; communications subsystem; database subsystem; and a subsystem for disseminating data to users, openly and free of charge over the internet. In EMA's the data collection is done through sensors to measure the meteorological parameters to be observed. The measures taken, at minute-by-minute intervals, and paid for within an hour, to be transmitted, are: Instant Air Temperature; Maximum Air Temperature; Minimum Air Temperature; Instant Relative Air Humidity; Maximum Relative Humidity of Air; Minimum Relative Humidity of Air; Instant dew point temperature; Maximum Dew Point Temperature; Minimum Dew Point Temperature; Instant Atmospheric Air Pressure; Maximum Atmospheric Air Pressure; Minimum Atmospheric Air Pressure; Instant Wind Speed; Wind Direction; Intensity of the Wind Gust; Solar Radiation and Precipitation accumulated in the period.

Models

The equations addressed in the present research are based on air temperature and precipitation, since these data were collected in all stations used in this study (Table 1). In addition to that, such variables can be measured with low-cost equipment. The mathematical models for estimating the studied global solar radiation, coefficients with demand for calibration and their respective references are presented in Table 2.

The models under evaluation were ordered according to the name of the author(s). Most of them are models from the proposals of Hargreaves (1981) and Bristow and Campbell (1984), in which there are different requirements regarding the parameterized coefficients with the need for calibration (Tanaka et al. 2016).

First, the coefficients of each model were calculated, to ascertain which model would have the least error for the cities studied.

The obtaining of the parameters of all models was done using the Matlab Software, with the *lsqcurvefit* function, which is indicated for solving nonlinear curve fitting problems (data adjustment) in the sense of least squares (Matlab 2019).

Therefore, the following function seeks to determine coefficients x that solve the problem mentioned above:

$$\min_x \|F(x, x\mathrm{data}) - ydata\|_2^2 = \min_x \sum_i (F(x, xdata_i) - ydata_i)^2,$$

In which the input data provided is *xdata* and the observed output values are *ydata*. Thus, *xdata* and *ydata* are matrices or vectors, and *F (x, xdata)* is a function with a matrix value or vector value of the same size as *ydata*.

The function *lsqcurvefit* requires the user-defined function to calculate the function with a vector value:

$$F(x, xdata) = \begin{bmatrix} F(x, xdata(1)) \\ F(x, xdata(2)) \\ \vdots \\ F(x, xdata(k)) \end{bmatrix}.$$

Table 1 Automatic meteorological stations in the state of Minas Gerais

Station Code	City name	Latitude (S)	Longitude (W)	Altitude (m)	Data period	Number of data	Effective data	Losses (%)
A549	1. Águas Vermelhas	− 15,751	− 41,457	754	09/07–12/18	4132	3758	9.05
A534	2. Aimorés	− 19,532	− 41,090	288	12/08–12/18	4167	2696	35.30
A508	3. Almenara	− 16,166	− 40,687	189	11/07–12/18	5861	3445	41.22
A505	4. Araxá	− 19,605	− 46,949	1.018	05/08–12/18	5857	3640	37.85
A502	5. Barbacena	− 21,228	− 43,767	1.169	07/03–12/18	5869	4870	17.02
A521	6. Belo Horizonte—Pampulha	− 19,883	− 43,969	854	10/06–12/18	4466	4345	2.71
A544	7. Buritis	− 15,524	− 46,435	894	11/07–12/18	4214	3514	16.61
A530	8. Caldas	− 21,918	− 46,382	1.077	11/06–12/18	4417	4107	7.02
A519	9. Campina Verde	− 19,539	− 49,518	559	07/06–12/18	4553	3877	14.85
A541	10. Capelinha	− 17,705	− 42,389	932	09/07–12/18	4140	3853	6.93
A554	11. Caratinga	− 19,735	− 42,137	609	05/07–12/18	4240	3885	8.37
A548	12. Chapada Gaúcha	− 15,300	− 45,617	873	06/07–12/18	4313	3584	16.90
A520	13. Conceição das Alagoas	− 19,985	− 48,151	573	07/06–12/18	4550	4032	11.38
A538	14. Curvelo	− 18,747	− 44,453	669	12/06–12/18	4397	4239	3.59
A537	15. Diamantina	− 18,231	− 43,648	1.359	06/07–12/18	4228	3761	11.05
A536	16. Dores do Indaiá	− 19,481	− 45,593	721	06/07–12/18	4232	3564	15.78
A543	17. Espinosa	− 14,912	− 42,808	565	11/07–12/18	4066	3769	7.30
A535	18. Florestal	− 19,885	− 44,416	754	06/08–12/18	3840	3792	1.25
A524	19. Formiga	− 20,454	− 45,453	878	08/06–12/18	4520	4345	3.87
A532	20. Governador Vala-dares	− 18,830	− 41,977	198	05/07–12/18	4235	3925	7.32
A533	21. Guanhães	− 18,786	− 42,942	853	06/07–12/18	4231	3782	10.61
A546	22. Guarda-Mor	− 17,561	− 47,199	997	07/07–12/18	4192	3863	7.85
A555	23. Ibirité (Rola Moça)	− 20,031	− 44,011	1.199	06/08–12/18	3861	3623	6.16
A550	24. Itaobim	− 16,575	− 41,485	272	09/07–12/18	4136	3714	10.20
A512	25. Ituiutaba	− 18,952	− 49,525	540	05/06–12/18	4617	4204	8.95
A553	26. João Pinheiro	− 17,784	− 46,119	877	07/07–12/18	4196	3876	7.63
A518	27. Juiz de Fora	− 21,769	− 43,364	937	05/07–12/18	4238	3893	8.14
A540	28. Mantena	− 18,780	− 40,986	255	08/07–12/18	4171	3884	6.88
A531	29. Maria da Fé	− 22,314	− 45,373	1.281	12/06–12/18	4413	4235	4.03
A539	30. Mocambinho	− 15,085	− 44,016	454	11/07–12/18	4069	3737	8.16
A526	31. Montalvânia	− 14,408	− 44,404	520	06/07–12/18	4207	3670	12.76
A506	32. Montes Claros	− 16,686	− 43,843	646	03/09–12/18	5857	3251	44.49
A509	33. Monte Verde	− 22,861	− 46,043	1.545	12/04–12/18	5126	4015	21.67
A517	34. Muriaé	− 21,104	− 42,375	283	08/06–12/18	4507	4118	8.63
A513	35. Ouro Branco	− 20,556	− 43,756	1.048	07/06–12/18	4540	4235	6.72
A529	36. Passa Quatro	− 22,395	− 44,961	1,017	06/07–12/18	4234	3618	14.55
A516	37. Passos	− 20,745	− 46,633	782	07/06–11/18	4550	3418	24.88
A523	38. Patrocínio	− 18,996	− 46,985	978	08/06–12/18	4515	4011	11.16
A551	39. Rio Pardo de Minas	− 15,723	− 4243	850	11/07–12/18	4063	3856	5.09
A525	40. Sacramento	− 19,875	− 47,434	913	08/06–12/18	4518	4307	4.67
A552	41. Salinas	− 16,160	− 42,310	487	09/07–12/18	4127	3909	5.28
A514	42. São João Del Rei	− 21,106	− 44,250	930	06/06–12/18	4589	3950	13.92
A547	43. São Romão	− 16,362	− 45,123	490	06/07–12/18	4203	3868	7.97
A522	44. Serra dos Aimorés	− 17,798	− 40,249	212	08/06–12/18	4516	3992	11.60
A527	45. Teófilo Otoni	− 17,892	− 41,515	467	08/06–12/18	4512	3827	15.18
A511	46. Timóteo	− 19,573	− 42,622	493	02/06–12/18	4696	3986	15.12
A528	47. Três Marias	− 18,200	− 45,459	931	08/06–12/18	4511	4327	4.08

Table 1 (continued)

Station Code	City name	Latitude (S)	Longitude (W)	Altitude (m)	Data period	Number of data	Effective data	Losses (%)
A507	48. Uberlândia	– 18,917	– 48,255	875	03/03–12/18	5858	4853	17.16
A542	49. Unaí	– 16,554	– 46,881	641	06/07–12/18	4217	3972	5.81
A515	50. Varginha	– 21,566	– 45,404	950	07/06–12/18	4555	4180	8.23
A510	51. Viçosa	– 20,762	– 42,864	698	09/05–12/18	4856	4255	12.38

Source: INMET (2018)

Table 2 Equations for estimating solar radiation, parameters and references

Model	Equation	Parameters	Reference
1. ABS	$H = 0.75\left(1 - \exp\left(-b\frac{\Delta T}{\Delta T_{\text{med}}}\right)\right)H_0$	B	Abraha and Savage (2008)
2. ASW	$H = 0.75\left[1 - \exp\left(-bf\left(T_{\text{med}}\right)\Delta T\left(T_{\text{min}}\right)\right)\right]H_0$ $f\left(T_{\text{med}}\right) = 0.017\exp\left[\exp\left(-0.053T_{\text{médio}}\right)\right]$ $f\left(T_{\text{min}}\right) = \exp\left(\frac{T_{\text{min}}}{tnc}\right)$	b, tnc	Abraha and Savage (2008); Weiss and Hays (2004)
3- ALM	$H = a\Delta T^b\left[1 - \exp\left(-c\left(\frac{e_{\text{smin}}}{e_{\text{smax}}}\right)d\right)\right]H_0$	a, b, c, d	Almorox et al. (2011)
4. ANN	$H = a\left(1 + 2, 7.10^{-5}Alt\right)\sqrt{\Delta TH_0}$	A	Annandale et al. (2002)
5. BRC	$H = a\left[1 - \exp\left(-b\Delta T^c\right)\right]H_0$	a, b, c	Bristow and Campbell (1984)
6. CHE	$H = (a\sqrt{\Delta T} + b)H_0$	a, b	Chen and Hu (2004)
7. DJS	$H = a\Delta T^b\left(1 + cP + dP^2\right)H_0$	a, b, c, d	Jong and Stewart (1993)
8. DOC	$H = a\left(1 - \exp\left(-b\frac{\Delta T^2}{\Delta T_{\text{med}}}\right)\right)H_0$	a, b, c	Donatelli and Campbell (1998)
9. GOO	$H = a\left(1 - \exp\left(-b\frac{\Delta T^c}{H_0}\right)\right)H_0$	a, b, c	Goodin et al. (1999)
10. HAR	$H = a\left(T_{\text{max}} - T_{\text{min}}\right)^{0.5}H_0$	A	Hargreaves (1981)
11. HUI	$H = a\sqrt{\Delta T}H_0 + b$	a, b	Hunt et al. (1998)
12. HU2	$H = a\sqrt{\Delta TH_0 + bT_{\text{max}} + cP + dP^2 + e}$	a, b, c, d	Hunt et al. (1998)
13. MAH	$H = a\Delta T^{0.69}H_0^{0.91}$	A	Mahmood and Hubbard (2002)
14.MEV	$H = 0.75(1 - \exp(-b\Delta T^2))H_0$	B	Meza and Varas (2000)
15. THR	$H = H_0\left[1 - 0.9\exp\left(-b\Delta T^{1.5}\right)\right]$	B	Thornton and Running (1999)

ΔT thermal amplitude, T_{med} average air temperature, T_{min} minimum air temperature; T_{max} maximum air temperature, es_{min} minimum vapor saturation pressure, es_{max} maximum vapor saturation pressure, *Alt* local altitude, *P* precipitation, *tnc* temperature factor of summer nights

Source: Adapted from Tanaka et al. (2016)

The function syntax is:

$$x = lsqcurvefit(fun, x0, xdata, ydata)$$

As an example of applying the function to a simple exponential fit model, assuming that the observation time data is *xdata* and the observed response data is *ydata*, the objective is to find the parameters *x* (1) and *x* (2) to fit the model:

$$ydata = x(1)\exp(x(2)xdata)$$

Thus, for the vectors:

$$xdata = [12345678910];$$

$$ydata = [455428124674328 13 - 4 - 1 - 5];$$

The associated simple exponential decay model will be:

$$function = @(x, xdata)x(1) * \exp(x(2) * xdata)$$

Adjusting the model using the starting point × 0 = [100, – 1], we have:

$$x0 = [100, -1];$$

$$x = lsqcurvefit(fun, x0, xdata, ydata)$$

The statistical performance indexes used in this work, to ascertain the accuracy of the models, were: the Coefficient of Determination for Linear Regression (R^2); Root-Mean-Square Error (RMSE) and Mean Relative Error (MRE). To assess whether the model performs well or not, the R^2 and RMSE values are observed. For the value of R^2, the best is that it is closer to 1, so that the estimated values are close to the measured values. For RMSE, the lower the value, the better the performance of the statistical model (Jacovides and Kontoyiannis 1995; Tanaka et al. 2016).

For the analysis of the best model, the position values (V_p) of the statistical indicatives were used to classify and determine the best method for estimating the global radiation. To obtain the V_p value, scores from 1 to "n" were assigned to each statistical indicator, with "n" being the number of models tested, that is, $n = 15$, in which case, the score of 1 was assigned to best model and the score of "n", to the worst. Then, to find the best model, the score is summed up and the best will be the one with the lowest sum of the assigned scores, that is, the lowest accumulated V_p value.

To verify the accuracy of the models studied, the coefficient of determination of linear regression (R^2) was observed, since it is one of the first indicators of the good performance of the model (Yorukoglu and Celik 2006). However, in addition to the R^2, it was necessary to analyze other evaluation parameters, such as the analysis of the degree of dispersion between the estimated values, overestimation and underestimation of the model and its degree of precision (Jacovides and Kontoyiannis 1995).

Results and discussion

Tables 3, 4 and 5 present the parameters of the equations for the global solar radiation estimation calibrated for all the cities studied. With that data, it is possible to observe a great variation between the values of the same model between the cities. The values for Linear Regression (R^2), also varied between cities, revealing that a model is great for certain cities, but for others it is not recommended.

Analyzing the data collected, it can be seen that the R^2 values ranged from 6.04 to 59.58%. The city with the lowest R^2 value was Passa Quatro (6.04%), and the highest value (59.58) was for Capelinha. The average of the R^2 values was 36.97%, values slightly below those found by Tanaka et al. (2016) for cities in the state of Mato Grosso, in which they ranged from 40 to 70%, and Borges (2010) for the city of Cruz das Almas in the state of Bahia, in which they ranged from 68 to 72%. This variation is expected, due to the climatic characteristics of each region, but also because of the large amount of data (51 cities were studied) analyzed in this work when compared to other similar works.

In Fig. 2, it is possible to analyze the variation of the values for the MRE models. It is observed that there was a tendency of overestimation for most of the models used in this study. Tanaka et al. (2016) also found a tendency towards overestimation for the state of Mato Grosso. However, Almorox et al. (2011) found a tendency towards underestimation, in the case of Spain. There is a major disadvantage in analyzing the MRE in isolation, where the underestimation of an isolated observation can cancel out the overestimation of another (STONE 1993).

Figure 3 shows the values for the RMSE of the coefficients calibrated for cities in the state of Minas Gerais. The dispersion between the measured values and the estimated values is, on average, 2.80 MJ m^{-2} day^{-1} for all models studied. They corroborate the work of Almorox et al. (2011), in Spain. Values lower than those found by Goodin et al. (1999), in which the RMSE was between 3.62 and 5.81 MJ m^{-2} day^{-1} in the United States, and by Tanaka et al. (2016), in the state of Mato Grosso.

The Willmott d index et al. (1985) demonstrates the degree of accuracy between the measured and estimated values and is represented in Fig. 4. It is observed that all models obtained results with almost perfect precision, with index values between 0.92 and 1.0, values above those found by Tanaka et al. (2016) and Silva et al. (2012).

Figure 5 represents the correlation between the observed solar radiation values and those estimated for the city of Varginha-MG. The models that showed the best performance for Varginha were Bristow and Campbell, Hunt 1 and Donatelli and Campbell. It is observed that most models showed a tendency towards overestimation. Silva et al. (2012) and Tanaka et al. (2016) also observed overestimations of the studied models, for the northwest region of Minas Gerais and for the state of Mato Grosso, respectively.

There is a greater dispersion of data from the estimates made by ABS and ASW, which means that the estimated values were not very accurate.

To obtain the best model for each city, an ordering was carried out according to the statistical indexes evaluated in this study. Table 6 is the result of the sum of the ordering of these indexes by city and for the state. Thus, by analyzing the line, one can understand that the lowest value indicates the best model and the highest value indicates the worst model for the city in question.

Based on a statistical analysis, it can be seen that the DOC model performed better in 33% of the cities studied in the state of Minas Gerais, followed by BRC (23%) and HU1 (18%).

Table 3 Calibrated parameters of the solar radiation estimation equations for cities in the state of Minas Gerais

N.	Model parameters	1. ABS		2. ASW			3. ALM					4. ANN		5. BRC			
		b	R^2 (%)	*b*	tnc	R^2 (%)	*a*	*b*	*c*	*d*	R^2 (%)	*a*	R^2 (%)	*a*	*b*	*c*	R^2 (%)
1	Águas Vermelhas	0.056	27.10	0.022	9.092	47.57	0.364	0.124	0.628	1.249	56.57	0.083	39.12	15.310	0.010	0.243	44.19
2	Aimorés	0.115	30.50	0.070	18.164	44.70	1.381	0.440	0.078	0.225	44.70	0.098	41.34	6.793	0.031	0.178	49.40
3	Almenara	0.109	24.49	0.028	10.743	49.33	5.269	0.451	0.016	0.470	45.76	0.095	38.05	2.734	0.050	0.374	41.07
4	Araxá	0.099	32.11	0.067	15.541	43.97	15.404	0.594	0.045	0.803	45.18	0.095	39.84	6.143	0.033	0.204	41.28
5	Barbacena	0.083	19.84	0.068	14.665	36.4	0.310	0.064	1.034	1.767	46.18	0.089	30.34	6.410	0.036	0.100	38.22
6	Belo Horizonte—Pampulha	0.099	15.69	0.045	11.672	35.46	0.294	0.112	0.924	1.386	46.10	0.094	27.06	2.645	0.059	0.319	30.33
7	Buritis	0.108	13.41	0.020	8.975	38.28	0.276	0.138	1.084	0.967	39.21	0.096	24.66	0.381	0.193	1.003	31.04
8	Caldas	0.038	10.81	0.029	9.090	41.47	0.390	0.009	0.722	2.696	54.62	0.078	26.50	1.631	0.107	0.245	32.56
9	Campina Verde	0.068	10.79	0.019	9.222	36.84	0.218	0.150	1.235	3.511	33.04	0.085	23.22	0.489	0.340	0.428	30.43
10	Capelinha	0.071	42.51	0.042	11.893	52.19	0.251	0.164	0.975	1.964	59.58	0.088	49.59	3.607	0.045	0.281	50.41
11	Caratinga	0.090	16.81	0.026	9.586	46.93	0.273	0.202	0.826	1.024	45.12	0.090	30.90	6.086	0.026	0.281	36.39
12	Chapada Gaúcha	0.099	35.25	0.061	15.733	45.33	0.211	0.229	1.201	1.801	50.23	0.098	43.84	4.260	0.028	0.437	44.42
13	Conceição das Alagoas	0.059	17.06	0.023	10.426	39.48	0.228	0.143	1.471	1.700	38.99	0.082	30.57	1.942	0.078	0.308	35.32
14	Curvelo	0.072	11.34	0.025	9.501	45.92	0.337	0.054	0.870	1.906	45.55	0.090	27.52	0.407	0.251	0.752	33.14
15	Diamantina	0.107	46.94	0.124	22.521	54.20	0.226	0.225	1.086	1.664	59.55	0.099	51.10	4.450	0.030	0.389	50.56
16	Dores do Indaiá	0.077	19.87	0.037	11.842	48.17	0.282	0.104	1.079	1.487	46.85	0.089	35.46	4.992	0.031	0.287	41.11
17	Espinosa	0.108	13.41	0.020	8.975	38.28	0.276	0.138	1.084	0.967	39.21	0.097	24.66	0.381	0.193	1.003	31.04
18	Florestal	0.041	6.95	0.020	8.946	48.17	0.380	0.001	0.664	3.013	47.71	0.079	23.55	1.195	0.142	0.278	32.17
19	Formiga	0.071	15.30	0.029	9.568	46.28	0.297	0.089	1.012	1.615	47.87	0.088	30.02	1.623	0.100	0.307	35.18
20	Governador Valadares	0.079	13.44	0.020	9.393	44.87	0.300	0.195	0.779	0.630	39.03	0.088	27.11	1.533	0.110	0.284	33.78
21	Guanhães	0.077	32.11	0.036	10.657	56.18	0.270	0.154	0.898	1.793	58.99	0.089	45.01	6.348	0.022	0.325	47.17
22	Guarda-Mor	0.083	20.78	0.041	11.347	36.00	0.239	0.153	1.217	2.687	39.88	0.094	32.71	2.925	0.046	0.384	34.95
23	Ibirité (Rola Moça)	0.114	38.60	0.109	20.264	48.22	0.180	0.308	1.284	1.358	49.98	0.100	44.53	3.553	0.036	0.425	44.31
24	Itaobim	0.090	21.41	0.023	10.437	47.35	3.492	0.267	0.040	0.353	46.54	0.092	34.82	0.574	0.217	0.537	37.85
25	Ituiutaba	0.060	10.72	0.017	9.071	38.47	0.244	0.109	1.045	3.932	36.31	0.083	23.81	0.359	0.279	0.780	32.75
26	João Pinheiro	0.112	33.91	0.056	13.130	54.29	0.183	0.312	1.424	0.650	51.35	0.099	46.53	7.019	0.022	0.325	49.18
27	Juiz de Fora	0.112	32.57	0.148	32.986	42.58	0.308	0.098	0.962	1.721	54.43	0.096	38.80	3.792	0.036	0.359	38.80
28	Mantena	0.099	24.04	0.036	12.141	47.26	1.933	0.6712	0.031	0.066	35.93	0.091	36.52	4.752	0.036	0.248	42.67
29	Maria da Fé	0.043	14.13	0.038	9.933	42.43	0.323	0.057	0.814	3.373	52.51	0.081	31.13	2.092	0.073	0.293	34.63
30	Mocambinho	0.076	20.06	0.016	8.685	44.59	0.205	0.207	0.933	4.462	40.31	0.092	32.57	0.432	0.249	0.726	37.67
31	Montalvânia	0.055	11.01	0.017	9.031	31.50	0.446	0.195	0.571	0.149	30.48	0.086	21.69	0.381	0.120	1.166	31.62
32	Montes Claros	0.075	22.77	0.027	10.515	43.21	0.218	0.215	1.371	0.668	36.16	0.089	31.89	0.537	0.244	0.528	32.27

Table 3 (continued)

N.	Model parameters	1. ABS		2. ASW			3. ALM					4. ANN		5. BRC			
		b	R^2 (%)	*b*	tnc	R^2 (%)	*a*	*b*	*c*	*d*	R^2 (%)	*a*	R^2 (%)	*a*	*b*	*c*	R^2 (%)
33	Monte Verde	0.044	17.72	0.046	9.628	34.18	0.320	0.058	0.919	2.875	46.35	0.084	29.85	2.819	0.063	0.236	32.51
34	Muriaé	0.080	27.29	0.034	12.078	51.94	0.243	0.158	1.203	1.466	49.47	0.089	40.73	2.739	0.058	0.286	45.17
35	Ouro Branco	0.071	11.41	0.048	13.278	25.33	0.291	0.065	1.231	1.200	34.25	0.084	20.98	2.265	0.082	0.208	26.88
36	Passa Quatro	0.049	6.04	0.029	9.801	24.71	0.348	-0.006	0.889	3.189	34.23	0.081	16.80	3.342	0.056	0.204	23.89
37	Passos	0.061	14.76	0.027	9.782	43.64	0.275	0.100	1.089	2.371	43.51	0.086	29.63	0.692	0.223	0.399	34.03
38	Patrocínio	0.056	25.41	0.029	10.063	44.73	0.267	0.117	1.166	1.750	48.46	0.084	37.87	3.476	0.039	0.338	40.11
39	Rio Pardo de Minas	0.067	22.57	0.021	8.386	53.12	0.287	0.107	0.933	1.769	48.18	0.086	36.89	4.974	0.029	0.318	41.08
40	Sacramento	0.081	27.53	0.042	12.372	44.73	0.203	0.218	1.372	1.280	45.42	0.090	39.07	6.119	0.027	0.265	42.26
41	Salinas	0.062	19.63	0.015	8.654	49.96	2.773	0.460	0.031	0.176	35.62	0.084	32.93	1.993	0.073	0.332	37.56
42	São João Del Rei	0.055	19.92	0.030	9.932	48.72	0.329	0.070	0.805	2.047	55.40	0.083	35.45	6.124	0.027	0.238	41.60
43	São Romão	0.060	15.70	0.017	8.731	43.19	0.233	0.156	0.940	0.940	39.96	0.088	29.30	0.392	0.219	0.868	37.30
44	Serra dos Aimorés	0.103	34.09	0.053	15.048	51.67	7.343	0.438	0.012	0.725	54.76	0.093	44.37	2.888	0.046	0.368	46.02
45	Teófilo Otoni	0.122	34.11	0.053	12.918	53.28	0.810	0.195	0.221	0.664	55.97	0.098	45.34	5.347	0.030	0.289	48.76
46	Timóteo	0.125	33.36	0.078	16.467	51.45	0.387	0.259	0.455	0.677	53.98	0.099	43.12	3.511	0.035	0.427	43.44
47	Três Marias	0.116	35.08	0.087	18.330	46.33	0.206	0.248	1.230	1.535	51.75	0.100	43.38	3.207	0.046	0.364	44.10
48	Uberlândia	0.113	16.08	0.052	12.973	26.30	0.243	0.159	1.218	1.385	31.82	0.097	22.80	1.352	0.09	0.430	23.96
49	Unaí	0.075	24.96	0.024	9.687	50.22	0.214	0.215	1.515	1.054	45.70	0.091	39.12	0.438	0.188	0.811	42.43
50	Varginha	0.067	27.39	0.041	11.659	53.37	0.273	0.122	1.078	1.436	53.85	0.087	41.87	6.269	0.028	0.234	46.14
51	Viçosa	0.057	12.95	0.029	10.114	42.17	0.374	0.053	0.732	1.593	50.41	0.081	26.60	2.434	0.074	0.208	34.08

Table 4 Calibrated parameters of the solar radiation estimation equations for cities in the state of Minas Gerais (Continuation)

N.	Model parameters	6. CHE			7. DJS					8. DOC				9. GOO			
		a	*b*	R^2 (%)	*a*	*b*	*c*	*d*	R^2 (%)	*a*	*b*	*c*	R^2 (%)	*a*	*b*	*c*	R^2 (%)
1	Águas Vermelhas	0.053	0.117	42.92	0.141	0.308	0.000	−0.000	44.35	0.342	5.404	0.900	29.18	0.402	15.370	0.615	36.63
2	Aimorés	0.085	0.041	42.57	0.112	0.447	0.000	−0.000	43.38	0.361	4.568	1.043	27.98	0.455	10.535	0.738	34.92
3	Almenara	0.075	0.066	40.46	0.125	0.385	0.000	−0.000	43.00	0.346	3.967	1.174	29.00	0.387	10.686	0.871	34.24
4	Araxá	0.090	0.028	40.28	−4.006	0.188	−0.040	0.000	26.47	0.380	3.578	1.037	27.80	0.535	9.008	0.684	35.24
5	Barbacena	0.052	0.126	34.30	0.156	0.268	0.000	−0.000	33.33	0.306	8.951	0.811	18.68	0.384	22.562	0.493	27.09
6	Belo Horizonte—Pampulha	0.064	0.104	29.93	0.146	0.324	0.000	−0.000	30.54	0.334	4.820	1.104	20.67	0.371	14.846	0.782	26.25
7	Buritis	0.060	0.129	29.24	0.156	0.311	0.000	−0.000	33.08	0.357	2.626	1.401	26.26	0.367	7.491	1.173	28.97
8	Caldas	0.039	0.156	32.89	0.167	0.226	0.000	−0.000	32.45	0.314	6.909	0.867	20.37	0.352	22.870	0.556	27.80
9	Campina Verde	0.046	0.146	30.40	0.162	0.253	0.000	−0.000	30.74	0.327	5.094	1.086	22.78	0.343	14.983	0.823	26.71
10	Capelinha	0.067	0.081	51.13	0.126	0.364	0.000	−0.000	49.95	0.361	5.500	0.815	33.01	1.323	4.104	0.474	43.98
11	Caratinga	0.057	0.114	35.64	0.147	0.304	0.000	−0.000	35.41	0.324	5.996	1.043	22.90	0.366	16.592	0.713	29.70
12	Chapada Gaúcha	0.097	0.011	43.99	0.105	0.479	0.000	−0.000	44.43	0.399	2.053	1.285	35.99	0.465	7.174	0.912	40.89
13	Conceição das Alagoas	0.050	0.125	35.26	0.147	0.287	0.000	−0.000	35.20	0.330	4.526	1.062	25.75	0.360	14.334	0.748	31.14
14	Curvelo	0.059	0.116	32.60	0.149	0.310	0.000	−0.000	33.86	0.348	2.808	1.314	25.60	0.365	9.175	1.020	30.10
15	Diamantina	0.095	0.024	51.37	0.107	0.483	−0.000	0.000	51.26	0.394	3.970	0.909	34.62	69.31	0.040	0.763	48.70
16	Dores do Indaiá	0.067	0.080	38.76	0.126	0.366	0.000	−0.000	38.62	0.338	4.479	1.071	24.70	0.387	12.881	0.754	31.71
17	Espinosa	0.060	0.129	29.24	0.156	0.311	0.000	−0.000	33.08	0.357	2.626	1.401	26.26	0.367	7.491	1.173	28.97
18	Florestal	0.041	0.152	32.24	0.163	0.240	0.000	−0.000	32.35	0.322	5.378	1.018	22.14	0.343	17.018	0.736	27.40
19	Formiga	0.054	0.125	35.04	0.153	0.289	−0.000	0.000	34.83	0.331	5.619	1.009	23.59	0.366	16.950	0.707	30.02
20	Governador Valadares	0.050	0.130	33.18	0.150	0.284	0.000	−0.000	34.06	0.321	6.482	1.020	22.14	0.351	17.571	0.719	27.52
21	Guanhães	0.066	0.085	47.61	0.129	0.358	0.000	−0.000	46.70	0.342	5.399	0.924	29.14	0.452	13.621	0.591	39.50
22	Guarda-Mor	0.073	0.076	34.94	0.130	0.374	0.000	−0.000	35.08	35.08	3.403	1.144	24.94	0.402	11.544	0.810	30.09
23	Ibirité (Rola Moça)	0.096	0.021	44.77	0.107	0.484	0.000	−0.000	44.79	0.386	3.943	0.980	29.73	0.811	6.482	0.594	40.17
24	Itaobim	0.067	0.088	37.86	0.130	0.362	0.000	−0.000	39.97	0.350	3.474	1.213	29.47	0.375	9.652	0.943	33.91
25	Ituiutaba	0.043	0.151	31.57	0.163	0.249	−0.000	0.000	32.33	0.329	3.498	1.211	27.34	0.339	10.405	0.988	30.22
26	João Pinheiro	0.097	0.016	46.95	0.105	0.484	0.000	−0.000	46.72	0.379	2.952	1.194	32.61	0.485	8.915	0.789	40.51
27	Juiz de Fora	0.064	0.102	40.86	0.148	0.315	0.000	−0.000	39.11	0.322	9.104	0.763	21.39	3.886	1.403	0.464	33.30
28	Mantena	0.064	0.092	40.06	0.133	0.344	0.000	−0.000	41.11	0.330	6.143	0.982	26.60	0.380	15.226	0.697	32.82
29	Maria da Fé	0.049	0.124	35.62	0.147	0.281	0.000	−0.000	34.54	0.314	6.031	0.900	19.37	0.383	19.471	0.539	28.60
30	Mocambinho	0.060	0.122	36.93	0.154	0.311	0.000	−0.000	37.87	0.373	3.419	1.179	31.24	0.387	9.349	0.972	34.89
31	Montalvânia	0.046	0.167	27.03	0.174	0.255	0.000	−0.000	29.95	0.372	1.832	1.418	28.90	0.3772	5.169	1.251	30.68
32	Montes Claros	0.062	0.103	32.08	0.139	0.333	0.000	−0.000	32.64	0.348	3.342	1.214	24.24	0.465	12.771	0.607	31.94

Table 4 (continued)

N.	Model parameters	6. CHE			7. DJS					8. DOC				9. GOO			
		a	*b*	R^2 (%)	*a*	*b*	*c*	*d*	R^2 (%)	*a*	*b*	*c*	R^2 (%)	*a*	*b*	*c*	R^2 (%)
33	Monte Verde	0.043	0.152	33.93	0.171	0.230	−0.000	0.000	32.47	0.317	8.391	0.722	18.70	0.405	24.473	0.412	27.61
34	Muriaé	0.054	0.120	45.70	0.148	0.295	0.000	−0.000	45.25	0.326	7.954	0.867	29.10	0.383	18.959	0.584	37.57
35	Ouro Branco	0.040	0.152	26.80	0.170	0.217	0.000	−0.000	26.40	0.295	10.580	0.790	16.15	0.333	28.197	0.517	21.54
36	Passa Quatro	0.034	0.177	24.22	0.186	0.190	−0.000	0.000	24.40	0.309	7.033	0.952	18.07	0.326	24.816	0.658	21.32
37	Passos	0.054	0.124	34.07	0.150	0.292	0.000	−0.000	34.56	0.340	4.657	1.041	23.89	0.372	14.384	0.756	30.22
38	Patrocínio	0.061	0.093	40.27	0.130	0.344	0.000	−0.000	39.86	0.347	4.278	0.978	27.49	0.419	13.249	0.646	35.04
39	Rio Pardo de Minas	0.061	0.096	40.62	0.134	0.333	0.000	−0.000	41.95	0.340	4.263	1.041	26.59	0.388	12.915	0.738	33.99
40	Sacramento	0.073	0.066	40.56	0.120	0.392	−0.000	0.000	40.21	0.351	3.899	1.061	28.02	0.432	11.642	0.703	35.56
41	Salinas	0.054	0.116	37.73	0.141	0.309	0.000	−0.000	38.17	0.344	4.484	1.049	27.55	0.372	12.824	0.782	32.43
42	São João Del Rei	0.051	0.122	40.26	0.147	0.288	−0.000	0.000	39.55	0.324	5.994	0.911	23.75	0.383	17.580	0.598	33.31
43	São Romão	0.051	0.149	34.90	0.167	0.270	0.000	−0.000	36.49	0.365	2.951	1.240	31.29	0.377	8.825	1.016	35.27
44	Serra dos Aimorés	0.069	0.079	47.01	0.130	0.361	0.000	−0.000	47.12	0.339	6.623	0.902	30.35	0.435	14.072	0.616	38.08
45	Teófilo Otoni	0.074	0.077	47.58	0.132	0.375	0.000	−0.000	48.02	0.351	5.526	0.980	32.89	0.428	13.652	0.682	40.85
46	Timóteo	0.086	0.042	44.12	0.114	0.441	0.000	−0.000	43.70	0.352	5.572	0.963	25.20	0.580	9.592	0.608	36.43
47	Três Marias	0.101	0.005	43.46	0.102	0.503	0.000	−0.000	43.69	0.391	2.847	1.161	31.27	0.548	7.938	0.751	38.90
48	Uberlândia	0.076	0.075	24.00	0.133	0.376	0.000	−0.000	24.49	0.357	3.957	1.131	18.87	0.393	11.624	0.850	21.67
49	Unaí	0.070	0.084	41.72	0.133	0.362	0.000	−0.000	42.69	0.370	1.979	1.368	35.90	0.391	6.992	1.056	39.77
50	Varginha	0.130	0.345	43.65	0.130	0.345	0.000	0.000	43.65	0.334	5.880	0.899	25.35	0.446	14.525	0.561	36.84
51	Viçosa	0.036	0.158	35.24	0.170	0.205	0.000	−0.000	34.25	0.291	12.482	0.734	19.76	0.335	30.012	0.461	27.00

Table 5 Calibrated parameters of the solar radiation estimation equations for cities in the state of Minas Gerais (Continuation)

NN.	Model parameters	10. HAR		11. HU1			12. HU2						13. MAH		14. MEV		15. THR	
		a	R^2 (%)	*a*	*b*	R^2 (%)	*a*	*b*	*c*	*d*	*e*	R^2 (%)	*a*	R^2 (%)	*b*	R^2 (%)	*b*	R^2 (%)
1	Águas Vermelhas	0.085	39.12	0.057	5.066	39.12	0.032	0.331	0.000	−0.000	0.075	48.76	0.072	37.11	0.002	35.38	0.004	36.61
2	Aimorés	0.098	41.34	0.094	0.553	41.34	0.046	0.386	−0.000	−0.000	−3.361	48.03	0.089	39.51	0.004	38.79	0.007	40.76
3	Almenara	0.095	38.05	0.085	1.589	38.05	0.032	0.503	0.000	−0.000	−5.777	50.54	0.085	35.19	0.004	32.96	0.007	34.81
4	Araxá	0.098	39.84	0.095	0.573	39.84	0.068	0.268	−0.000	−0.000	−2.354	45.97	0.088	38.96	0.004	39.06	0.007	39.94
5	Barbacena	0.092	30.34	0.056	5.521	30.34	0.030	0.234	0.000	−0.000	3.784	36.25	0.084	29.30	0.004	29.38	0.007	30.78
6	Belo Horizonte - Pampulha	0.096	27.06	0.070	4.222	27.06	0.033	0.380	0.000	−0.000	−0.516	36.99	0.087	24.98	0.004	22.97	0.007	24.12
7	Buritis	0.098	24.66	0.069	4.971	24.66	0.020	0.536	0.001	−0.000	−3.982	39.67	0.087	21.41	0.004	18.76	0.007	19.22
8	Caldas	0.081	26.50	0.040	7.443	26.50	0.026	0.336	0.000	−0.000	1.325	40.37	0.069	24.52	0.002	22.07	0.004	23.48
9	Campina Verde	0.086	23.22	0.050	6.341	23.22	0.020	0.371	−0.000	0.000	0.142	35.70	0.074	20.38	0.002	17.28	0.005	18.93
10	Capelinha	0.091	49.59	0.069	3.531	49.59	0.053	0.167	0.000	−0.000	1.780	51.17	0.080	49.32	0.003	50.39	0.006	51.48
11	Caratinga	0.092	30.90	0.064	4.606	30.90	0.031	0.440	−0.000	0.000	−3.077	46.26	0.082	28.35	0.003	26.02	0.006	27.68
12	Chapada Gaúcha	0.100	43.84	0.102	−0.255	43.84	0.080	0.189	0.000	−0.000	−2.257	45.49	0.089	42.35	0.004	41.33	0.007	41.89
13	Conceição das Alagoas	0.084	30.57	0.053	5.537	30.57	0.031	0.278	−0.000	0.000	1.030	38.44	0.071	28.06	0.002	25.23	0.004	26.75
14	Curvelo	0.092	27.52	0.067	4.384	27.52	0.031	0.523	0.000	−0.000	−4.942	45.12	0.079	24.07	0.003	20.66	0.005	22.08
15	Diamantina	0.103	51.10	0.098	0.760	51.10	0.089	0.085	−0.000	0.000	0.077	51.67	0.095	51.61	0.005	54.08	0.009	54.81
16	Dores do Indaiá	0.090	35.46	0.075	2.583	35.46	0.038	0.414	0.000	−0.000	−3.132	48.47	0.079	32.68	0.003	30.52	0.006	32.57
17	Espinosa	0.098	24.66	0.069	4.971	24.66	0.020	0.536	0.000	−0.000	−3.982	39.67	0.087	21.41	0.004	18.76	0.007	19.22
18	Florestal	0.080	23.55	0.046	6.540	23.55	0.015	0.535	0.000	−0.000	−3.193	47.25	0.067	20.60	0.002	17.32	0.004	19.17
19	Formiga	0.090	30.02	0.058	5.428	30.02	0.031	0.419	−0.000	0.000	−1.619	45.11	0.079	27.45	0.003	24.77	0.006	26.28
20	Governador Valadares	0.088	27.11	0.057	5.210	27.11	0.015	0.497	0.000	−0.000	−3.031	45.35	0.077	24.45	0.003	21.79	0.005	23.64
21	Guanhães	0.091	45.01	0.071	3.377	45.01	0.035	0.379	0.000	−0.000	−1.122	54.40	0.081	43.54	0.003	43.02	0.006	44.66
22	Guarda-Mor	0.095	32.71	0.080	2.657	32.71	0.054	0.286	0.000	−0.000	−0.987	37.15	0.084	30.36	0.003	28.03	0.006	29.64
23	Ibirité (Rola Moça)	0.103	44.53	0.100	0.530	44.53	0.082	0.164	0.000	−0.000	−0.984	45.96	0.095	44.60	0.005	46.14	0.009	46.78
24	Itaobim	0.092	34.82	0.076	2.861	34.82	0.026	0.495	0.000	−0.000	−4.737	48.84	0.081	31.81	0.003	29.15	0.006	30.48
25	Ituiutaba	0.084	23.81	0.046	6.851	23.81	0.021	0.362	−0.000	0.000	0.087	36.20	0.072	20.61	0.002	17.01	0.004	18.39
26	João Pinheiro	0.102	46.53	0.105	−0.463	46.53	0.069	0.382	−0.000	−0.000	−5.571	54.64	0.092	44.56	0.005	42.98	0.008	44.98
27	Juiz de Fora	0.099	38.80	0.068	4.466	38.80	0.038	0.227	−0.000	0.000	3.132	43.22	0.092	38.94	0.005	41.53	0.008	42.34
28	Mantena	0.092	36.52	0.071	3.320	36.52	0.029	0.400	0.000	−0.000	−2.125	48.31	0.083	34.22	0.004	32.68	0.006	34.53
29	Maria da Fé	0.084	31.13	0.052	5.534	31.13	0.037	0.321	−0.000	0.000	0.614	42.46	0.072	29.55	0.002	28.47	0.005	30.13
30	Mocambinho	0.093	32.57	0.065	5.130	32.57	0.029	0.484	0.000	−0.000	−3.928	43.89	0.079	29.35	0.003	26.22	0.005	27.26
31	Montalvânia	0.088	21.69	0.049	7.731	21.69	0.028	0.340	0.000	−0.000	0.650	29.07	0.073	18.77	0.002	15.69	0.004	16.16

Table 5 (continued)

NN.	Model parameters	10. HAR		11. HU1			12. HU2						13. MAH		14. MEV		15. THR	
		a	R^2 (%)	*a*	*b*	R^2 (%)	*a*	*b*	*c*	*d*	*e*	R^2 (%)	*a*	R^2 (%)	*b*	R^2 (%)	*b*	R^2 (%)
32	Montes Claros	0.090	31.89	0.062	5.004	31.89	0.035	0.390	0.000	−0.000	−2.095	43.43	0.078	31.48	0.003	30.77	0.005	30.44
33	Monte Verde	0.087	29.85	0.044	7.268	29.85	0.034	0.181	−0.000	0.000	4.973	33.86	0.076	29.01	0.003	28.33	0.005	29.60
34	Muriaé	0.089	40.73	0.059	5.088	40.73	0.021	0.350	0.000	−0.000	0.796	51.84	0.079	38.66	0.003	37.37	0.006	39.00
35	Ouro Branco	0.086	20.98	0.044	6.864	20.98	0.020	0.217	0.000	−0.000	4.963	26.43	0.077	19.47	0.003	18.46	0.005	19.63
36	Passa Quatro	0.084	16.80	0.038	8.039	16.80	0.014	0.284	−0.000	0.000	4.722	24.59	0.072	15.00	0.002	12.83	0.004	14.20
37	Passos	0.088	29.63	0.058	5.405	29.63	0.032	0.375	0.000	−0.000	−0.841	41.19	0.076	26.98	0.002	24.33	0.005	25.29
38	Patrocínio	0.086	37.87	0.063	4.107	37.87	0.042	0.310	−0.000	−0.000	−0.725	44.30	0.074	36.10	0.002	34.61	0.005	35.72
39	Rio Pardo de Minas	0.088	36.89	0.068	3.526	36.89	0.020	0.544	0.000	−0.000	−3.797	52.04	0.077	34.21	0.003	32.20	0.005	33.61
40	Sacramento	0.092	39.07	0.077	2.570	39.07	0.055	0.248	−0.000	0.000	−0.882	43.76	0.081	37.40	0.003	36.26	0.006	37.31
41	Salinas	0.085	32.93	0.061	4.557	32.93	0.017	0.537	0.000	−0.000	−4.607	48.01	0.073	30.07	0.002	27.28	0.004	28.91
42	São João Del Rei	0.085	35.45	0.055	5.344	35.45	0.029	0.341	−0.000	0.000	0.648	46.90	0.074	33.26	0.002	31.34	0.005	32.80
43	São Romão	0.089	29.30	0.053	6.782	29.30	0.022	0.469	0.001	−0.000	−2.596	42.43	0.075	26.05	0.002	22.50	0.005	23.38
44	Serra dos Aimorés	0.094	44.37	0.076	2.784	44.37	0.030	0.380	0.000	−0.000	−1.393	52.73	0.085	42.92	0.004	42.95	0.007	44.99
45	Teófilo Otoni	0.099	45.34	0.080	2.909	45.34	0.040	0.360	0.000	−0.000	−1.339	53.61	0.091	43.41	0.005	42.57	0.008	43.49
46	Timóteo	0.100	43.12	0.093	1.045	43.12	0.048	0.391	−0.000	0.000	−3.283	51.31	0.092	42.39	0.005	43.46	0.008	45.08
47	Três Marias	0.103	43.38	0.106	−0.591	43.38	0.077	0.258	0.000	−0.000	−3.225	46.85	0.093	42.43	0.005	42.13	0.008	43.13
48	Uberlândia	0.099	22.80	0.081	2.893	22.80	0.054	0.289	0.000	−0.000	1.142	27.34	0.090	21.28	0.004	19.94	0.008	20.55
49	Unaí	0.093	39.12	0.074	3.287	39.12	0.040	0.431	0.000	−0.000	−3.948	49.57	0.080	35.95	0.003	32.83	0.005	33.90
50	Varginha	0.089	41.87	0.066	3.840	41.87	0.043	0.296	−0.000	0.000	−0.262	50.89	0.078	40.42	0.003	39.87	0.005	41.42
51	Viçosa	0.082	26.60	0.039	7.244	26.60	0.016	0.306	0.000	−0.000	2.951	41.73	0.072	24.93	0.002	23.86	0.005	25.70

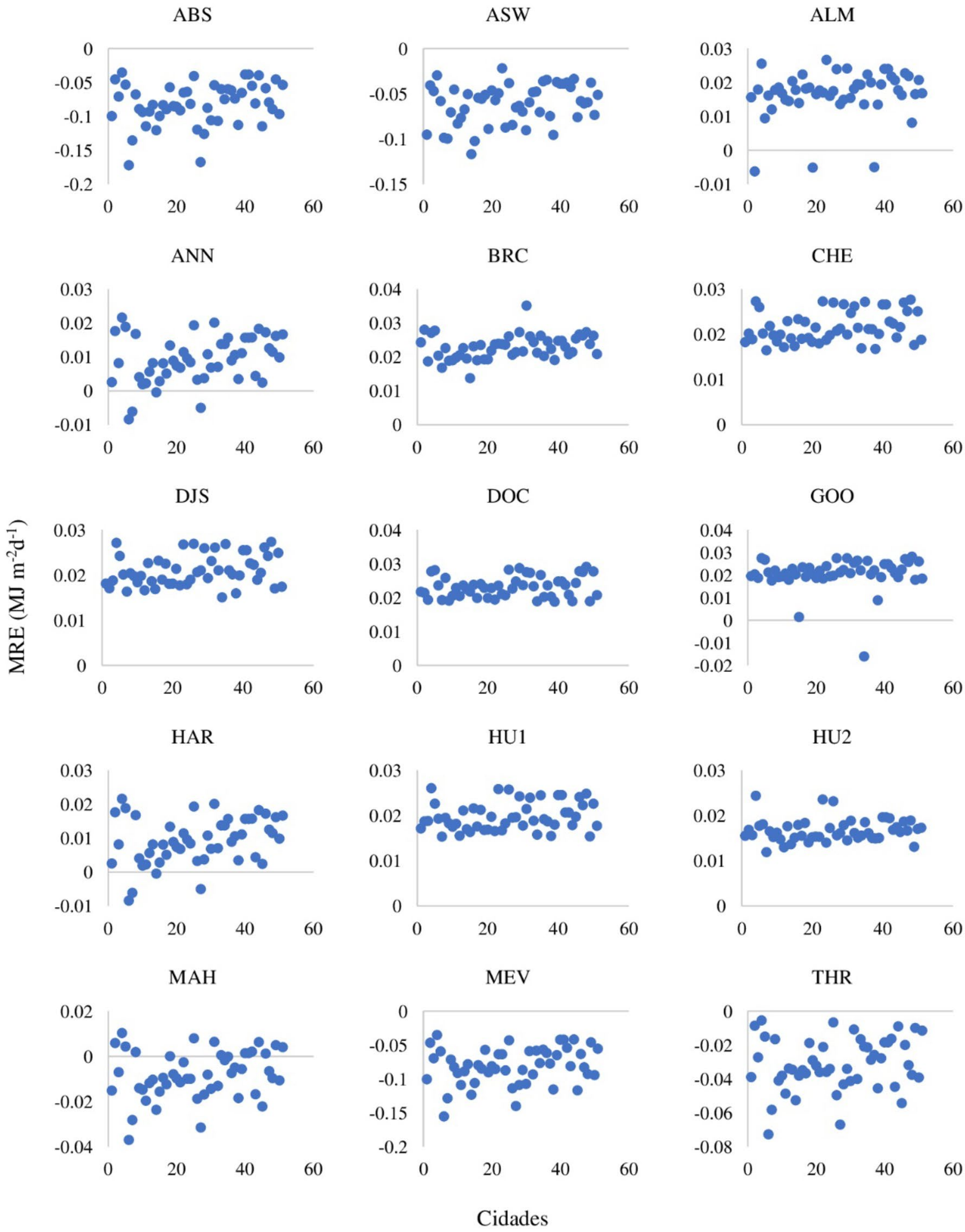


Fig. 2 Mean Relative Error (MRE) of the global radiation estimates for models with calibrated coefficients for different weather stations in the state of Minas Gerais

In Table 6, in addition to the best model for each city under study, the best model is also observed according to each hydrographic region of Minas Gerais. As it can be seen, the following models have the best performance for each hydrographic region: the DOC is best suited for the the Rio Doce basin; the BRC, for the Rio Grande; the DOC and HU1 for the Jequitinhonha River basin; the DOC for the Paranaíba river, and the DOC and HU1 for the São Francisco river.

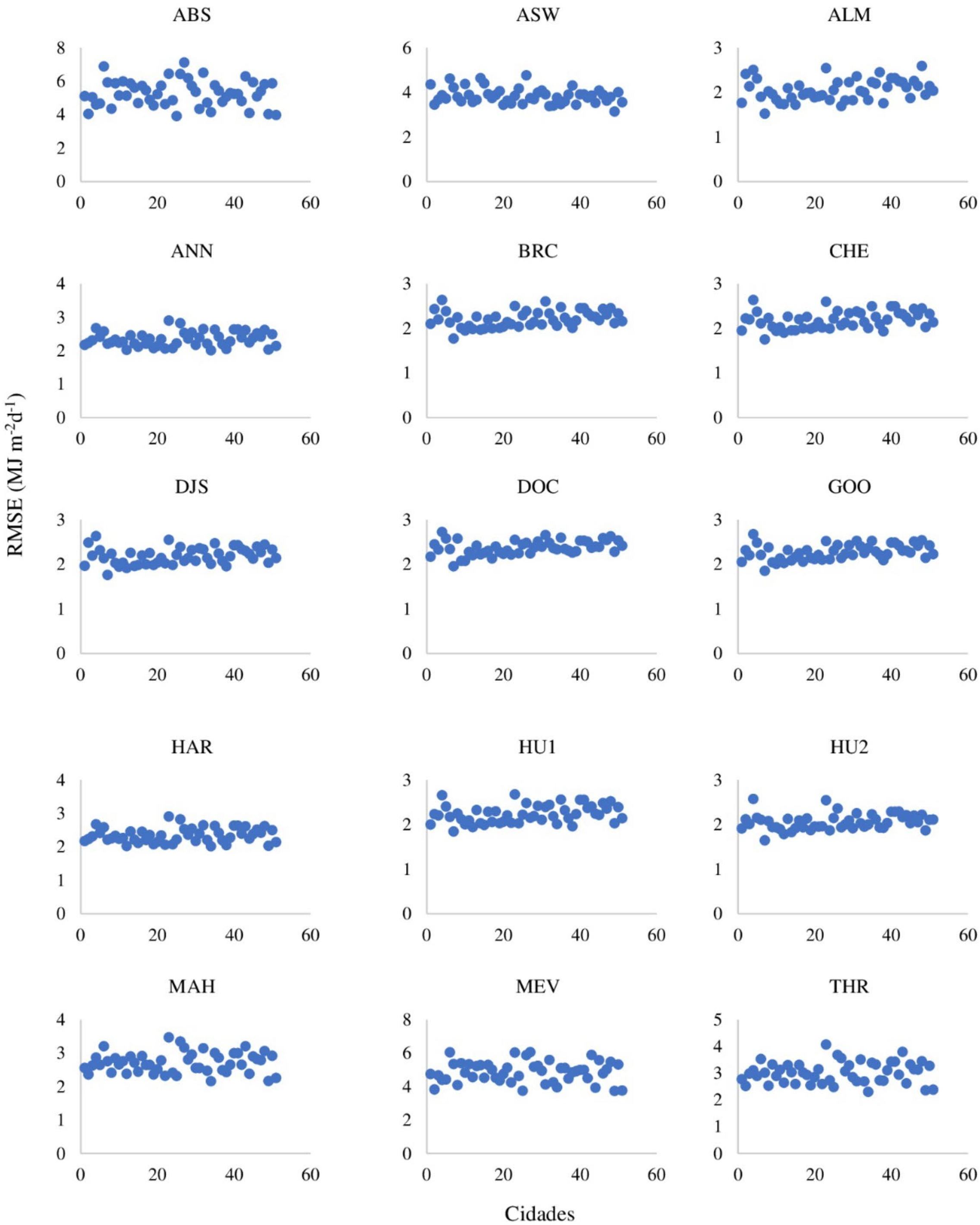


Fig. 3 Root-Mean-Square Error (RMSE) of the estimates of global radiation for models with calibrated coefficients for different weather stations in the state of Minas Gerais

Therefore, in the same way as in most cities, the model that had the best performance in most of the state's hydrographic basins was the DOC.

Due to the lack of automatic meteorological stations installed in the regions of Rio Mucuri, Rio Paraíba do Sul and Rio Pardo, only two cities were studied and, for the São Mateus river basin, only one city was studied.

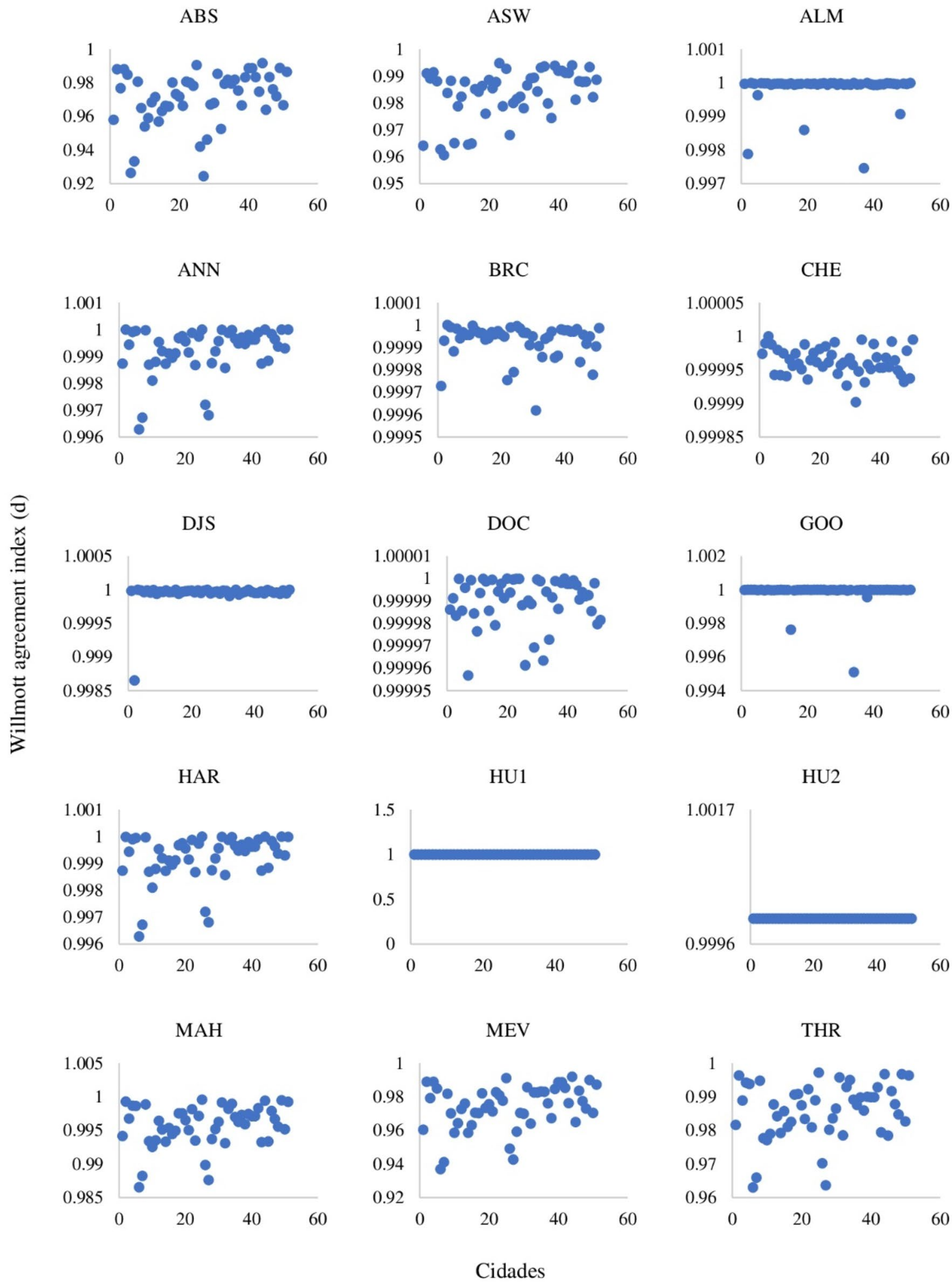


Fig. 4 Willmott agreement index (d) for global radiation estimation models calibrated for different meteorological stations in the State of Minas Gerais

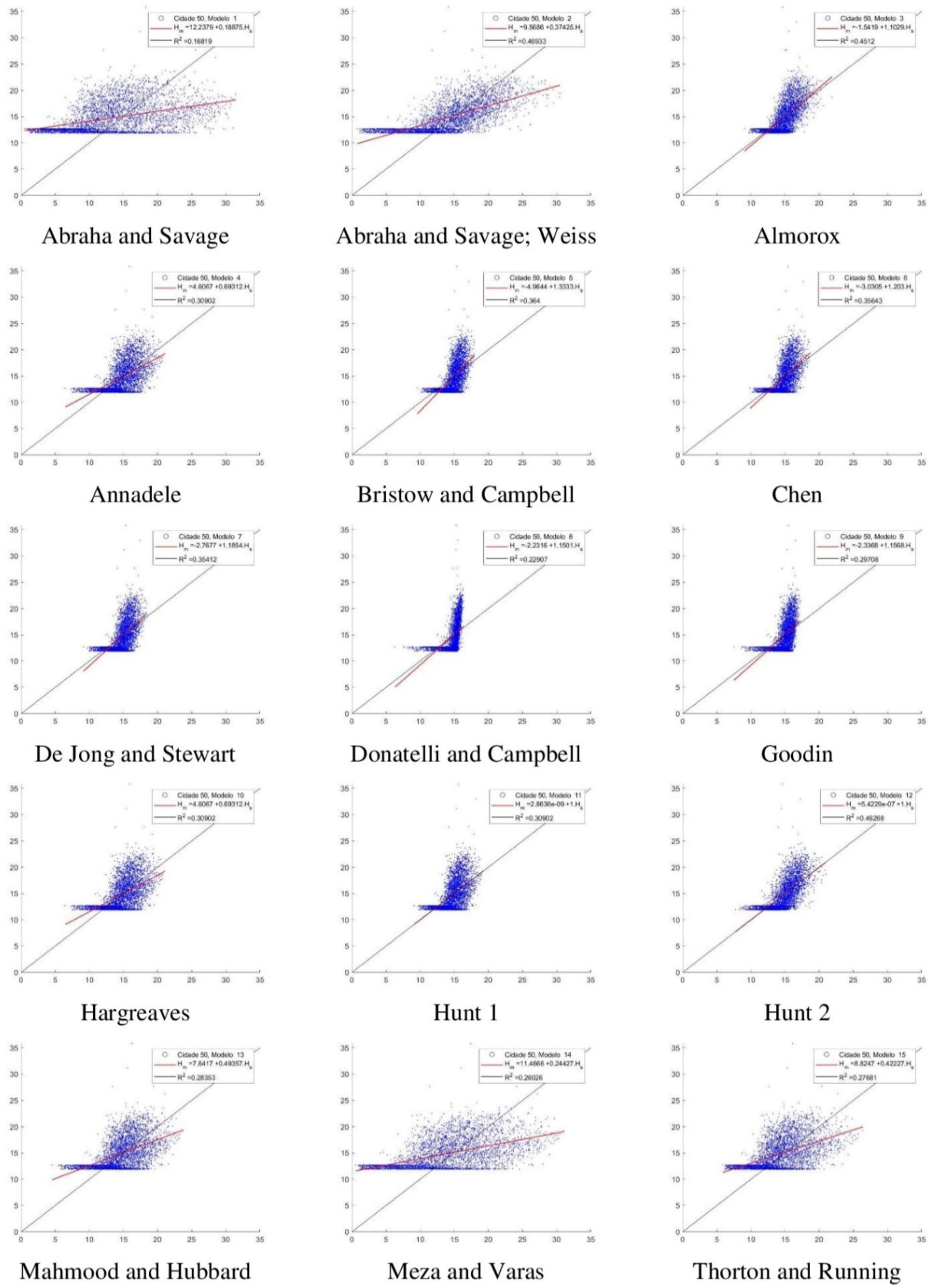


Fig. 5 Correlations between the measured global solar radiation and the global radiation estimated by different models calibrated by the Varginha meteorological station

Table 6 Best models according to the V_p (value position) for the cities of Minas Gerais ordered by river basin regions

Cities	Hydrographic Basin (H.B.)	ABS	ASW	ALM	ANN	BRC	CHE	DJS	DOC	GOO	HAR	HU1	HU2	MAH	MEV	THR	Best city model	Best model H.B.
Aimorés	Rio Doce	43	34	37	31	18	30	30	25	30	27	27	28	40	42	38	BRC	DOC
Caratinga	Rio Doce	46	30	28	33	25	29	29	24	27	35	26	27	38	43	40	DOC	
Governador Valadares	Rio Doce	46	31	29	36	27	29	28	25	22	34	25	26	38	44	40	GOO	
Guanhães	Rio Doce	44	31	28	35	26	28	29	25	27	35	26	27	38	43	38	DOC	
Timóteo	Rio Doce	43	32	29	36	30	31	28	24	26	34	27	29	40	38	33	DOC	
Viçosa	Rio Doce	46	31	26	37	28	28	28	28	22	33	25	27	39	43	39	GOO	
Barbacena	Rio Grande	44	32	30	36	20	28	28	29	29	34	26	28	39	42	35	BRC	BRC
Caldas	Rio Grande	46	29	28	37	26	28	30	26	24	32	25	26	38	43	42	GOO	
Conceição das Alagoas	Rio Grande	46	29	30	35	24	27	30	25	23	35	25	28	38	44	41	GOO	
Maria da Fé	Rio Grande	46	31	27	34	26	29	29	25	28	34	26	25	38	43	39	HU2	
Monte Verde	Rio Grande	46	31	29	35	26	28	29	26	28	32	25	27	38	42	38	HU1	
Passa Quatro	Rio Grande	46	31	29	38	26	27	28	22	24	34	24	27	39	44	41	DOC	
Passos	Rio Grande	46	29	32	34	27	25	28	26	24	34	26	27	38	43	41	GOO	
Sacramento	Rio Grande	46	31	29	35	23	28	28	25	27	36	27	27	37	42	39	BRC	
São João Del Rei	Rio Grande	46	31	29	35	22	29	30	25	26	34	25	27	38	43	40	BRC	
Varginha	Rio Grande	45	31	29	38	22	30	28	26	27	34	25	27	38	42	38	BRC	
Almenara	Rio Jequitinhonha	44	32	37	29	27	30	27	24	26	32	25	27	37	44	39	DOC	DOC/HU1
Capelinha	Rio Jequitinhonha	44	31	28	38	24	27	27	27	36	37	27	26	39	38	31	BRC	
Diamantina	Rio Jequitinhonha	44	32	28	34	30	28	30	30	39	34	25	26	33	35	32	HU1	
Itaobim	Rio Jequitinhonha	45	31	29	35	28	26	29	23	26	35	24	26	38	45	40	DOC	
Salinas	Rio Jequitinhonha	45	29	35	34	26	27	28	25	26	30	25	26	38	45	41	HU1	
Serra dos Aimorés	Rio Mucuri	43	33	34	35	26	28	28	25	26	33	27	26	39	42	35	DOC	DOC
Teófilo Otoni	Rio Mucuri	42	34	29	37	23	29	28	26	27	33	27	26	38	43	38	BRC	
Juiz de Fora	Rio Paraíba do Sul	42	33	28	36	36	26	26	25	40	34	27	23	35	37	32	HU2	HU2
Muriaé	Rio Paraíba do Sul	45	30	30	37	26	29	27	24	27	33	25	27	38	44	38	DOC	DOC
Araxá	Rio Paranaíba	43	32	32	30	20	30	38	28	28	30	28	27	39	41	34	BRC	DOC
Campina Verde	Rio Paranaíba	46	29	28	33	28	27	28	23	24	35	27	27	39	44	42	DOC	
Ituiutaba	Rio Paranaíba	46	29	28	37	27	25	27	23	25	35	25	28	39	44	42	DOC	
Patrocínio	Rio Paranaíba	46	30	30	35	26	27	28	24	28	33	26	27	37	43	40	DOC	
Uberlândia	Rio Paranaíba	45	32	31	36	26	27	28	24	23	36	24	26	38	44	40	GOO	
Águas Vermelhas	Rio Pardo	45	31	29	34	25	29	28	25	27	35	25	25	37	44	41	HU1. HU2. DOC. BRC	DOC
Rio Pardo de Minas	Rio Pardo	45	29	29	35	26	29	28	24	27	33	26	27	37	44	41	DOC	

Table 6 (continued)

Cities	Hydrographic Basin (H.B.)	ABS	ASW	ALM	ANN	BRC	CHE	DJS	DOC	GOO	HAR	HU1	HU2	MAH	MEV	THR	Best city model	Best model H.B.
Belo Horizonte—Pampulha	Rio São Francisco	46	32	30	35	26	28	27	24	26	33	26	26	38	43	40	DOC	DOC/HU1
Buritis	Rio São Francisco	43	32	31	33	26	23	26	25	25	37	26	26	39	46	42	CHE	
Chapada Gaúcha	Rio São Francisco	45	32	34	28	24	27	27	32	26	30	27	28	38	43	39	BRC	
Curvelo	Rio São Francisco	46	29	28	36	27	25	27	25	26	34	24	28	39	44	42	HU1	
Dores do Indaiá	Rio São Francisco	46	31	29	35	26	28	29	25	26	33	27	26	37	43	39	DOC	
Espinosa	Rio São Francisco	43	32	31	36	26	23	26	25	25	34	26	26	39	46	42	CHE	
Florestal	Rio São Francisco	46	30	27	34	28	27	29	23	24	34	26	28	39	44	41	DOC	
Formiga	Rio São Francisco	46	30	28	36	25	29	29	26	23	32	27	27	38	43	41	GOO	
Guarda-Mor	Rio São Francisco	46	32	30	36	25	29	27	24	24	34	27	26	37	43	40	DOC	
Ibirité (Rola Moça)	Rio São Francisco	44	31	28	34	30	30	28	31	29	38	26	28	36	35	32	HU1	
João Pinheiro	Rio São Francisco	44	31	31	31	23	31	30	26	26	31	28	28	39	43	38	BRC	
Mocambinho	Rio São Francisco	46	29	29	35	26	25	26	27	25	35	25	27	39	44	42	HU1	
Montalvânia	Rio São Francisco	45	29	28	33	26	24	24	29	27	37	24	27	40	44	43	HU1	
Montes Claros	Rio São Francisco	46	30	31	37	25	24	27	29	27	35	21	26	38	42	42	HU1	
Ouro Branco	Rio São Francisco	46	35	29	33	24	27	27	26	22	35	27	28	39	43	39	GOO	
São Romão	Rio São Francisco	45	28	30	36	27	25	27	23	25	34	26	27	39	45	43	DOC	
Três Marias	Rio São Francisco	44	32	34	28	20	28	29	32	27	28	30	28	39	43	38	BRC	
Unaí	Rio São Francisco	46	29	28	38	27	24	25	27	26	34	25	27	38	44	42	CHE	
Mantena	Rio São Mateus	44	32	35	33	22	28	28	26	27	35	25	25	38	44	38	BRC	BRC

ABS Abraha and Savage (2008), *ASW* Abraha and Savage (2008); Weiss and Hays (2004), *ALM* Almorox et al. (2011), *ANN* Annandale et al. (2002), *BRC* Bristow and Campbell (1984), *CHE* Chen and Hu (2004), *DJS* Jong and Stewart (1993), *DOC* Donatelli and Campbell (1998), *GOO* Goodin et al. (1999), HAR Hargreaves (1981), HU1—Hunt et al. (1998); HU2—Hunt et al. (1998); MEV—Meza and Varas (2000); THR—Thornton and Running (1999), *H.B.* Hydrographic Basin

Conclusion

In view of the studies and calculations performed, the results made it possible to conclude that the performance of the methods of estimating global solar radiation differed between the cities analyzed.

Based on the statistical analysis and the ordering of the indexes, that is, the use of the position values (V_p) of the statistical indicators to classify and define the best method for the estimation of the global radiation, it can be observed that the DOC model obtained better performance in 33% of the cities studied in the state of Minas Gerais, Brazil, followed by the BRC and HU1 models. These three best models add up to 74% of the studied cities. The DOC model also achieved the best performance for most of the state's river basins.

Acknowledgements The authors would like to thank the José do Rosário Vellano University (UNIFENAS) for the academic support; the Faculty of Science and Engineering (UNESP / Tupã) and Minas Gerais ResearchFoundation (FAPEMIG) for supporting the development of this work; and the National Institute of Meteorology(INMET) for making the used data available. This work was supported by the National Council for Scientific andTechnological Development (CNPq) (grant number 303923/2018-0 and 313570/2017-5) for the researchproductivity scholarship grant granted to the second and last author, respectively.

References

Abraha MG, Savage MJ (2008) Comparison of estimates of daily solar radiation from air temperature range for application in crop simulations. Agric For Meteorol 148(3):401–416

Almorox J, Hontoria C, Benito M (2011) Models for obtaining daily global solar radiation with measured air temperature data in Madrid (Spain). App Energy 885:1703–1709

Angströn A (1924) Solar and terrestrial radiation. Q J R Meteorol Soc 50:121–126

Annandale J, Jovanovic N, Benade N, Allen R (2002) Software for missing data error analysis of Penman-Monteith reference evapotranspiration. Irrig Sci 21(2):57–67

Antunes FZ (1986) Caracterização climática de Minas Gerais. Climat Agríc Inf Agropecu 12:9–13

Berchin II, Nunes NA, de Amorim WS, Zimmer GAA, da Silva FR, Fornasari VH, de Andrade JBSO (2019) The contributions of public policies for strengthening family farming and increasing food security: the case of Brazil. Land Use Policy 82:573–584

Borges VP, Oliveira AS, Coelho Filho MA, Silva TSM, Pamponet Bruce M (2010) Avaliação de modelos de estimativa da radiação solar incidente em Cruz das Almas, Bahia. Rev Bras Eng Agricola Ambient 14(1):74–80

Bristow KL, Campbell GS (1984) On the relationship between incoming solar radiation and daily maximum and minimum temperature. Agric For Meteorol 31:159–166

Brusseau ML, Matthias AD, Musil SA, Bohn HL (2019) Physical-chemical characteristics of the atmosphere. In: Brusseau ML et al (ed) Environmental and pollution science, 3rd edn. Academic Press, New York, pp 47–59

Buriol GA, Estefanel V, Heldwein AB, Prestes SD, Horn JFC (2012) Estimation of global radiation from insolation data for Santa Maria, RS, Brazil. Ciênc Rural 42(9):1563–1567

Callisto M, Gonçalves JF, Ligeiro R (2016) Water resources in the rupestrian grasslands of the Espinhaço Mountains. In: Fernandes GW (ed) Ecologyand conservation of mountaintop grasslands in Brazil, 1st edn. Springer, Switzerland, pp 87–102

Chen X, Hu Q (2004) Groundwater influences on soil moisture and surface evaporation. J Hydrol 297(1–4):285–300

CEPEA (2019) PIB agro mineiro. https://www.cepea.esalq.usp.br/br. Accessed 28 Agu 2019

Das A, Park JK, Park JH (2015) Estimation of available global solar radiation using sunshine duration over South Korea. J Atmos Sol-Terr Phys 134:22–29

Donatelli M, Campbell GS (1998) A model to estimate global solar radiation using daily air temperature. In: Proceedings of the 5th European society of agronomy congress, Nitra, Slovakia

Dubreuil V, Fante KP, Planchon O, Sant'Anna Neto JL (2019) Climate change evidence in Brazil from Köppen's climate annual types frequency. Int J Climatol 39(3):1446–1456

FAEMG (2019) Indicadores do agronegócio. http://www.faemg.org.br/. Accessed 28 Agu 2019

Garcia JR, Vieira Filho JER (2014) Política agrícola brasileira: produtividade, inclusão e sustentabilidade. Revista de Política Agrícola 23(1):91–104

Goodin DG, Hutchinson JMS, Vanderlip RL, Knapp MC (1999) Estimating solar irradiance for crop modeling using daily air temperature data. Agron J 91:845–851

Hargreaves GH (1981) Responding to tropical climates. The 1980–81 food and climate review, the food and climate forum. Aspen Institute for Humanistic Studies, Boulder, pp 29–32

Hunt LA, Kuchar L, Swanton CJ (1998) Estimation of solar radiation for use in crop modelling. Agric For Meteorol 91(3–4):293–300

IEF (2018) Biodiversidade em Minas. http://www.ief.mg.gov.br/biodiversidade. Accessed 6 Feb 2018

INMET (2018) Instituto Nacional de Meteorologia http://www.inmet.gov.br. Accessed 30 Jan 2018

Jacovides CP, Kontoyiannis H (1995) Statistical procedures for the evaluation of evapotranspiration computing models. Agric Water Manag 27:365–371

Jahani B, Dinpashoh Y, Nafchi AR (2017) Evaluation and development of empirical models for estimating daily solar radiation. Renew Sust Energ Rev 73:878–891

Jong RD, Stewart DW (1993) Estimating global solar radiation from common meteorological observations in western Canada. Canadian J Plant Sci 73(2):509–518

Mahmood R, Hubbard KG (2002) Effect of time of temperature observation and estimation of daily solar radiation for the Northern Great Plains, USA. Agron J 94(4):723–733

MATLAB and Statistics Toolbox Release (2019) The MathWorks, Inc., Natick

Meyer LFF, Braga MJ (2019) The growth of technological inequalities in the farm sector of the brazilian state of Minas Gerais. Rev Econ Sociol Rural 36(2):177–210

Meyer LFF, Silva JMA (2019) The dynamics of technical progress in the agricultural sector of the brazilian state of Minas Gerais: results and contradictions of the modernization policy from 1970 to 1985. Rev Econ Sociol Rural 36(4):169–198

Meza F, Varas E (2000) Estimation of mean monthly solar global radiation as a function of temperature. Agric For Meteorol 100(2–3):231–241

Mohammadi K, Shamshirband S, Danesh AS, Abdullah MS, Zamani M (2015) Temperature-based estimation of global solar radiation using soft computing methodologies. Theor Appl Clim 125(1):101–112

Oliveira VA, de Mello CR, Viola MR, Srinivasan R (2017) Assessment of climate change impacts on streamflow and hydropower potential in the headwater region of the Grande river basin, Southeastern Brazil. Int J Climatol 37(15):5005–5023

Querino CAS, Moura MAL, Querino JKADS, Von Radow C, Marques Filho ADO (2011) Estudo da radiação solar global e do índice de transmissividade (kt), externo e interno, em uma floresta de mangue em Alagoas-Brasil. Rev Brasil Meteorol 26(2):204–214

Rodriguez SC, Alvarado JCC, Santo MME, Nunes YR (2017) Changes in forest structure and composition in a successional tropical dry forest. Rev For Meso Kurú 14(35):12–23

Scherrer S, Lepesqueur C, Vieira MC, Almeida-Neto M, Dyer L, Forister M, Diniz IR (2016) Seasonal variation in diet breadth of folivorous Lepidoptera in the Brazilian cerrado. Biotropica 48(4):491–498

Shamshirband S, Mohammadi K, Khorasanizadeh H, Yee L, Lee M, Petković D, Zalnezhad E (2016) Estimating the diffuse solar radiation using a coupled support vector machine–wavelet transform model. Renew Sustain Energ Rev 56:428–435

Silva CRD, Silva VJD, Alves Júnior J, Carvalho HDP (2012) Radiação solar estimada com base na temperatura do ar para três regiões de Minas Gerais. Rev Bras Eng Agricola Ambient 16(3):281–288

Silva ETD, Peixoto MAA, Leite FS, Feio RN, Garcia PC (2018) Anuran distribution in a highly diverse region of the Atlantic Forest: the Mantiqueira mountain range in southeastern Brazil. Herpetologica 74(4):294–305

Silveira FA, Negreiros D, Barbosa NP, Buisson E, Carmo FF, Carstensen DW, Garcia QS (2016) Ecology and evolution of plant diversity in the endangered campo rupestre: a neglected conservation priority. Plant Soil 403(1–2):129–152

Souza MJ, Guimarães MC, Guimarães CD, Freitas WDS, Oliveira Â (2006) Potencial agroclimático para a cultura da acerola no Estado de Minas Gerais. Rev Bras Eng Agricola Ambient 10(2):390–396

Stone RJ (1993) Improved statistical procedure for the evaluation of solar radiation estimation models. Sol Energy 51:289–291

Szabó MPJ, Martins MM, de Castro MB, Pacheco RC, Tolesano-Pascoli GV, dos Santos KT, Labruna MB (2018) Ticks (Acari: Ixodidae) in the Serra da Canastra National Park in Minas Gerais, Brazil: species, abundance, ecological and seasonal aspects with notes on rickettsial infection. Exp Appl Acarol 76(3):381–397

Tanaka AA, Souza APD, Klar AE, Silva ACD, Gomes AWA (2016) Evapotranspiração de referência estimada por modelos simplificados para o Estado do Mato Grosso. Pesq Agropec Brasil 51(2):91–104

Thornton PE, Running SW (1999) An improved algorithm for estimating incident daily solar radiation from measurements of temperature, humidity, and precipitation. Agric For Meteorol 93(4):211–228

Weiss A, Hays CJ (2004) Simulation of daily solar irradiance. Agric For Meteorol123(3-4):187–199

Yang K, Koike T, Ye B (2006) Improving estimation of hourly, daily, and monthly solar radiation by importing global data set. Agric For Meteorol 137:43–55

Yorukoglu M, Celik AN (2006) A critical review on the estimation of daily global solar radiation from sunshine duration. Energy Energy Convers Manag 47:2441–2450