EVALUATION OF GLOBAL SOLAR RADIATION USING MULTIPLE WEATHER PARAMETERS AS PREDICTORS FOR SOUTH AFRICA PROVINCES

by

Adeyemi A. ADEALA[a], Zhongjie HUAN[b], and Christopher C. ENWEREMADU[c*]

[a] Department of Mechanical Engineering, Vaal University of Technology, Vanderbijlpark, South Africa
[b] Department of Mechanical Engineering, Tshwane University of Technology, Pretoria, South Africa
[c] Department of Mechanical and Industrial Engineering, University of South Africa, Florida, South Africa

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Models for estimating monthly average daily global solar radiation were developed for South African provinces. These models, in addition to the traditional sunshine hours used in existing models incorporates ambient temperature, relative humidity, and wind speed as variable parameters for predicting global solar radiation, making it different from most of the existing models that use only sunshine hours as variable. Meteorological data obtained for nine locations in South Africa were employed in the model formulation. The accuracy of the models were verified by comparing estimated values with measured values in terms of the following statistical error tests: mean bias error, mean absolute bias error, mean absolute percentage error, root mean square error, and the regression coefficient.The values of regression coefficient for the formulated models are between the ranges of 90%-99%. It was also observed that for an accurate estimation of global solar radiation in Eastern Cape Province, all weather elements are needed. This implies that the models give an excellent prediction for global solar radiation for their corresponding locations. Also, different errors calculated for the formulated models are close to zero especially mean absolute percentage error. The result shows that the formulated models are good enough to be used to predict monthly average daily radiation for South Africa and also, the inclusion of some other elements in some of the models improved the accuracy of the predictions made by the models.

Key words: *modeling, solar radiation, South Africa, multiple predictors, weather parameters*

Introduction

The importance of affordable and environmentally friendly energy in day-to-day activities of human life cannot be overemphasized. Majority of the world's energy sources are derived from fossil fuels with the highest percentage coming from petroleum and coal. The combustion of these fuels leads to the release of CO_2 and CO among other gasses into the atmosphere.

* Corresponding author; e-mail: enwercc@unisa.ac.za

Scientists have shown that the increasing concentration of CO_2 in the atmosphere is the most substantial cause of global warming [1]. The phenomenon is such that the atmospheric CO_2 acts as a cover which prevents reflected radiation from the Earth's surface from getting back into space and hence, heating up the atmosphere. The effects of global warming include severe flooding, drought, and increase in ambient temperature, *etc*.

Also, the release of CO into the atmosphere has been shown to be the cause of ozone layer depletion which in turn has led to the entrance of more ultraviolet rays from the sun into the atmosphere [2]. Large dosages of these rays have been shown to be dangerous to both plant and animal.

In order to mitigate or possibly reverse the effect of global warming and ozone layer depletion, the exploitation, development and use of environmental-friendly alternative and renewable energy sources with their associated technologies is very important. The sun has been identified to possess this energy in abundance. Technologies that employ these renewable energy sources are often referred to as green technologies.

As the world is going *green*, one of the major setbacks in designing, implementing, and analyzing the performance of green technologies, especially as related to solar equipment is the availability of solar data. Although, the best way to obtain solar radiation data is the *in-situ* measurement of the data, constraints such as cost of installation, maintenance, and re-calibration of radiometers which are used for solar data acquisition are mostly on the high side. Also some institutional constraints have been known to be creating difficulties in obtaining these data and where available, they may be incomplete. Hence, the need to develop models which may be used to accurately predict global solar radiation (GSR).

It is possible to develop models which employ other weather parameters that can easily be measured (and which are most of the time readily available) to predict the GSR at a particular location of interest. One of the earliest known radiation models was developed by Angstrom [3]. The equation was modified by Prescott [4], such that the model is expressed as a function of extraterrestrial on horizontal surface and sunshine hour:

$$\frac{\overline{H}}{\overline{H}_0} = a + b\frac{S}{S_0} \tag{1}$$

The ratio $\overline{H}/\overline{H}_0$ is termed monthly average clearness index and it is the ratio of a particular day terrestrial radiation, $\overline{H}$ to its extraterrestrial radiation, $\overline{H}_0$. It has been reported that in practice, the ratio $\overline{H}/\overline{H}_0$ rarely exceed 0.9 though it is possible that $\overline{H}/\overline{H}_0$ ratio can approach a unit (*i. e.* 1) during perfectly clear sky [4]. The $\overline{H}_0$ is the component of the extraterrestrial radiation normal to the horizontal surface obtained using the average day number, n_d (a day in the month which best approximates the month's average daily GSR) and integrating over the period of sunrise to sunset [5-7]. The $\overline{H}_0$ is expressed by eq. (2) [7]:

$$\overline{H}_0 = \frac{24 \cdot 3600 G_{sc}}{\pi}\left(1 + 0.033\cos\frac{360 n_d}{365}\right)\left(\cos\phi\cos\delta\cos\omega_s + \frac{\pi\omega_s}{180}\sin\phi\sin\delta\right) \tag{2}$$

where G_{sc} is the solar constant and it is the energy from the Sun per unit time received on a unit area of surface perpendicular to the direction of the radiation at mean Earth-Sun distance outside the atmosphere, and the value of which has be adopted by World Radiation Centre to be 1367 W/m^2 [7]. The sunset hour angle, ω_s for the month is obtained using eq. (3) and δ is the solar declination which is obtained using eq. (4). The notation ϕ is the latitude of the location being considered:

$$\cos\omega_{\rm s} = -\frac{\sin\phi\sin\delta}{\cos\phi\cos\delta} = -\tan\phi\tan\delta \tag{3}$$

$$\delta = 23.45\sin\left(360\frac{284+n_{\rm d}}{365}\right) \tag{4}$$

Also, the values S and S_0 in eq. (1) are the monthly average daily hours of sunshine and monthly mean daily maximum possible sunshine-duration, respectively. The S_0 may be obtained using eq. (5), [7]. The coefficients a and b in eq. (1) are empirically determined regression constants which are dependent on the location where the meteorological data were gathered:

$$S_0 = \frac{2\omega_{\rm s}}{15} \tag{5}$$

Sequel to the works of Angstrom [3] and Prescott [4], researchers have developed several other models which are either same or higher order of eq. (1), [8, 9]. Several studies have also been conducted by different researchers in the area of solar radiation model formulation. Many of the models developed used only sunshine hour to predict the solar radiation for the selected locations [8-15], while a few other models also considered some other weather parameters like air temperature, precipitation, relative humidity, cloudiness, altitude (*i .e.* height above sea level), and number of dusty days to predict global radiation [16-19].

Different methods (mostly statistical) have been employed to develop GSR models and in recent times, researchers employed artificial neural networks to obtain GSR models [20-22]. Even with these new methods, most of the models developed are restricted to using sunshine hours as the only predicting parameter.

In a study, Ulgen and Hepbasli [23] developed two empirical correlations to predict monthly average daily GSR over city of Izmir in Turkey. One of the models relates the monthly average daily solar radiation to extraterrestrial radiation, sunshine hour and the latitude of the location of interest. The other model is a third order polynomial which correlates the monthly average daily global radiation to extraterrestrial radiation and sunshine hour. The authors reported an regression coefficient (R^2) value of 0.9152 and 0.9106, respectively, for these models. In another study by Ulgen and Hepbasli [24], the solar radiation components (direct and diffuse solar radiation) are correlated with respect to ambient temperatures in the fifth-order polynomial form for city of Izmir in Turkey. The model was reported to have an regresion coefficient (R^2) value of over 0.95 for the predictions.

Sahin [25], employed a simple formulation which eradicates the need to calculate the Angstrom [3] constants a and b to obtain solar radiation for three locations in Turkey. Values R^2 with a maximum and minimum of 0.94 and 0.87, respectively, were obtained for the locations considered.

Studies have also been conducted in which solar radiation models were formulated using average relative humidity. In a study, Yang and Koike [17] estimated surface solar radiation from upper-air humidity. The authors developed a model for solar radiation by parameterizing sky clearness indicator from relative humidity profiles within three atmospheric sub-layers. In another study, Akinnubi *et al.* [26], developed correlation equation between relative humidity and solar radiation for city of Ibadan in Nigeria and it was concluded that the relative humidity is inversely proportional to the solar radiation of the city. Models for estimating solar radiation using only ambient temperature as parameter had also been developed [27-30].

The objective of this study is to employ statistical method to develop models which can be used to estimate monthly average daily global radiation on horizontal surface for South Africa. The models will use data obtained from weather stations which are located in the nine provinces in the country. These models, in addition to the traditional extraterrestrial radiation and sunshine hours which are common features in existing models, will incorporate other weather parameters. These parameters include the relative humidity, average ambient air temperature, and average wind speed. The inclusion of these parameters shall be based on some calculated statistical parameters.

Data description, collection, and processing

South Africa is located between latitudes 25°S and 30°S and between longitudes 17°E and 32°E. The country is divided into nine administrative provinces and is richly blessed with solar radiations. The availability of solar radiation data in South Africa has been described to be quite extensive relative to other African nations [31].

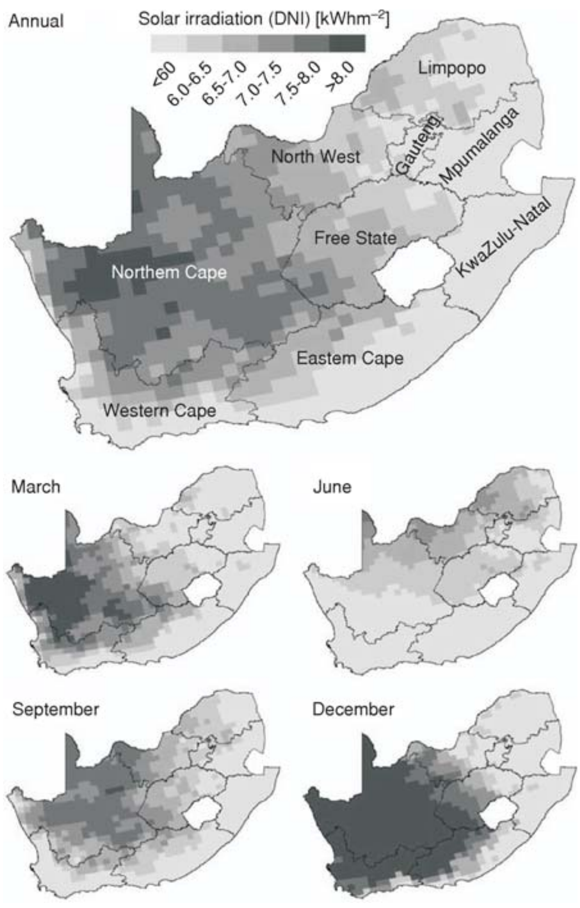

Figure 1. Maps derived from NREL data showing the average daily DNI for South Africa for the whole year and for the months of March, June, September, and December (Gauteng; Mpumalanga), [32]

Fluri [32] used direct normal irradiation (DNI) data obtained from National Renewable Energy Laboratory (NREL) to develop a thermal map for South Africa (fig. 1). The author also reported that variation in solar radiation in the country is found to be a yearly phenomenon.

Measurement of surface meteorological data are carried out by several organizations in South Africa and these include the South African Weather Service (SAWS) and the Agricultural Research Council (ARC). Most of the site measurements done by these organizations varies over length of time from site to site and employs automatic weather station (AWS) which takes measurements such as the solar radiation, temperature, and wind speed. However, the accuracy of these data from site to site is also variable as reported by Bekker [33].

It is a common practice to use a multiplier to amplify the reading of an AWS if it is noticed that there is a gradual decline in the values of data being recorded over the years. This is an indication that the measuring equipment is degrading and there is a need for recalibration. However, the use of wrong multiplier (also called multiplier error) can be more of a problem than solution. In addition to multiplier errors, it is also possible that directly measured data contain periods of bad or missing data. Several methods are used to correct the datasets and have been highlighted by different authors including Closikosz [34].

In this study, an eleven year data obtained from ARC for nine locations were analyzed. A location is selected from each of the provinces in the country. Table 1 gives a brief description of the various stations whose data were collected for analysis.

The data obtained from ARC include total radiation, ambient air temperature, and relative humidity. The non-availability of sunshine hour data on ARC dataset made it compulsory to import and use the sunshine hour as supplied from SAWS dataset, but ensuring that the data used were those for locations which have closest proximity to the locations obtained from ARC.

Table 1. Province, city, geographical locations, and period of data collection

	Station	Province	Lat. [°S]	Long. [°E]	Alt. [m]	Period of observation
I	Pietermaritzburg Indlovu DC	KwaZulu-Natal	29.67	30.41	812	2001-2011
II	Pieterburg, Polokwane	Limpopo	23.73	29.60	1153	2001-2011
III	Nelspruit	Mpumalanga	25.45	30.97	674	2001-2011
IV	Roodeplaat, Pretoria	Gauteng	25.60	28.35	1168	2001-2011
V	Lichtenburg	North West	25.99	26.50	1534	2001-2011
VI	Waterford, Stellenbosch	Western Cape	34.00	18.86	259	2001-2011
VII	Upington	Northern Cape	28.46	21.21	803	2001-2011
VIII	Dohne, Stutterheim	Eastern Cape	32.53	27.46	907	2001-2011
IX	Glen, Bloemfontein	Free State	28.93	26.33	1232	2001-2011

Source: ARC, South Africa (2012)

The available dataset were not totally error-free as some data were missing while some were totally not within the expected measurement range. These problems were corrected by interpolating or taking average of the affected data. Interpolation is done only when the missing data in a month for a particular weather parameter has related parameter available for the same month. For example, relative humidity and ambient temperature are related. So, interpolation can be done to calculate the relative humidity if ambient temperature is available and *vice versa*. The monthly average of a measurement over the collection period is used only if two consecutive measurements are missing and interpolation is not possible. It should be noted that it is the monthly average of the data over the period of data collection that is used in this circumstance.

Selection of parameters

This work developed a model for each for the province in South African to predict solar radiation based on metrological data obtained from ARC and SAWS.

The model formulation is based on the use of different weather parameters to predict the monthly average daily solar radiation. It employs monthly average daily sunshine hour S, monthly average daily relative humidity φ, monthly average daily ambient temperature T_a, and monthly average daily wind speed c_w, as predictors for the models. For any weather parameter to qualify as a predictor, a two-tailed correlation analysis of the parameter is run against the ratio, $\overline{H}/\overline{H}_0$. Any weather parameter whose correlation coefficient is not significant is dropped [35].

Model formulation

After the appropriate weather parameters have been selected, models for solar radiation for different locations were developed. These predictors which were used in model formulations were selected by running a correlation analysis on each of the prospective weather parameter. It is worth noting that a parameter is only considered a candidate (or a predictor) to participate in the model formulation if its correlation is significant at 0.01 or 0.05 level, otherwise it is dropped. Based on the results of the correlation analyses (tab. 2), qualifying weather parameters were selected to participate in the model formulation for the particular location of interest.

Table 2. Correlation analyses results for selected locations

			S/S_0	Relative humidity (φ)	Ambient temp. (T_a)	Wind speed (c_w)
I	$\overline{H}/\overline{H}_0$	Pearson correlation Sig. (two-tailed) N	0.721** 0.000 132	–0.721** 0.000 132	–0.515** 0.000 132	–0.041 0.642 132
II	$\overline{H}/\overline{H}_0$	Pearson correlation Sig. (two-tailed) N	0.616** 0.000 132	–0.565** 0.000 132	–0.517** 0.000 132	0.053 0.543 132
III	$\overline{H}/\overline{H}_0$	Pearson correlation Sig. (two-tailed) N	0.781** 0.000 132	–0.569** 0.000 132	–0.596** 0.000 132	0.395** 0.000 132
IV	$\overline{H}/\overline{H}_0$	Pearson correlation Sig. (two-tailed) N	0.736** 0.000 132	–0.658** 0.000 132	–0.538** 0.000 132	–0.151 0.084 132
V	$\overline{H}/\overline{H}_0$	Pearson correlation Sig. (two-tailed) N	0.679** 0.000 132	–0.686** 0.000 132	–0.448** 0.000 132	0.073 0.407 132
VI	$\overline{H}/\overline{H}_0$	Pearson correlation Sig. (two-tailed) N	0.410** 0.000 132	–0.180* 0.038 132	0.369** 0.000 132	–0.030 0.732 132
VII	H/H_0	Pearson correlation Sig. (two-tailed) N	0.757** 0.000 132	–0.879** 0.000 132	–0.652** 0.000 132	0.539 0.000 132
VIII	$\overline{H}/\overline{H}_0$	Pearson correlation Sig. (two-tailed) N	-0.588** 0.000 132	0.843** 0.000 132	–0.543** 0.000 132	–0.613** 0.000 132
IX	$\overline{H}/\overline{H}_0$	Pearson correlation Sig. (two-tailed) N	0.610** 0.000 132	–0.475** 0.000 132	–0.240** 0.006 132	0.099 0.259 132

* Correlation is significant at the 0.05 level (two-tailed); ** Correlation is significant at the 0.01 level (two-tailed)

From tab. 2, it may be observed that for location VI, there is a weak correlation between $\overline{H}/\overline{H}_0$ and relative humidity, but since it is still significant at 0.038 confidence intervals with a two-tailed test, it was decided to have it along in the model formulation. This weak correlation is also noticed between $\overline{H}/\overline{H}_0$ and temperature for location VII, and also the same rule applies. The essence of this is to ensure that all weather parameters (*i. e.* probable predictors), no matter how small the correlation coefficients and inasmuch it is within the confidence interval, are given a fair chance to contribute in the model formulation and hence improving the model performance.

Table 3 shows the participating weather parameters for different locations as inferred from results obtained from the correlation analyses. Using the various weather parameters as listed in tab. 3, models were developed by running a multiple linear regression analysis on the dependent variable, $\overline{H}/\overline{H}_0$ for the selected locations. The regression equation is of the form;

Table 3. Solar radiation predictors for different locations

	S/S_0	Relative humidity (φ)	Ambient temperature (T_a)	Wind speed (c_w)
I	✔	✔	✔	✖
II	✔	✔	✔	✖
III	✔	✔	✔	✔
IV	✔	✔	✔	✖
V	✔	✔	✔	✖
VI	✔	✔	✔	✖
VII	✔	✔	✔	✖
VIII	✔	✔	✔	✔
IX	✔	✔	✔	✖

$$y = a + \sum_{i=1}^{n} b_i x_i \pm e \tag{6}$$

where y is analogous to the dependent variable $\overline{H}/\overline{H}_0$, a – a constant and n – the number of predictors used in the models. Variables b_i and x_i are coefficient and the predictors (*i. e.* independent variables), respectively, used in the model and e – the standard error of estimation.

During the regression analyses, any predictor whose coefficient equals zero was dropped and did not take part in the model formulation. Equations (7)-(15) (as shown in tab. 4) are the respective final model equations with their corresponding standard errors of estimation e, for location I through IX.

Table 4. The GSR model for nine locations with their respective error of estimation using multiple predictors

	$\overline{H}/\overline{H}_0$	e [%]	Eq.
I	$0.589 + 0.235(S/S_0) - 0.004(\varphi) + 5.369\exp(-5)(T_a)$	±5.4019	(7)
II	$0.711 + 0.242(S/S_0) - 0.005(\varphi) - 0.002(T_a)$	±6.2087	(8)
III	$0.230 + 0.503(S/S_0) - 0.004(c_w)$	±5.4776	(9)
IV	$0.746 + 0.242(S/S_0) - 0.004(\varphi) - 0.003(T_a)$	±5.2805	(10)
V	$0.558 + 0.285(S/S_0) - 0.004(\varphi)$	±5.5508	(11)
VI	$0.120 + 0.396(S/S_0) - 0.001(\varphi) - 0.005(T_a)$	±11.1925	(12)
VII	$0.686 + 0.259(S/S_0) - 0.004(\varphi) - 0.003(T_a)$	±7.5738	(13)
VIII	$0.953 + 0.136(S/S_0) - 0.007(\varphi) + 0.001(T_a) - 0.002(c_w)$	±3.3714	(14)
IX	$0.511 + 0.343(S/S_0) - 0.002(\varphi) - 0.003(T_a)$	±6.1744	(15)

Also, the performances of model eqs. (7)-(15) are compared to the ones developed when only sunshine hour or relative humidity or ambient temperature is used as model parameter. The resulting equations for sunshine hour, relative humidity, and ambient temperature are as summarized in tabs. 5, 6, and 7, respectively. These equations shall be compared to one another in other to pick the one that gives the most accurate result for a selected location. It is important to note that wind speed is not used as a separate parameter for the models because not all locations have wind speed correlating to $\overline{H}/\overline{H}_0$ as shown in tab. 3.

Table 5. The GSR model for nine locations with their respective error of estimation using only sunshine hour

	$\overline{H}/\overline{H}_0$	e [%]	Eq.
I	$0.220 + 0.434(S/S_0)$	±5.6102	(16)
II	$0.249 + 0.392(S/S_0)$	±6.6955	(17)
III	$0.212 + 0.512(S/S_0)$	±5.4185	(18)
IV	$0.301 + 0.441(S/S_0)$	±5.6914	(19)
V	$0.172 + 0.483(S/S_0)$	±6.1622	(20)
VI	$0.172 + 0.514(S/S_0)$	±11.1496	(21)
VII	$0.228 + 0.503(S/S_0)$	±7.8338	(22)
VIII	$0.760 + 0.549(S/S_0)$	±9.2821	(23)
IX	$0.206 + 0.538(S/S_0)$	±6.3204	(24)

Table 6. The GSR model for nine locations with their respective error of estimation using only relative humidity

	$\overline{H}/\overline{H}_0$	e [%]	Eq.
I	$0.945 - 0.007(\varphi)$	±5.6127	(25)
II	$1.067 - 0.008(\varphi)$	±7.0117	(26)
III	$1.086 - 0.008(\varphi)$	±7.1415	(27)
IV	$1.069 - 0.008(\varphi)$	±6.3275	(28)
V	$0.917 - 0.006(\varphi)$	±6.1082	(29)
VI	$0.924 - 0.006(\varphi)$	±12.0226	(30)
VII	$0.849 - 0.004(\varphi)$	±7.9802	(31)
VIII	$-0.334 + 0.012(\varphi)$	±6.1742	(32)
IX	$0.849 - 0.005(\varphi)$	±7.0178	(33)

Table 7. The GSR model for nine locations with their respective error of estimation using only ambient temperature

	$\overline{H}/\overline{H}_0$	e [%]	Eq.
I	$0.774 - 0.016(T_a)$	±6.9436	(34)
II	$0.722 - 0.010(T_a)$	±7.2724	(35)
III	$0.878 - 0.015(T_a)$	±6.9699	(36)
IV	$0.818 - 0.011(T_a)$	±7.0815	(37)
V	$0.692 - 0.008(T_a)$	±7.5069	(38)
VI	$0.296 + 0.014(T_a)$	±11.3608	(39)
VII	$0.704 - 0.003(T_a)$	±8.2927	(40)
VIII	$0.134 + 0.023(T_a)$	±9.6308	(41)
IX	$0.705 - 0.006(T_a)$	±7.3626	(42)

Model evaluation

It is a common practice to evaluate developed models by comparing the computed value as obtained from the model to the measured value using some statistical tools [24, 25, 36-38]. From tab. 2, the total number of observations over the selected period of time per location, N = 132.

The developed model performance was evaluated in terms of the following statistics: mean bias error, (MBE), eq. (25); mean absolute bias error, (MABE), eq. (26); mean absolute percentage error, (MAPE), eq. (27); root mean square error, (RMSE), eq. (28), and R^2, eq. (29).

$$\text{MBE} = \sum_{i=1}^{n} \frac{H_{c,i} - H_{m,i}}{n} \tag{43}$$

$$\text{MABE} = \sum_{i=1}^{n} \frac{|H_{c,i} - H_{m,i}|}{n} \tag{44}$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{H_{c,i} - H_{m,i}}{H_{m,i}} \right| \cdot 100 \tag{45}$$

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(H_{c,i} - H_{m,i})^2}{n}} \tag{46}$$

$$R^2 = \left[1 - \left(\frac{\sum_{i=1}^{n} |H_{c,i} - H_{m,i}|^2}{\sum_{i=1}^{n} H_{m,i}}\right)\right] \tag{47}$$

where n is the number of observations per location (n = 12 in a year for each location), $H_{c,i}$ and $H_{m,i}$ – the ith month calculated and measured global radiation for a particular location, respectively.

The MBE gives the overall long term performance of the model. The lower the MBE the better the performance of the model. The major drawback in its use is that error effect due to overestimation by the model is cancelled by the model's underestimation, that is, it is characterized by unfair error cancellation. A positive MBE implies that the model generally is overestimating while a negative MBE implies underestimation of the solar radiation. The desire is to have MBE as close as possible to zero. In an ideal scenario where MBE is zero, it implies that the developed model has an excellent long term performance, but also bearing in mind that MBE is not a good statistical tool for evaluating model performance in terms of error computation due to its intrinsic unfair error cancellation. This means that a model with a very small MBE does not really imply that it has a good performance in terms of its prediction.

The MABE is the mean of the absolute error of the model and it gives the general overview or total error occurrence regardless of underestimation or overestimation by the model. It eliminates the unfair error cancellation which is found in MBE. The MABE with a value of zero implies that the model is perfectly predicting the solar radiation without any error.

The MAPE is a measure of MABE but in the percentage of the measured quantity. Also, it is desired that the value of this error be near to or perfect zero for accurate prediction.

The RMSE is particularly useful in estimating the error between the measured and computed data and hence it is good for evaluating short term performance of the model [9]. The RMSE is always positive, though a zero value is ideal, a few large errors in the sum can produce a significant increase in RMSE.

The R^2 is a statistic which measures how successful the fit is in explaining the variation of the data [38]. It also called coefficient of determination or regression coefficient.

It is important to note that R^2 is not actually giving the error of prediction the percentage of the data that are properly fitted by the model. Most R^2 is a positive value number ranging between 0 and 1 ($0 \leq R^2 \leq 1$) depicting how much of data the model is able to fit (*i. e.* the model goodness of fit). The closer R^2 is to unity, the better and the more reliable the model.

Results and discussion

Using multiple weather parameters, monthly average daily global radiation is computed (from January to December) for selected locations as modelled by eqs. (7)-(15), and results presented in tab. 8. Table 8 also shows the statistics MBE, MABE, MAPE, RMSE, and *R*2 for the calculated data against the measured data. It is important to note that, the values of these statistics shown in tab. 8 are the annual values and that both $H_{m,i}$ and $H_{c,i}$ are measured in MJ/m^2. Also, figs. 2(a)-(i) show the graphs of measured and calculated monthly average daily solar radiation for different locations plotted on the same axes.

Furthermore, monthly average daily global radiation models were developed for the selected locations using only a single weather parameter in each of the models, namely sunshine hour, average relative humidity and average ambient temperature as depicted by eqs. (16)-(24), (25)-(33), and (34)-(42), respectively. The results are also presented in tabular form in tabs.

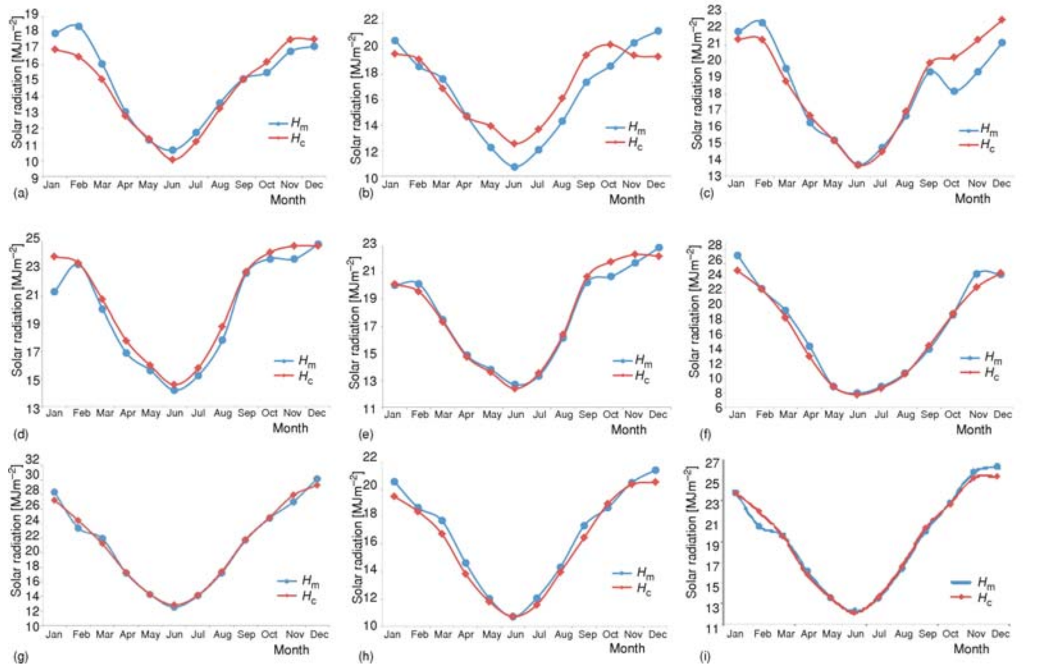

Figure. 2. Measured, H_m, and calculated, H_c, monthly average daily solar radiation, (a) Location I, (b) Location II, (c) Location III, (d) Location IV, (e) Location V, (f) Location VI, (g) Location VII, (h) Location VIII, (i) Location IX

(8)-(11) in the respective order of sunshine hour, average relative humidity, and average ambient temperature.

Table 8. Measured and computed average daily solar radiation with the associated annual MBE, MABE MAPE, RMSE, and R^2 using multiple predictors

Month	Location																	
	I		II		III		1V		V		VI		VII		VIII		IX	
	^aH_m	H_c	^aH_m	H_c	^aH_m	H_c	^aH_m	H_c	^aH_m	H_c	^aH_m	H_c	^aH_m	H_c	^aH_m	H_c	^aH_m	H_c
JAN	17.96	16.95	20.68	19.62	21.85	21.39	21.34	23.89	20.06	20.12	27.20	26.74	28.28	27.23	20.58	19.49	23.79	23.72
FEB	18.39	16.49	18.63	19.18	22.41	21.34	23.32	23.42	20.15	19.57	22.51	24.07	23.40	24.40	18.68	18.39	20.49	21.89
MAR	16.06	15.06	17.63	16.88	19.59	18.80	20.07	20.75	17.49	17.36	19.44	19.77	21.95	21.24	17.73	16.76	19.57	19.52
APR	13.06	12.79	14.72	14.67	16.27	16.70	16.88	17.78	14.88	14.77	14.57	14.05	17.19	17.26	14.62	13.82	16.18	15.80
MAY	11.28	11.34	12.26	13.94	15.21	15.18	15.63	15.97	13.83	13.60	8.93	9.76	14.31	14.30	12.03	11.8	13.54	13.59
JUN	10.65	10.06	10.74	12.55	13.71	13.67	14.17	14.57	12.70	12.41	7.97	8.27	12.52	12.82	10.69	10.71	12.24	11.06
JUL	11.74	11.19	12.06	13.66	14.76	14.49	15.26	15.80	13.35	13.54	8.87	8.94	14.08	14.16	12.06	11.56	13.48	13.65
AUG	13.60	13.24	14.32	16.1	16.69	16.95	17.82	18.80	16.19	16.41	10.76	11.15	17.23	17.42	14.32	13.96	16.40	16.64
SEP	15.11	15.07	17.37	19.51	19.39	19.93	22.67	22.78	20.26	20.66	14.12	15.47	21.71	21.82	17.37	16.49	20.09	20.36
OCT	15.51	16.16	18.68	20.35	18.21	20.27	23.73	24.20	20.70	21.79	18.96	20.11	24.74	24.84	18.68	18.96	22.73	22.62
NOV	16.83	17.55	20.5	19.49	19.41	21.34	23.72	24.66	21.70	22.33	24.60	24.01	26.98	27.90	20.50	20.36	25.73	25.17
DEC	17.15	17.57	21.43	19.4	21.17	22.56	24.78	24.67	22.86	22.21	24.54	26.29	30.17	29.25	21.43	20.53	26.27	25.31
MBE	0.3225		–0.5275		–0.3292		–0.6583		–0.05		–0.51		–0.0067		0.4883		0.015	
MABE	0.6308		1.3442		0.7725		0.6767		0.3817		0.7750		0.4550		0.5383		0.37	
MAPE	4.0696		7.9260		4.0032		3.5001		2.0313		4.7100		1.9279		3.1665		1.8295	
RMSE	1.9501		1.4812		1.0213		0.9328		0.4794		0.9360		0.6096		0.6435		0.5442	
R^2	0.9571		0.8677		0.9428		0.9564		0.9871		0.9480		0.9820		0.9750		0.9846	

[a] Source: ARC, South Africa (2012)

Table 9. Measured and computed average daily solar radiation with the associated annual MBE, MABE MAPE, RMSE, and R^2 using sunshine hours only

Month	Location																	
	I		II		III		1V		V		VI		VII		VIII		IX	
	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c
JAN	17.96	17.91	20.68	19.91	21.85	21.01	21.34	23.00	20.06	20.53	27.20	25.70	28.28	27.41	20.58	24.81	23.79	23.95
FEB	18.39	17.23	18.63	17.59	22.41	21.00	23.32	23.35	20.15	20.24	22.51	23.05	23.40	24.64	18.68	24.45	20.49	22.42
MAR	16.06	15.91	17.63	15.39	18.50	18.80	20.07	20.34	17.49	18.00	19.44	19.05	21.95	21.78	17.73	17.73	19.57	20.10
APR	13.06	13.5	14.72	14.35	16.47	16.70	16.88	17.62	14.88	15.53	14.57	13.54	17.19	17.79	14.62	12.72	16.18	15.93
MAY	11.28	11.58	12.26	13.94	15.03	15.18	15.63	15.92	13.83	14.08	8.93	9.23	14.31	14.55	12.03	8.73	13.54	13.53
JUN	10.65	10.09	10.74	12.54	13.53	13.67	14.17	14.20	12.70	12.64	7.97	8.01	12.52	13.08	10.69	6.73	12.24	11.90
JUL	11.74	11.15	12.06	1359	14.35	14.49	15.26	15.29	13.35	13.61	8.87	8.95	14.08	14.12	12.06	7.66	13.48	13.38
AUG	13.60	13.29	14.32	15.77	16.77	16.95	17.82	17.87	16.19	16.09	10.76	11.00	17.23	17.11	14.32	10.71	16.40	16.31
SEP	15.11	15.1	17.37	18.60	19.69	19.93	22.67	21.28	20.26	18.99	14.12	15.11	21.71	21.01	17.37	15.93	20.09	19.81
OCT	15.51	16.29	18.68	20.23	19.95	20.27	23.73	22.66	20.70	20.42	18.96	19.63	24.74	24.40	18.68	20.08	22.73	22.42
NOV	16.83	18.15	20.5	19.81	20.97	21.34	23.72	23.59	21.70	21.49	24.60	23.39	26.98	27.00	20.50	24.13	25.73	25.41
DEC	17.15	18.28	21.43	20.11	22.18	22.56	24.78	24.03	22.86	22.30	24.54	25.41	30.17	28.92	21.43	25.32	26.27	25.83
MBE	–0.095		–0.8075		–0.0650		0.0200		0.0208		0.0333		0.0625		0.1642		–0.0400	
MABE	0.567		1.1492		0.7500		0.5367		0.3925		0.6550		0.5125		2.9375		0.3967	
MAPE	3.803		7.3075		3.8828		2.5330		2.1631		3.6827		2.3822		19.1705		2.0136	
RMSE	1.738		1.3004		0.9457		0.7704		0.5086		0.7937		0.6608		3.20185		0.6257	
R^2	0.966		0.8980		0.9509		0.9703		0.9855		0.9627		0.9793		0.3809		0.9796	

[a] Source: ARC, South Africa (2012)

Table 10. Measured and computed average daily solar radiation with the associated annual MBE, MABE MAPE, RMSE, and R^2 using average relative humidity only

Month	Location																	
	I		II		III		1V		V		VI		VII		VIII		IX	
	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c	${}^{a}H_m$	H_c
JAN	17.96	17.88	20.68	21.41	21.85	20.9	21.34	24.62	20.06	21.92	27.20	23.95	28.28	28.59	20.58	27.21	23.79	24.39
FEB	18.39	17.31	18.63	20.99	22.41	20.19	23.32	23.11	20.15	20.69	22.51	21.75	23.40	26.03	18.68	24.13	20.49	21.77
MAR	16.06	15.42	17.63	18.37	18.50	17.95	20.07	20.61	17.49	18.28	19.44	18.13	21.95	22.25	17.73	18.66	19.57	18.6
APR	13.06	12.9	14.72	15.29	16.47	14.66	16.88	16.81	14.88	15.15	14.57	13.95	17.19	17.63	14.62	13.76	16.18	14.97
MAY	11.28	11.48	12.26	13.67	15.03	13.29	15.63	14.41	13.83	13.4	8.93	9.75	14.31	14.08	12.03	8.89	13.54	12.26
JUN	10.65	10.33	10.74	12.45	13.53	12.18	14.17	13.2	12.70	12.29	7.97	8.4	12.52	12.31	10.69	6.97	12.24	10.74
JUL	11.74	11.44	12.06	13.36	14.35	13.31	15.26	14.4	13.35	13.38	8.87	9.9	14.08	13.43	12.06	6.99	13.48	12.2
AUG	13.60	13.56	14.32	16.27	16.77	15.77	17.82	17.97	16.19	16.51	10.76	12.06	17.23	16.72	14.32	9.53	16.40	15.28
SEP	15.11	15.85	17.37	20.58	19.69	19.41	22.67	22.88	20.26	21.73	14.12	15.42	21.71	21.51	17.37	14.44	20.09	19.9
OCT	15.51	17.39	18.68	21.83	19.95	20.79	23.73	25	20.70	23.45	18.96	19.83	24.74	25.28	18.68	19.45	22.73	22.49
NOV	16.83	18.58	20.5	21.81	20.97	20.71	23.72	25.16	21.70	24.16	24.60	22.44	26.98	28.63	20.50	23.75	25.73	24.72
DEC	17.15	18.71	21.43	21.81	22.18	21.23	24.78	24.92	22.86	23.61	24.54	24.31	30.17	29.85	21.43	26.47	26.27	25.11
MBE	–0.2925		–1.5683		0.6900		–0.3080		–0.8670		0.2150		–0.3125		–0.1300		0.6733	
MABE	0.7292		1.5683		1.3500		0.8633		1.0067		1.1733		0.6658		3.5483		0.9867	
MAPE	4.6390		9.8183		7.7410		4.4515		5.1650		7.3420		3.1169		22.4393		5.7983	
RMSE	2.3896		1.8135		1.5395		1.2261		1.3305		1.4146		0.9675		4.0078		1.0663	
R^2	0.9356		0.8017		0.8699		0.9246		0.9008		0.2150		0.9555		0.0299		0.9408	

[a]Source: ARC, South Africa (2012)

The selection of a model for a particular location will be primarily based on the R^2 value of the model. Table 12 gives a summary of the statistics for various locations as given by different developed models. Models which give most accurate estimate of global radiation for different locations are the ones whose R^2 value are shown in bold font face.

The models developed using multiple predictors gave good prediction of global radiation for the locations considered and it was observed that for the model eqs. (7)-(15), the non-inclusion of any of the predictor in these models have a significant effect on the accuracy of prediction.

Table 11. Measured and computed average daily solar radiation with the associated annual MBE, MABE MAPE, RMSE, and R^2 using average ambient temperature only

Month	Location																	
	I		II		III		1V		V		VI		VII		VIII		IX	
	[a]H_m	H_c	[a]H_m	H_c	[a]H_m	H_c	[a]H_m	H_c	[a]H_m	H_c	[a]H_m	H_c	[a]H_m	H_c	[a]H_m	H_c	[a]H_m	H_c
JAN	17.96	18.54	20.68	20.74	21.85	21.86	21.34	23.82	20.06	22.2	27.20	26.26	28.28	26.77	20.58	25.22	23.79	24.21
FEB	18.39	16.44	18.63	19.54	22.41	20.37	23.32	22.37	20.15	20.96	22.51	23.91	23.40	24.73	18.68	23.81	20.49	22.53
MAR	16.06	14.81	17.63	18.07	18.50	18.65	20.07	20.24	17.49	18.96	19.44	19.44	21.95	21.77	17.73	18.96	19.57	20.03
APR	13.06	12.89	14.72	16.03	16.47	16.53	16.88	17.83	14.88	16.35	14.57	14.1	17.19	19.95	14.62	13.6	16.18	16.61
MAY	11.28	10.79	12.26	14.07	15.03	14.59	15.63	15.5	13.83	13.9	8.93	10.05	14.31	14.63	12.03	9.49	13.54	13.86
JUN	10.65	10.07	10.74	13.29	13.53	13.73	14.17	14.38	12.70	12.87	7.97	8.15	12.52	13.02	10.69	7.31	12.24	12.41
JUL	11.74	10.67	12.06	14.07	14.35	14.5	15.26	15.16	13.35	13.53	8.87	8.6	14.08	13.78	12.06	7.93	13.48	13.21
AUG	13.60	12.64	14.32	15.89	16.77	16.54	17.82	17.27	16.19	15.7	10.76	10.87	17.23	16.76	14.32	10.41	16.40	15.89
SEP	15.11	15.31	17.37	17.95	19.69	18.9	22.67	19.91	20.26	18.1	14.12	14.96	21.71	20.65	17.37	14.32	20.09	19.23
OCT	15.51	17.62	18.68	19.71	19.95	20.88	23.73	21.99	20.70	20.34	18.96	19.53	24.74	24.13	18.68	18.87	22.73	22.18
NOV	16.83	19.77	20.5	20.9	20.97	22.56	23.72	23.86	21.70	22.02	24.60	23.05	26.98	26.58	20.50	21.93	25.73	24.32
DEC	17.15	19.43	21.43	21.17	22.18	22.5	24.78	24.37	22.86	22.51	24.54	25.72	30.17	27.37	21.43	24.19	26.27	24.85
MBE	–0.1367		–1.0342		–0.2450		0.2242		–0.2725		–0.1808		0.3683		0.2208		0.0983	
MABE	1.2150		1.0775		0.9950		0.8825		0.8325		0.7192		0.8533		2.7842		0.7383	
MAPE	7.8810		7.7926		5.1774		4.1648		4.5498		4.3194		3.7887		18.0530		3.5984	
RMSE	3.6543		1.3118		1.4332		1.2646		1.1137		0.8785		1.1112		3.1573		0.9240	
R^2	0.8494		0.8962		0.8873		0.9198		0.9305		0.9543		0.9413		0.3981		0.9556	

[a]Source: ARC, Sout Africa (2012)

Table 12. Statistics of different models for all locations

Parameters	Statistics	Locations								
		I	II	III	IV	V	VI	VII	VIII	IX
Multiple predictors	MBE	0.3225	–0.5275	–0.329	–0.658	–0.0500	–0.5100	–0.0067	0.4883	0.015
	MABE	0.6308	1.3442	0.7725	0.6767	0.3817	0.775	0.455	0.5383	0.37
	MAPE	4.0696	7.926	4.0032	3.5001	2.0313	4.71	1.9279	3.1665	1.8295
	RMSE	1.9501	1.4812	1.0213	0.9328	0.4794	0.936	0.6096	0.6435	0.5442
	R^2	0.9571	0.8677	0.9428	0.9564	0.9871	0.948	0.982	0.975	0.9846
Sunshine hours	MBE	–0.095	–0.8075	–0.065	0.02	0.0208	0.0333	0.0625	0.1642	–0.04
	MABE	0.567	1.1492	0.75	0.5367	0.3925	0.655	0.5125	2.9375	0.3967
	MAPE	3.803	7.3075	3.8828	2.533	2.1631	3.6827	2.3822	19.1705	2.0136
	RMSE	1.738	1.3004	0.9457	0.7704	0.5086	0.7937	0.6608	3.20185	0.6257
	R2	0.966	0.898	0.9509	0.9703	0.9855	0.9627	0.9793	0.3809	0.9796
Average relative humidity	MBE	–0.2925	–1.5683	0.69	-0.308	–0.867	0.215	–0.3125	–0.13	0.6733
	MABE	0.7292	1.5683	1.35	0.8633	1.0067	1.1733	0.6658	3.5483	0.9867
	MAPE	4.639	9.8183	7.741	4.4515	5.165	7.342	3.1169	22.4393	5.7983
	RMSE	2.3896	1.5951	1.8135	1.5395	1.2261	1.3305	1.4146	0.9675	4.0078
	R2	0.9356	0.8017	0.8699	0.9246	0.9008	0.215	0.9555	0.0299	0.9408
Average ambient temperature	MBE	–0.1367	–1.0342	–0.245	0.2242	–0.2725	–0.1808	0.3683	0.2208	0.0983
	MABE	1.215	1.0775	0.995	0.8825	0.8325	0.7192	0.8533	2.7842	0.7383
	MAPE	7.881	7.7926	5.1774	4.1648	4.5498	4.3194	3.7887	18.053	3.5984
	RMSE	3.6543	1.3118	1.4332	1.2646	1.1137	0.8785	1.1112	3.1573	0.924
	R2	0.8494	0.8962	0.8873	0.9198	0.9305	0.9543	0.9413	0.3981	0.9556

An interesting observation made from the study is that except for location VIII, global radiation can be accurately estimated using combination of different weather parameter eqs. (7)-(15) or using single weather parameter eqs. (16)-(42) with exception of wind speed.

Comparing the four sets of equation in terms of parameter composition, the equations set with multiple weather parameters eqs. (7)-(15) did fairly well in estimating global radiation for all locations. For this set, the analyses show that R^2 is in the range 0.8677- 0.9871. Also, except for location VIII, the set of equations employing sunshine hours eqs. (16)-(24), average relative humidity eqs. (24)-(33), and average ambient temperature eqs. (34)-(42) gave fair estimate for global radiation.

The very low values of R^2 for sets of equation with only sunshine hours, average relative humidity, and average ambient temperature for location VIII may not be unconnected with the high convection due to relative high wind speed in this location. This is one distinct climatic feature of Eastern Cape, and the reason why most of South Africa wind farm is located in this province.

Generally, eqs. (16)-(19) and (21) are recommended for estimating global radiation for locations I, II, III, IV and VI, respectively, but where data for sunshine hour is not readily available, equations using average relative humidity or average ambient temperature may as well be employed without any significant loss in accuracy. Also global radiation estimates are best computed for locations V, VI, VII and VIII by using by eqs. (11), (13)-(15), respectively, and except for location VIII, a fairly accurate estimation of global radiation can also be obtained using any of the given single parameter models.

A comparison of the results obtained using the suggested models in this study to the ones obtained by Enweremadu *et al*. [35] for the same locations shows that the recommended models obtained in this study do give better prediction in terms of accuracy and hence, a lesser error.

Conclusions

Weather data were collected and analyzed for the nine provinces in South African to model GSR of each of the provinces. Generally, all the suggested models were able to give a good estimate of solar radiation for their respective provinces with goodness of fit in the range $0.898 \leq R^2 \leq 0.9871$.

The inclusion of some other weather parameters like percentage relative humidity, average ambient temperature, and average wind speed in addition to the traditional sunshine hours in some models for some provinces improved the accuracy of this model, while in some other provinces some of them were of no effect.

In conclusion, to improve the accuracy and performance of solar radiation models, it is important to consider other weather parameters to see how much they help in improving the error of predictions of these models.

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Nomenclature

c_w – monthly daily average wind speed, [ms^{-1}]
$\overline{H}$ – monthly average daily solar radiation, [MJm^{-2}]
$H_{c,i}$ – calculated monthly average daily solar radiation, [MJm^{-2}]
H_m – measured monthly average daily solar radiation, [MJm^{-2}]
$\overline{H}_0$ – monthly average daily extraterrestrial solar radiation, [MJm^{-2}]
G_{SC} – solar constant, [1367 Wm^{-2}]
n_d – average month day
R^2 – regression coefficient
S – monthly average daily sunshine hour
S_0 – monthly mean daily maximum possible sunshine duration

T_a – ambient temperature, [°C]

Greek symbols

δ – solar declination in degrees
ϕ – latitude of the location
φ – percentage relative humidity
ω_s – sunset hour angle for the month in degrees

Acronyms

ARC – agricultural research council
AWS – automatic weather station
DNI – direct normal irradiation
GSR – global solar radiation
MBE – mean bias error
MABE – mean absolute bias error
MAPE – mean absolute percentage error
NREL – national renewable energy laboratory
RMSE – root mean square error
SAWS – South African weather service

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