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Authors: Farah Benharrats, Farah Benharrats

Date: 2025-06-03T14:50:11+00:00

Abstract

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Full Text

Preamble

Astronomical Techniques and Instruments, Vol. 2, May 2025, 186–197
Article Open Access

Estimating global surface solar irradiance using Landsat satellite data for three sites in Algeria

Farah Benharrats*

Centre des Techniques Spatiales, Agence Spatiale Algérienne, 1 Avenue de la Palestine, BP13, Oran, Arzew, 31200, Algeria

*Correspondence: fbenharrats@cts.asal.dz

Received: January 19, 2025; Accepted: March 4, 2025; Published Online: April 1, 2025

<https://doi.org/10.61977/ati2025016>; <https://cstr.cn/32083.14.ati2025016>

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Citation: Benharrats F. 2025. Estimating global surface solar irradiance using Landsat satellite data for three sites in Algeria. *Astronomical Techniques and Instruments*, 2(3): 186–197. <https://doi.org/10.61977/ati2025016>.

Abstract: Exploiting remote sensing data is a promising approach to estimate surface solar irradiance (SSI). In this study, we propose a method to estimate global SSI using a lookup table and Landsat data. Despite the low temporal resolution of the data used, the developed method produces SSI maps with adequate spatial resolution. It combines physical parameters extracted from Landsat metadata files with the physical laws governing global solar irradiance, its transmission through the atmosphere, and surface reflectance. The results obtained are compared with those in the literature, particularly one study that uses Meteosat data and two others that use radiometric spectral and temporal models. Additionally, experiments are conducted at three sites in Algeria: Oran, In Amenas, and Tamenghasset. The findings indicate that the proposed approach aligns with the tested literature methods while providing SSI maps with superior spatial resolution. The obtained solar irradiances exhibit a root mean square error of approximately $190 \text{ W m}^{-2} \mu\text{m}^{-1}$ compared with those of the Bird and Riordan spectral model, and approximately 50 W m^{-2} compared with the results from the Bird and Hulstrom temporal model, and are also comparable to the results of previous studies.

Keywords: Surface solar irradiance; Satellite data; Lookup table; Landsat; Dark object subtraction

1. Introduction

The atmosphere acts as a continuous and variable filter affecting the propagation of solar radiation toward the Earth's surface. Atmospheric gases, aerosols, water vapor, and cloud droplets modify the solar energy distribution as a function of wavelength. Therefore, it is important to have a reference spectrum, especially in the field of photovoltaic energy conversion, to serve as a common frame of comparison for choosing materials in conversion systems.

Most solar energy conversion systems use only a portion of the solar spectrum.

For example, the energy used for lighting falls within the range visible to the human eye (i.e., from 380 nm to 850 nm), while silicon-based photovoltaic cells operate from 350 nm to 1100 nm [1].

In this context, assessing SSI and the variations in its hourly and spectral distributions from the visible to the infrared spectrum is of great interest for installing, designing, developing, and evaluating the performance of photovoltaic conversion systems [2].

Several methods have been developed to estimate SSI. The most direct method for mapping SSI is to interpolate ground-based observations obtained from radiometric stations. However, owing to their poor distribution, this interpolation can be subject to errors. In contrast to ground-based observations, satellite assessments of radiation, particularly for 10-km-range pixels, tend to be more accurate than estimation using interpolation of measurements from meteorological stations, especially when the distance to the stations exceeds 34 km for hourly radiation and 50 km for daily radiation [3,4].

Only space-based observations can provide global coverage. Earth images taken by polar-orbiting and geostationary satellites offer the potential for mapping the global SSI on a horizontal surface at ground level, with various spatial resolutions [5–9]. A geostationary orbit allows for coverage of the Earth’s surface with high temporal resolution; however, its limitation is the increase in the apparent size of a pixel with latitude and longitude. In contrast, polar satellites, which operate at much lower altitudes, provide higher spatial resolution but have restricted temporal coverage [10]. Nevertheless, with the availability of significant amounts of continuous remote sensing data at medium to high spatial resolutions, it is now possible to map solar potential at a finer scale for large regions.

Several models have been proposed to estimate SSI from satellite data over the last three decades [11–21]. Primarily developed for mid- and high-latitude zones [22], these models vary in complexity and accuracy. In this work, we focus on using lookup tables (LUTs).

LUT-based methods use two-path LUTs to simplify radiative transfer processes and subsequently retrieve SSI. The information is stored in LUTs along both the solar-to-surface path and the surface-to-top-of-atmosphere (TOA) path. These methods typically involve two main steps: (1) establishing the relationships between TOA albedos or reflectances and atmospheric transmittances in the form of LUTs through extensive radiative transfer simulations for various atmospheric conditions, and (2) estimating SSI by matching a given satellite TOA observation with predefined LUT values [19].

LUT-based methods offer a direct strategy for retrieving SSI from raw satellite data, eliminating the need for atmospheric state parameters (e.g., cloud properties).

Two-path LUTs can be simplified into a one-path mode, where only informa-

tion about the solar-to-surface path is used to estimate SSI [23]. However, this method has some weaknesses: the algorithm is often computationally inefficient and highly sensor-specific and does not account for all radiative extinction processes in the interest of efficiency [19].

Taking these considerations into account, this study proposes a method that uses an LUT with Landsat 5 and Landsat 8 OLI/TIRS satellite data as TOA observations. Furthermore, validations are conducted using the Bird and Riordan spectral model [24], the Bird and Hulstrom time model [25], and radiation data from the Copernicus Atmosphere Monitoring Service (CAMS) extracted from the Solar (SoDa) server [26].

The radiometric models developed by Bird and Riordan and by Bird and Hulstrom are clear-sky models that provide estimates of clear-sky direct-beam, diffuse hemispherical, and total hemispherical solar irradiance on both horizontal and tilted surfaces.

The other comparisons are conducted with the CAMS radiation extracted from the SoDa server [26]. This database is created using the Heliosat-2 method, which processes Meteosat Second Generation satellite images collected between 3:00 UT and 20:45 UT (72 images) to compute each 15-minute global irradiance over a horizontal plane (GIH) [26].

The Heliosat-2 method was developed by MINES ParisTech in November 2002, partly with the support of the European Commission (project SoDa, contract DG “INFSO” IST-1999-12245). The method converts images acquired by meteorological geostationary satellites such as Meteosat (Europe), GOES (USA), or GMS (Japan) into data and maps of solar radiation received at ground level. The original Heliosat-2 method is described in [4] and [27].

The comparison is made with these SSI estimation sources because, despite being clear-sky models, radiometric models use instantaneous meteorological data and atmospheric transmittance functions as inputs. However, Heliosat-2 is a model derived from satellite images using pyranometric measurements taken by 35 meteorological stations to assess performance [26], which provides more reliable and accurate validation.

The remainder of this paper is organized as follows. The materials and methods employed in this study are detailed in the source data and study regions section. The main results and the subsequent discussion are presented in the following sections. Finally, a summary of the work and the conclusion are provided.

2. Materials and Methods

2.1. Landsat Data

The remote sensing images, archived at Landsat receiving stations around the world, are a unique resource for research on planetary changes and other applications in several domains [28].

Landsat data were acquired from USGS Earth Explorer, which is a quick and easy tool to freely download Landsat imagery and other remote sensing data. Satellite data like Landsat consist of several spectral bands. The SSI of each of these spectral bands can be determined for an area with a spatial resolution of $30\text{ m} \times 30\text{ m}$ [28].

Landsat data have spatial resolutions of 100 m in the thermal infrared band and 30 m in the visible and near-infrared bands. The programmed revisit time is 16 days, and the images are acquired from approximately 10:00 UT to 10:30 UT [28].

2.2. Tested Areas

To evaluate the proposed method, three regions in Algeria were selected on the basis of the optical thickness of the aerosol: Oran ($35^{\circ}42'23''\text{N}$, $0^{\circ}34'43''\text{W}$), In Amenas (Illizi) ($28^{\circ}2'46''\text{N}$, $9^{\circ}34'43''\text{E}$), and Tamenghasset ($22^{\circ}47'20''\text{N}$, $5^{\circ}31'33''\text{E}$) (Fig. 1 [Figure 1: see original paper]).

Tamenghasset and In Amenas are located in southern Algeria and experience a hot desert climate, i.e., very hot summers and mild winters. The sky is mostly clear throughout the year, and the relative humidity is very low, especially during summer months. The general prevailing weather conditions of these two regions are long-term mean temperatures of approximately 23.4°C for In Amenas and 21.58°C for Tamenghasset, and exceptionally moderate or low humidity throughout the year, with annual averages of approximately 33.16% for In Amenas and 22.82% for Tamenghasset [29].

Oran, a coastal city, has a Mediterranean climate, i.e., summer is the warmest season and winter is the coolest with many days of cloudless skies throughout the year. The general prevailing weather conditions are a long-term mean temperature of approximately 19.69°C and a high humidity approximately 63.17% [29].

The Landsat image acquisition dates are in summer, a period with a lot of sunstroke: June 26, 2016 for In Amenas, July 10, 2016 for Tamenghasset, and August 5, 2016 and July 13, 2019 for Oran. The year 2011 is chosen for studying the global SSI time variation of the Tamenghasset region.

3. Method

The proposed LUT–Landsat approach is based on the physical parameters extracted from the metadata file of Landsat images and on dark object subtraction (DOS), which is an atmospheric correction method [30] (Fig. 2 [Figure 2: see original paper]).

The key terms in the equations of this method are presented in Table 1 and Fig. 3 [Figure 3: see original paper].

The spectral reflectance of the land surface, ρ_{gr} , is the ratio of reflected to total power. From the Landsat formula, this is:

$$\rho_{gr} = \pi(L_{sat} - L_d) d^2 T_s (E_o \cos \theta_z T_z + E_d) \quad (1)$$

The spectral radiance at the sensor's aperture is then determined by the difference between the at-satellite spectral radiance L_{sat} and path radiance L_d , which is the radiance that has undergone atmospheric scattering. Both of these radiances are obtained from the formulas provided by Landsat products [31].

The spectral radiance at the satellite sensor, L_{sat} , is the combination of the contributions of the spectral radiance on the ground and the atmospheric effects. It can be expressed on the basis of the ground reflectance in Equation (1) as:

$$L_{sat} = L_{gr} T_s + L_d \quad (2)$$

$$L_{gr} = (\rho_{gr} / \pi) d^2 (E_o \cos \theta_z T_z + E_d) \quad (3)$$

The second term of Equation (3) is similar to the general formula of global SSI [32] and is given by the sum $SSI = I_d + D$, where I_d is the beam solar irradiance and D is the diffuse solar irradiance. Then, the following formula is deduced:

$$SSI(\lambda) = E_o \cos \theta_z T_z + E_d \quad (4)$$

Due to atmospheric scattering (path radiance), dark objects have a minimum surface reflectance of 1% because very few targets on the Earth's surface are absolutely black [33]. This allows deducing the upwelling atmospheric radiance as:

$$L_d = L_{min} - L_{DO1}\% \quad (5)$$

$$L_d = ML DN_{min} + AL - 0.01 (E_o \cos \theta_z T_z + E_d) T_s / (\pi d^2) \quad (6)$$

$$L_{min} = ML DN_{min} + AL \quad (7)$$

In Equation (4), the variables that cannot be deduced from Landsat metadata are the atmospheric transmittance, the upwelling atmospheric spectral radiance, and the diffuse irradiance. Atmospheric correction through DOS is needed to determine these variables, assuming that radiances of fully shaded pixels received at the satellite are:

$$L_{DO1}\% = 0.01 (E_o \cos \theta_z T_z + E_d) T_s / (\pi d^2) \quad (8)$$

The DOS method includes four cases with different condition sets consisting of transmittances (Table 2) [34].

In Table 2, case DOS1 assumes no atmospheric transmittance loss ($T_z = T_s = 1.0$) and no diffuse downward irradiance at the surface ($E_d = 0$). Case DOS2 approximates $T_z T_s$ as $\cos \theta_z$ for TM bands 1–4 and as 1.0 for TM bands 5 and 7. Case DOS3 computes T_z assuming Rayleigh scattering only,

which means that there is no aerosol [34]. In this case, the optical thickness for Rayleigh scattering, τ_r , depending on wavelength λ in μm , is:

$$\tau_r = 0.008569 \lambda^{-4} (1 + 0.0113 \lambda^{-2} + 0.00013 \lambda^{-4}) \quad (9)$$

E_d is estimated using the 6S atmospheric radiative transfer code, which means that there is zero aerosol optical depth at 550 nm. Finally, case DOS4, which is considered in this study, adds the atmospheric effects of aerosol on T_z and assumes an isotropic sky radiance, which allows an exo-atmospheric irradiance loss of $4\pi L_d$.

Both forms of this equation give atmospheric transmittances in the illumination direction. Substituting this into Equation (6) leads to:

$$T_z = e^{-\tau} = \cos \theta_z = 1 - (4\pi L_d) / (E_o \cos \theta_z) \quad (10)$$

$$\tau = -\cos \theta_z \ln[1 - (4\pi L_d) / (E_o \cos \theta_z)] \quad (11)$$

where ML is the band-specific multiplicative rescaling factor from Landsat metadata ($RADIANCE_{\{\{MULTI\}\}\{BAND\}}x$, where x is the band number), AL is the band-specific additive rescaling factor from Landsat metadata ($RADIANCE_{\{\{ADD\}\}\{BAND\}}x$, where x is the band number), and the minimum digital number (DN), DN_{\min} , is selected as the darkest DN with at least one thousand pixels for the entire image [32]. The radiance of dark objects, $L_{DO1}\%$, considered to have a reflectance of 0.01, is given by Equation (8).

The iteration process is as follows. First, the initial values $T_z = T_s = 1.0$ are input into Equation (10) to calculate the initial value of τ [34]. The new transmittances obtained are re-inputted into Equation (11), and the process is repeated until τ converges, which means the final obtained value of τ is equal to the previous one [34].

With these assumptions, it is also possible to map the spatial SSI distribution on the ground surface. From Equations (1) and (4), the global SSI can then be written as:

$$SSI(\lambda) = \pi d^2 (L_{\text{sat}} - L_d) T_s / \theta_{gr} \quad (12)$$

where the only remaining unknown variable, land surface reflectance θ_{gr} , is estimated using the Normalized Difference Vegetation Index (NDVI) threshold method [36,37]. The first step is to compute:

$$P_v = (NDVI - NDVI_s) / (NDVI_v + NDVI_s)^2 \quad (13)$$

where $NDVI_s$ is the soil NDVI equal to 0.2, and $NDVI_v$ is the vegetation NDVI equal to 0.5. Assuming different geometrical distributions, F is equal to 0.55 [38]. The surface reflectance is assumed to be:

$$\theta_{gr} = \theta_v P_v + \theta_s (1 - P_v) + d \quad (14)$$

The vegetation and bare soil reflectivity are estimated from typical reflectance curves [39] of common Earth surface materials in the visible and near- to mid-infrared ranges (Fig. 4 [Figure 4: see original paper]). For each center wave-

length of Landsat 8 spectral bands, it is easy to extract approximate reflectivities for bare soil and vegetation, as shown in Table 3 .

The accuracy of the proposed method is evaluated by calculating the root mean square error (RMSE) of its SSI values relative to those obtained with the other models. The RMSE represents the sample standard deviation of the differences between estimated and observed values [40,41]. This index is defined as:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_{\{\text{Mod}\},i} - X_{\{\text{Sat}\},i})^2} \quad (15)$$

where $X_{\{\text{Sat}\}}$ is the global SSI estimated from our Landsat method, $X_{\{\text{Mod}\}}$ is the global SSI obtained from the radiometric model or the Meteosat-based model, and N is the number of observations.

4. Results and Discussion

4.1. SSI Spectral Distribution

The spectral distribution is a typical representation of the amount of solar radiation reaching the ground over the wavelength range from 400 nm to 2200 nm (Fig. 5 [Figure 5: see original paper], computed from reference [1]), which is also the spectral range of Landsat TM bands.

This range spans from the limit of the visible (blue) to the infrared spectrum. Fig. 6A [Figure 6: see original paper] shows the spectral distribution of the global SSI for the three chosen sites obtained from Landsat data. A punctual variation is evident because the radiation is averaged over small bandwidths centered at a single wavelength. The radiation reaching the ground is maximum in the visible range and rapidly decreases toward the infrared range. In addition, more radiation reaches the ground at the desert sites of Tamenghasset and In Amenas than at the coastal site of Oran. Overall, the estimated values agree well with those provided by the spectral model of Bird and Riordan, with a maximum RMSE of $190 \text{ W m}^{-2} \mu\text{m}^{-1}$ (Table 4).

In Fig. 6B, a noticeable difference is observed between the transmittances obtained with the proposed method and those estimated with the spectral model. This could be explained by the fact that, in the spectral model of Bird and Riordan, the total atmospheric transmittance is obtained through a product of individual atmospheric transmittances, which means that it takes into account the effects of the different atmospheric constituents (such as ozone, water vapor, and aerosol). However, the proposed estimation is made by determining one representative transmittance from the optical thickness obtained through the iteration process. Furthermore, the transmittances determined for Tamenghasset and In Amenas are higher than those for Oran, and the transmittance is a measure of the transparency of the atmosphere to radiation. The sky transmits solar radiation more when the transmittance is greater. The desert atmosphere of Tamenghasset and In Amenas is less loaded with aerosols and other atmospheric elements than the urban and maritime atmosphere of Oran [23,42]. However, although both study areas are located in the Algerian Sahara,

we observe a difference in their transmittances. The primary reason for this difference is the position of the sun, which varies between the two acquisition dates. A change in the sun's position alters the interaction of solar radiation with the atmosphere.

In Fig. 7 [Figure 7: see original paper], the spectral distribution of the global SSI for each Landsat 8 spectral band is extracted for a single location at Oran (Latitude = 35.69° ; Longitude = -0.63°) to show the appeal of this method, which allows both a located point estimate and a spatialized estimate. The large figure shows the continuous variations of the spectral distributions obtained from the radiometric model of Bird and Riordan and from the proposed method, while the inset figure shows the same variations for the center band wavelength. However, there is a significant discrepancy between the two estimates in the visible range, particularly in the shortwave interval. A possible explanation for this is that, within this wavelength range, the sensor has better sensitivity than the radiometric model.

We further compare the result of the proposed method with the spectral SSI extracted from HELIOCLIM-3, which provides spectral radiation values computed from the satellite-derived solar radiation database HELIOCLIM-3 version 5 over a horizontal plane. The geographical coverage corresponds to the Meteosat satellite field of view, i.e., it covers Europe, Africa, the Atlantic Ocean, and the Middle East. The spatial resolution is 3 km at the Nadir and increases away from this point, and the temporal data coverage is from February 1, 2004 until December 31, 2006 [44]. Hence, for July 25, 2006 in the photosynthetically active radiation (PAR) wavelength range from 400 nm to 700 nm, Landsat 5 TM data provide a spectral SSI of approximately $1514.70 \text{ W m}^{-2} \mu\text{m}^{-1}$, and HELIOCLIM-3 data provide a spectral SSI of approximately $1636.97 \text{ W m}^{-2} \mu\text{m}^{-1}$. Thus, there is good agreement despite the different spans, and the difference in SSIs does not exceed $122.27 \text{ W m}^{-2} \mu\text{m}^{-1}$.

4.2. SSI Time Distribution

The proposed method was also applied to obtain a time-dependent estimate of global SSI from Landsat data (one estimate for each day). For this purpose, all the Landsat 5 images [45] available for 2011 for the Tamenghasset site were considered. However, it should be noted that the disadvantage with this type of data is their availability for a cycle of only 16 days at a fixed time (10 h), as shown in Fig. 8 [Figure 8: see original paper].

Fig. 8 presents the global SSI from the Landsat method compared with that from the Meteosat data, which are freely accessible from the SoDa server [26]. Here, the CAMS radiation service is considered. This service provides time series of global, direct, and diffused radiation for horizontal surfaces as well as direct-to-normal radiation for real and clear weather conditions [26]. A usual variation is obtained according to the day of the year, with a radiation peak in summer for all three methods. However, the fluctuation in the SSI determined

from the Meteosat data is clearly avoided in the proposed approach and is the closest to the theoretical values [42].

Table 5 shows the obtained SSIs with the estimation errors. The three methods agree very well compared with the spectral evaluation. The estimate match is almost perfect, with RMSEs of 31.71 W m^{-2} relative to the Bird and Hulstrom model and 49.47 W m^{-2} relative to the CAMS radiation service.

4.3. SSI Spatial Distribution

Satellite-derived products provide global coverage and therefore account for regional specificities [18]. The SSI is computed for each geographical point of an entire Landsat scene, thus allowing more precision in the obtained values. The produced map (Fig. 9 [Figure 9: see original paper]) is therefore not the result of interpolation of data obtained from a common Geographic Information System (GIS) tool, which could induce a loss of information, particularly if the points are too scattered [46].

With its 30 m resolution, the spatial distribution of the global SSI from Landsat data over Oran on July 13, 2019 (Fig. 9) has local values ranging from a few hundred W m^{-2} to a maximum of 1199 W m^{-2} [43]. This is not the case, for example, with the map produced by the Solar Atlas for the Mediterranean (SOLARMEDATLAS) portal [47], which has good coverage of the Algerian territory but poor spatial resolution at a regional scale, as shown by the solar radiation values in Fig. 10 [Figure 10: see original paper]. It should be noted here that SOLARMEDATLAS is a portal for global horizontal and direct normal solar radiation data for the southern and eastern Mediterranean regions, with a spatial resolution of 1 km [47].

5. Conclusion

This work has proposed a method for estimating global solar radiation from Landsat satellite data. This approach uses an iterative process with an LUT. This is the first use of this type of sensing and serves as an interesting alternative to ground measurement devices.

Three regions in Algeria were selected: Oran, In Amenas, and Tamenghasset. A comparative study was carried out with values obtained from two radiometric models and from Meteosat data. Good agreement was found with maximum RMSEs of $190 \text{ W m}^{-2} \mu\text{m}^{-1}$ for the spectral model and 50 W m^{-2} for the time model.

Finally, under the assumptions made in this investigation, the validity of using Landsat remote sensing data to map the spatial distribution of global radiation has been proved, as supported by the good spatial resolution of these data.

The proposed method has shown significant advantages in accuracy and convenience, and clearly demonstrated its potential for extracting surface physical parameters, particularly surface solar parameters, from remote sensing data.

Potential future investigation consists of covering the entire Algerian territory and considering real sky conditions by taking into account the effect of clouds and integrating the atmospheric transmittances of other sensors like MODIS.

Acknowledgements: This work was supported by the Earth Observation Research Department, Centre des Techniques Spatiales (CTS), Algerian Space Agency (ASAL).

The author thanks Dr. Moussa Sofiane Karoui (CTS, ASAL), Dr. Abdelkrim Mebarki and Dr. Sarra Samra Benharrats (Oran University) (USTO-MB University), for providing help during the research, writing assistance, and proof-reading of the article.

Author Contributions: The author states his exclusive contribution to this work.

Declaration of Interests: The authors declare no competing interests.

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