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Mahfoud Hamidia

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# New Method for Clear Day Selection Based on Normalized Least Mean Square Algorithm

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**Abstract.** A new method is proposed to select clear days from data sets of solar irradiation recorded with ground-based instruments. The knowledge of clear days for a given site is of prime importance both for the study of turbidity and for the validation of empirical models of Global Solar Radiation (GSR). Our innovative method is based on the Normalized Least Mean Square (NLMS) algorithm that estimates noise according to a GSR model. The developed method named Clear Day Selection Method (CDSM) is compared to the well-known clearness index criteria ( $k_t$ ) taking data collected at Tamanrasset in Algeria during the period 2005-2009. The root mean square error (rmse), the mean absolute percentage error (mape) and the dependence of model error (mbe) are considered for the comparison. A different number of clear days is found with both methods, with additionally a  $k_t$  dependency for the clearness index criteria. The average values of rmse, mape and mbe between the daily average of the measured GSR and its estimate using a model are better in case of CDSM for the period 2005-2009. Indeed, we found 25.28 W/m<sup>2</sup>, 4.61 % and 2.09 W/m<sup>2</sup> respectively for CDSM and 42.48 W/m<sup>2</sup>, 7.63 % and -5.91 W/m<sup>2</sup> for the clearness index method with  $k_t = 0.7$ . We also found that GSR of clear days is well correlated with the model in case of CDSM, which gives good confidence in our results.

**Keywords** clearness index, NLMS, adaptive algorithm, solar radiation

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## 27 1- Introduction

28 The Global Solar Radiation (GSR) is the total amount of solar radiation received by the Earth surface and  
29 corresponds to the contribution of direct, diffuse and reflected solar radiation. Direct solar radiation is the  
30 propagation of the beam directly through the atmosphere to the surface of the Earth, while diffuse solar radiation is  
31 scattered in the atmosphere. Solar radiation is affected during its propagation through the atmosphere by atoms and  
32 molecules (ozone, water vapor, carbon dioxide ...) as well as by liquid and solid aerosols dispersed or grouped in  
33 clouds (Kaskaoutis 2008). Solar radiation measurements on the ground then depend on the site location. The  
34 location must indeed be taken into account when we are interested in the quality and amount of solar radiation. GSR  
35 is one of the most important parameters in solar energy designs and/or applications (Badescu et al. 2013; Reno et al.  
36 2012). Analyzing solar radiation properties in a given location requires long-term data and both use of empirical,  
37 semi-empirical or physical models and specific techniques such as neural networks (Senkal 2015; Mohandes 2012).  
38 Many studies were carried out to estimate and/or predict solar radiation using available meteorological (air  
39 temperature, relative humidity ...) and geographical (sunshine hours, latitude ...) parameters (Wong and Chow 2001;  
40 Victor et al. 2016; Gueymard 2012). These models are needed to obtain the correct designs and outputs of solar  
41 power plants in case of clear sky conditions. Selecting clear days from recorded datasets is the first step in modelling  
42 solar radiation under these conditions. The clearness index method, based essentially on the calculation of a  
43 parameter  $k_t$  related to measured solar radiation, is widely used for this purpose (Alves et al. 2013; Khem et al.  
44 2012; Mellit et al. 2008). Authors then sorted day types using the  $k_t$  parameter according to their own criteria. The  
45 sky is, for some, clear when its value is between 0.65 and 1, partly cloudy when  $0.3 \leq k_t \leq 0.65$  and cloudy if  $0 \leq$   
46  $k_t \leq 0.3$  (Gueymard 2012; Alves et al. 2013). For other authors, a clear sky is when  $0.5 \leq k_t \leq 0.85$  (Bendt et al.  
47 1981; Ahmed et al. 2008), higher than 0.6 (Reindl et al. 1990) or 0.7 (Li and Lam 2001; Li et al. 2004). Iqbal  
48 considers that the sky is clear when  $k_t$  is between 0.7 and 0.9 (Iqbal 1983).  $k_t$  also varies in time (Serban 2009) and  
49 depends on regions. Its value in most tropical regions is between 0.68 and 0.75 for a clear sky (Ndilemeni et al.  
50 2013). We see clearly with this short bibliographic that there is a great disparity in the definition of a clear sky using  
51 this parameter and there is no clear method for its estimation. The choice of its value can be crucial to distinguish  
52 clear days from turbid ones. A wrong choice will affect mainly the number of clear and turbid days in a dataset  
53 analysis and, therefore, modelling of solar irradiance data will depend heavily on  $k_t$ . This brief retrospective around

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4 54 the issue of the clearness index choice led us to develop a new method for classifying clear and turbid days. The  
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6 55 method is based on the Normalized Least Mean Square algorithm (Sharma and Mehra 2016; Dixit and Nagaria  
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8 56 2017), which is an adaptive algorithm based on minimization of the norm of differences between estimate and real  
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10 57 signal. This method is often used in signal processing for noise identification or cancellation (Sahu and Sinha 2015;  
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12 58 Gupta and Bansal 2016) and is therefore suited for GSR measurements. Indeed, its perturbations are due to solar  
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14 59 radiation propagation through the atmosphere and are well assimilated as noise in our process. In this work, we first  
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16 60 present the clearness index algorithm used to distinguish clear and turbid days, and then introduce CDSM, the  
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18 61 NLMS method for Clear Days Selection. A comparison of these methods will then be made and the results  
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20 62 discussed.

## 23 63 2- The Clearness index method

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26 64 The clearness index  $k_t$  was introduced by Liu and Jordan to quantify stochastic property conditions for a given site  
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28 65 (Liu and Jordan 1960). Interval values for  $k_t$  are taken to separate clear and turbid days but are often site dependent  
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30 66 (see Section 1), which leads to misinterpretation of the results, especially when authors compare and study empirical  
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32 67 models. The clearness index  $k_t$  is defined over time  $t$  as the ratio between the terrestrial global solar radiation  
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34 68  $GSR(t)$  on a horizontal surface and the extraterrestrial one  $G_0$ :

$$36 \quad 37 \quad 38 \quad 39 \quad 40 \quad 41 \quad 42 \quad 43 \quad 44 \quad 45 \quad 46 \quad 47 \quad 48 \quad 49 \quad 50 \quad 51 \quad 52 \quad 53 \quad 54 \quad 55 \quad 56 \quad 57 \quad 58 \quad 59 \quad 60 \quad 61 \quad 62 \quad 63 \quad 64 \quad 65$$

$$69 \quad k_t = \frac{GSR(t)}{G_0} \quad (1)$$

70 where  $G_0$  in  $W/m^2$  is given by:

$$71 \quad G_0 = I_{sc} * [1 + 0,0033 * \cos(\frac{360*N}{365})] * (\cos\phi * \cos\delta * \cos\omega * \sin\phi * \sin\omega) \quad (2)$$

72  $I_{sc}$  is the Total Solar Irradiance (TSI) equal to  $1361 W/m^2$  (Myhre et al. 2013) and N the day number in the year  
73 (N=1 is the first day in the year and N=365 the last one).  $\phi$ ,  $\delta$  and  $\omega$  are respectively the latitude of the location, the  
74 solar declination angle and the hour angle at sunrise in degrees.

75 An algorithm based on the instantaneous clearness index was first developed for our work to automatically select  
76 days from a huge dataset. The main steps of the algorithm are:

- 77 • Selection of  $GSR(t)$  records of a given day where the Sun elevation is higher than  $10^\circ$ .

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4 78 This condition is only intended to prevent the presence of haze early in the morning or late in the afternoon.  
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6 79 This could lead to considering a clear day as not being one.  
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9 80 • Calculation of the extraterrestrial solar radiation  $G_0$  for the same day.  
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11 81 • Calculation of the instantaneous clearness index  $k_t$  between sunrise and sunset using Equation 1.  
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14 82 **3- Normalized Least Mean Square Method for Clear Days Selection**

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16 83 We present in this section the Normalized Least Mean Square (NLMS) algorithm and then how we use it to select  
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18 84 clear days from data sets.  
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21 85 **3-1. The NLMS algorithm**

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24 86 The Least Mean Square (LMS) algorithm was first developed by Widrow and Hoff in 1959 for speech recognition  
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26 87 applications. It is today one of the most widely used algorithms in adaptive filtering mainly due to its efficiency and  
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28 88 computational simplicity. LMS algorithms are a class of adaptive filters used to generate a desired filter that  
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30 89 produces least mean squares of the error signal i.e. difference between desired and real signal. The algorithm starts  
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32 90 by assuming small weights (zero in most cases) at each step and finding the gradient of the estimated error. Weights  
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34 91 are then updated according to the following equation (Dixit and Nagaria 2017):  
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$$w_{n+1} = w_n + \alpha \times e(n) \times x(n)$$

37 92  
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39 93 Here  $x(n)$  is an input vector with  $L$  delayed values in time.  $w(n) = [w_0(n) w_1(n) w_2(n) \dots w_{L-1}(n)]^T$  is a vector with  $L$   
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41 94 components containing the tap weight coefficients of the adaptive FIR (Finite Impulse Response) filter at time  $n$ ,  
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43 95  $e(n)$  is the estimated filter error at  $n$  and the subscript  $T$  stands for transpose operator. The  $\alpha$  parameter is known as  
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45 96 the step size parameter and is a small positive constant. This parameter controls the influence of the updating factor.  
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47 97 Selection of a suitable value of  $\alpha$  is imperative for the performance of the LMS algorithm. The time taken by the  
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49 98 adaptive filter to converge into the optimal solution will be too long if its value is too small. The adaptive filter  
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51 99 becomes unstable if  $\alpha$  is too large and its output diverges (Sharma and Mehra 2016; Dixit and Nagaria 2017). The  
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53 100 stability condition of the LMS algorithm is  $0 < \alpha < 2/\lambda_{max}$ , where  $\lambda_{max}$  is the largest eigenvalue of the  
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55 101 autocorrelation matrix of the input signal  $x(n)$ . The main disadvantage of LMS algorithm is the fixed step size  
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4 102 parameter for every iteration. This requires knowledge of the input signal statistics prior to starting the adaptive  
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6 103 filtering operation. The NLMS algorithm is an extension of the LMS one, which by passes this issue by calculating  
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8 104 the maximum step size value. This step size is proportional to the inverse of the total expected energy of  
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10 105 instantaneous coefficients of the input vector  $x(n)$ . The recursion formula for NLMS algorithm is given by  
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12 106 (Hamidia and Amrouche 2016):

$$w(n+1) = w(n) + \frac{\mu}{\epsilon + x^T(n) \times x(n)} \times e(n) \times x(n) \quad (4)$$

17 108 where  $0 < \mu < 2$  is the adaptation step size of NLMS and  $\epsilon > 0$  is a regularization constant used to avoid division  
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20 109 by zero.

22 110 The NLMS algorithm is implemented according to the following steps:

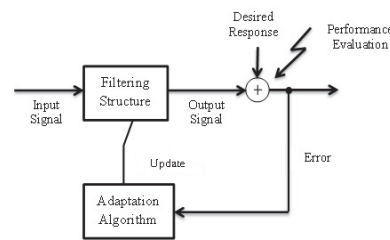
- 24 111 • The output signal  $y(n)$  of the adaptive filter is calculated by:

$$y(n) = w^T(n) \times x(n) \quad (5)$$

- 29 113 • The estimated filter error signal  $e(n)$  at step (n) is computed as the difference between the desired signal and  
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31 114 the filter output:

$$e(n) = d(n) - y(n) \quad (6)$$

- 36 116 • The filter tap weights are updated in preparation for the next iteration using Equation 4.



49 Figure 1. Adaptive filtering

51 117 Basic modules of an adaptive filter are shown in Figure 1 (Dixit and Nagaria 2017). The output of the adaptive filter  
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53 118 and the desired response are processed to assess its quality with respect to requirements of a particular application.  
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55 119 This module generates the filter output using input signal measurements. The filtering structure is linear or nonlinear  
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57 120 according to the designer and its parameters are adjusted by the adaptive algorithm.  
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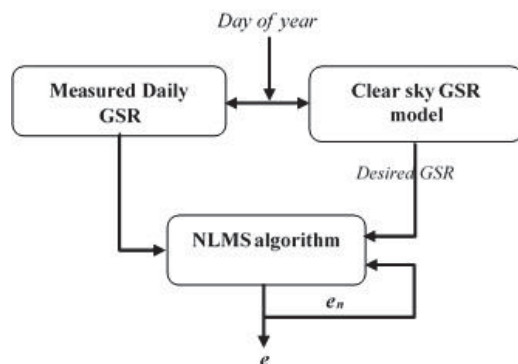


Figure 2. Flowchart of CDSM

### 3-2. The CDSM algorithm

Our proposed method for selecting clear days present in dataset is based on the NLMS algorithm and any parametric GSR model. The Capderou model has been used in this work (Capderou 1987). This parametric model uses the Linke turbidity to compute the global, direct and diffuse components of clear sky solar radiation. The main idea of the method is to compare estimated GSR with measurements i.e. GSR resulting from adaptive filtering when taking GSR measurements as input are compared to GSR model of clear sky. CDSM is summarized by the following steps (Figure 2) (Quadri et al. 2017):

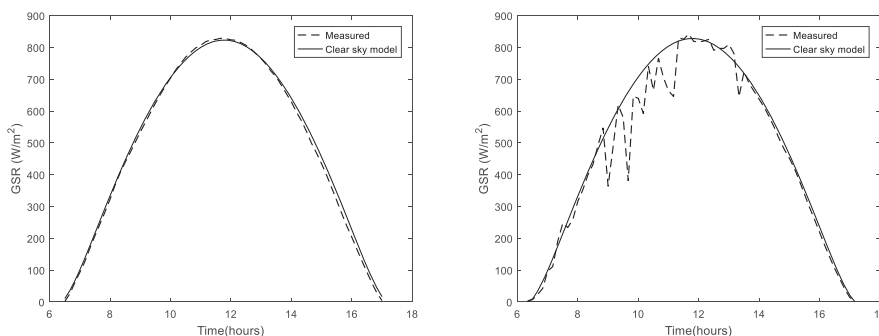


Figure 3. Examples of daily recorded GSR (dashed line) superposed to the clear sky model (full line).

- Each daily GSR is fitted with a clear sky GSR model.
- The measured GSR is subjected to a parameterized FIR filtering with  $w_n$  coefficients (see previous section):

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- 131 a sample of the modeled GSR is obtained.
- 132 • The estimated filter error between samples of modelled GSR and clear sky GSR model is calculated.
  - 133 • The obtained estimated filter error is used to calculate the next step that is used to readjust FIR filter coefficients ( $w_{n+1}$ )
  - 134
  - 135 • Steps 1-4 are considered for all samples of the measured GSR

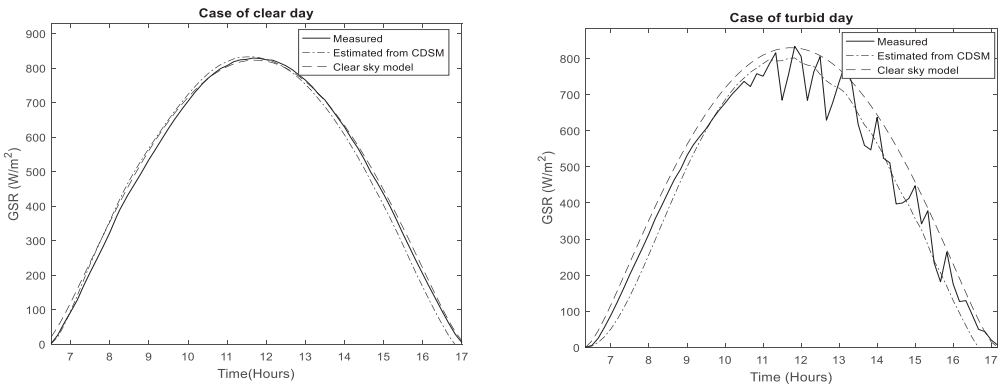


Figure 4. CDSM behavior in case of a clear (left) and a turbid day (right).

136 Figure 3 plots an example of daily measured GSR (dashed line) superposed to the clear sky GSR model (full line)  
137 for both clear (left plot) and turbid (right plot) days. Figure 4 shows CDSM behavior to estimate GSR in case of  
138 clear (left plot) and turbid days (right plot). The adaptive filter takes a measured GSR as input and produces a  
139 modeled GSR by recursively adjusting the filter parameters to handle the disturbances present in the GSR  
140 measurement. Figure 5 plots the estimated filter error obtained when CDSM is run on data of Figure 4. We see that  
141 the method allows having a modelled GSR more or less disturbed according to the data considered. It will be close  
142 to the GSR model when the estimated filter error is small i.e. the case of clear days. We will consider in our study  
143 that clear days correspond to the estimated filter error less than  $20 W/m^2$  ; otherwise they are considered as turbid.



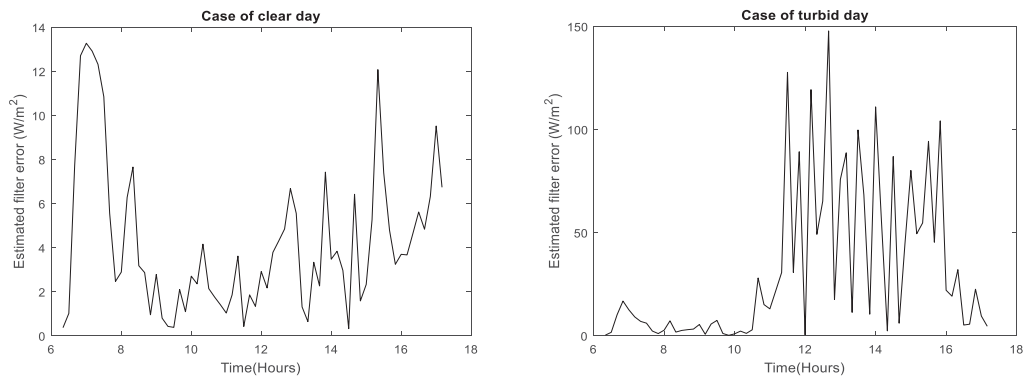


Figure 5. Estimated filter error of the GSR estimate for a clear (left) and a turbid day (right).

144 **4- Comparison of clear day selection methods. Results and discussion.**

145 We use GSR data recorded from 2005 to 2009 in southern Algeria to compare the efficiency of CDSM relative to  
 146 other methods. Let us first present the data set.

147 **4-1. Data set of solar radiation**

148 Data used in this work were collected at the Regional Meteorological Center (Direction Météo Régional Sud, Office  
 149 National de la Météorologie, Algeria) at Tamanrasset (22.79°N, 5.53°E, 1377 m a.s.l.) in southern Algeria between  
 150 2005 and 2009. Instruments and methods for data collection are the same as those described in detail by Djafer and  
 151 Irbah (Djafer and Irbah 2013). The main difference is that the three components of solar radiation are recorded every  
 152 minute at Tamanrasset together with temperature, humidity and pressure. Instruments that measure direct, global and  
 153 diffuse solar radiation components are EKO type instruments (<http://eko-eu.com/>) (see Figure 6). They are cleaned  
 154 two to three times a week depending on weather conditions and calibrated every three years. Data were calibrated  
 155 with the TSI of 1367  $W/m^2$  since it was the current value at this period (2005 - 2009). A correction factor is applied  
 156 to the data since the TSI of 1361  $W/m^2$  is now adopted. This factor is the ratio between current and previous TSI.

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Figure 6. Radiometric station for measuring global, direct and diffuse solar radiation: (1) Pyranometer for measuring the global solar irradiance. (2) Pyranometer for measuring the diffuse. (3) Pyrliometer for measuring the direct solar irradiance, (4) Shaded pyranometer. (5) The 2-axis solar tracker.

**4-2. Results and discussion**

We used the five years of GSR measurements (see section 4.1) and determined clear days present in the data set with the clearness index, wavelet based method (Djafer et al. 2017) and CDSM. Results are given in Table 1 and plotted in Figure 7 where error bars are one standard deviation.  $k_t$  values widely used in the literature to select clear days were considered for the comparison, that is  $0.5 \leq k_t \leq 0.8$ .

Table 1. Number of clear days per year selected with different methods

Years	2005	2006	2007	2008	2009
<b>Wavelet method</b>	59	30	65	98	24
<b>CDSM</b>	136	133	173	173	120
<b><math>k_t=0.5</math></b>	303	316	319	322	305
<b><math>k_t=0.6</math></b>	244	254	279	274	254
<b><math>k_t=0.7</math></b>	114	133	158	170	139
<b><math>k_t=0.8</math></b>	2	7	6	14	7

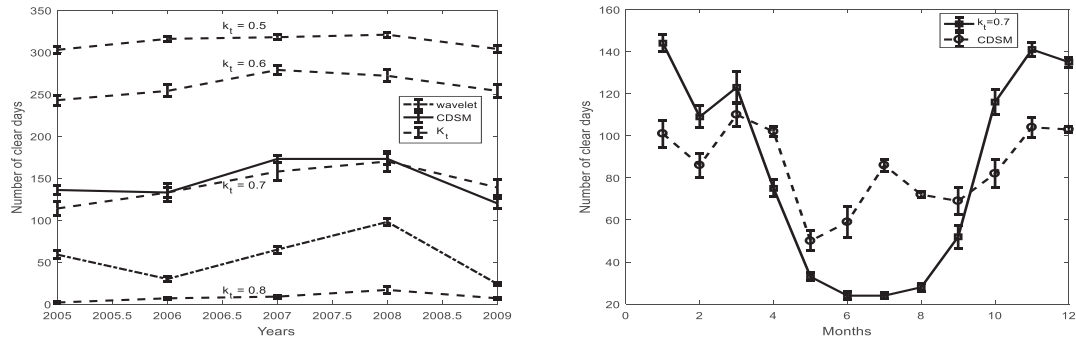


Figure 7. Number of clear days selected with the different methods: number per year (left) and per month (right).

We observe in the left plot of Figure 7 that the number of clear days per year obtained with CDSM is close to what is found with  $k_t = 0.7$ . Lower  $k_t$  values overestimate the number of clear days while higher ones underestimate it. The wavelet method seems to underestimate the yearly number of clear days due to excessive constraints on GSR disturbances when setting the selection threshold. The three methods show the same trend of the yearly number of clear days with a maximum around 2008. If we look at the monthly values of clear days computed over the period 2005-2009, we observe a difference between CDSM results and those obtained with the clearness index with  $k_t = 0.7$  (see right plot of Figure 7). Curves have similar shapes but the number range for the clearness method is large relative to the CDSM one. There is quasi no clear days found for months between May and August with  $k_t = 0.7$  leading to suppose that its value needs to be adjusted during processing as reported in section 1. We note that the number of clear days at Tamanrasset is lower during the months of May and September-October compared to the others.

Finally, we compared GSR of clear days obtained with both  $k_t = 0.7$  and CDSM to those estimated by the model described in Zaiani *et al.* (2017). This parametric model used Artificial Neural Network to estimate GSR of a given clear day. We used several parameters to quantify the comparison among which are the root mean square error (rmse), the normalized root mean square error (normse), the mean absolute percentage error (mape), the dependence of model error (mbe) and the normalized dependence of model error (nmbe). Comparison results are given in Table 2. We note that the model fits better the measured GSR of clear days determined with CDSM. Indeed, we have a mean  $R^2$  of 0.97, an rmse of  $25.28 W/m^2$ , an mbe of  $2.09 W/m^2$  and a mape of 4.16 % while we have a mean  $R^2$  of

0.94, an rmse of  $42.58 \text{ W/m}^2$ , an mbe of  $1.97 \text{ W/m}^2$  and a mape of 7.55 % for the clearness index method. Figure 8 plots the correlation between daily average measured GSR of clear days selected with CDSM (left plot) and with the clearness index method ( $k_t = 0.7$ ) (right plot) versus daily average calculated GSR. We note that GSR of clear days selected with CDSM are very well correlated with the model compared to what we obtain with the clearness index method. The correlation factor is 0.99 for CDSM and 0.95 using  $k_t$  criteria. We may conclude when looking at this plot that we can be confident in the results obtained from CDSM.

Table 2. Annual average errors between measured and calculated GSR

Method	Errors	2005	2006	2007	2008	2009	Average
<b>CDSM</b>	rmse ( $\text{W/m}^2$ )	24.63	24.72	26.75	25.51	24.79	25.28
	nrmse (%)	3.63	3.64	4.43	4.19	3.54	3.88
	mape (%)	4.26	4.27	5.33	5.01	4.20	4.16
	mbe ( $\text{W/m}^2$ )	2.01	2.00	2.25	2.15	2.05	2.09
	nmbe (%)	0.27	0.27	0.59	0.55	0.27	0.39
	$R^2$	0.99	0.99	0.95	0.95	0.99	0.97
<b><math>k_t</math></b>	rmse ( $\text{W/m}^2$ )	42.00	41.45	44.11	37.47	47.84	42.58
	nrmse (%)	6.92	6.60	7.07	5.89	7.38	6.77
	mape (%)	7.56	7.29	7.82	6.68	8.40	7.55
	mbe ( $\text{W/m}^2$ )	1.24	2.97	2.89	2.54	-0.2	1.97
	nmbe (%)	0.11	0.43	0.40	0.35	0.03	0.27
	$R^2$	0.94	0.94	0.94	0.95	0.93	0.94

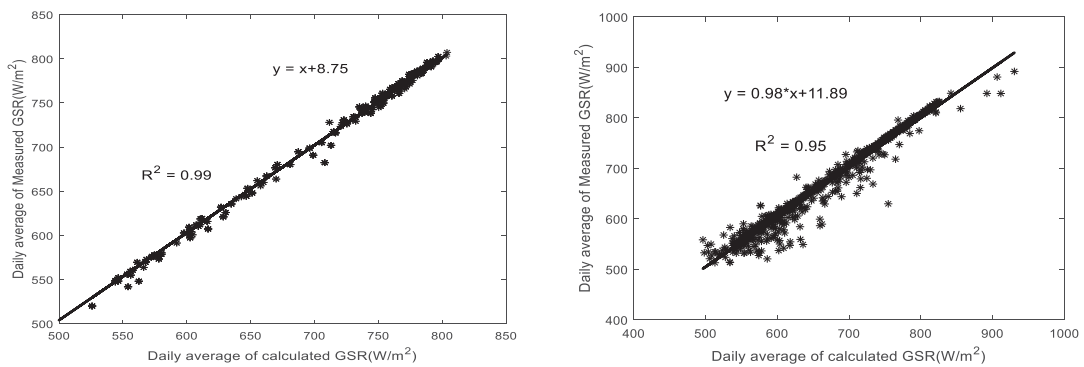


Figure 8. Correlation between daily average of calculated and measured GSR obtained with CDSM (left) and with the clearness index with  $k_t = 0.7$  (right) .

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4 189 **5- Conclusion**  
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7 190 A new method to select clear days in data sets of solar radiation is presented in this work. This method we denoted  
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9 191 CDSM, is based on NLMS algorithm. We first compared CDSM to the clearness index method taking the most used  
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11 192 value  $k_t = 0.7$  and found that our method gives a higher number of clear days when using the same data set. We  
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13 193 took a data set of 5 years of solar radiation measurements collected at the Tamanrasset ONM. We then validated  
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15 194 CDSM using the clear days selected by both methods to model daily GSR. The analysis of the difference between  
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17 195 GSR of the clear days selected with CDSM and calculated for these days with the model shows a very good  
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19 196 agreement. We found that yearly values vary between (i) 4.20 and 5.33 % for mape, (ii) 0.95 and 0.99 for  $R^2$ , (iii)  
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21 197 24.63 and 26.75  $W/m^2$  for rmse and (iv) 2.00 and 2.25  $W/m^2$  for mbe. Finally, we performed a comparison of daily  
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23 198 average GSR of clear days obtained with both CDSM and the clearness index method with  $k_t = 0.7$  and those  
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25 199 estimated with the model. We found that the GSR of clear days selected with CDSM are better correlated with the  
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27 200 model than those obtained with the clearness index method. The correlation coefficient is 0.99 for CDSM and 0.95  
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29 201 using  $k_t$  criteria. We can emphasize that our method was developed using daily measured GSR but may also be  
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31 202 adapted to detect clear and turbid short periods in measurements. These short periods are very useful for studying  
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33 203 the environment and regional frequency of clouds. In addition, knowledge of the occurrence of clear days on a site  
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35 204 also has many other interests. This is particularly the case before any photovoltaic or thermal installation for which  
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37 205 solar radiometric measurements over a longer or shorter period are necessary. Our work is then very useful to give  
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39 206 the relevant information on the number of clear days for a given site and consequently to predict the energy that  
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41 207 these facilities will produce in this region.

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