

Surface solar radiation trends over Europe assessed from ground-based measurements and satellite imagery and their comparison with climate models

L. C. Segado-Moreno¹ J. A. Ruiz-Arias² J. P. Montávez¹

¹Physics of the Earth, Regional Campus of International Excellence (CEIR) "Campus Mare Nostrum", University of Murcia, Spain.

²Department of Applied Physics I, University of Málaga, Málaga, Spain

EGU General Assembly 2023 Vienna, Austria, April 25, 2023



- Downward surface solar radiation (SSR) is the main component of the surface energy budget.
- SSR sustains a large number of natural processes and is the fundamental source of energy in various forms of solar thermal and photovoltaic technologies.
- Changes in SSR can have profound environmental, social and economic implications.



Figure: Schematic diagram of the Earth's global annual average energy balance (Wild et al., 2015).



Figure: Pyranometer, used to measure Global Horizontal Irradiance (GHI), also known as SSR.

- **Ground-based observations** have been the most reliable data source for SSR monitoring.
- However, multi-decadal stations are scarce and located only in specific regions.



Figure: Satellite image in the visible spectrum, obtained by the SEVIRI (Spinned Enhanced Visible and InfraRed Imager) device on board the Meteosat Second Generation (MSG). Source: Eumetsat¹.

- At monthly scale, the uncertainty of **satellite-based estimates** can be comparable to that of ground sensors², with the additional benefit that they are **spatially continuous**³.
- This approach has already been considered by previous studies⁴.

¹https://navigator.eumetsat.int/start.

²Perez et al. (2017)

³With a nominal spatial resolution of \approx 5 km, or finer.

⁴Pfeifroth et al. (2018); Pinker et al. (2005); Sanchez-Lorenzo et al. (2013, 2017).

In summary, this work has two main objectives:

⁵Lee et al. (2022).

Leandro Segado-Moreno

In summary, this work has two main objectives:

• Determining the **capability** of the satellite-based SSR estimations to reproduce surface measurements.

In summary, this work has two main objectives:

• Determining the **capability** of the satellite-based SSR estimations to reproduce surface measurements.

One and a set of the long-term trends of SSR in Europe:

- During the study period from 1994 to 2019.
- For the forthcoming decades up to 2050 based on results of Coupled Model Intercomparison Project Phase 6 (CMIP6) climate model runs under multiple SSP scenarios⁵.

⁵Lee et al. (2022).

Ground-based dataset

SSR measurements used in this study are a **subset** of the Global Energy Balance Archive⁶(**GEBA**) over Europe.

Maintained by the Institute for Climate and Atmospheric Sciences at the ETH Zurich⁷.

Contains **monthly averages** of various energy flux components, including more than 2,500 locations and 500,000 monthly average values.



Figure: Spatial distribution of the GEBA SSR measurement stations.

⁶Gilgen et al. (1998); Gilgen and Ohmura (1999); Wild et al. (2017). ⁷http://www.geba.ethz.ch/



Figure: Cumulative global horizontal irradiance (GHI) map over Spain, provided by Solargis.

Satellite-based dataset

Satellite-based SSR data belong to the high-resolution **Solargis** database⁸.

Built and operated by the Solargis company⁹, SSR database is **generated with a proprietary model** that integrates satellite imagery and weather model outputs.

The Solargis SSR product has undergone multiple validations, proving an **outstanding performance**¹⁰.

Leandro Segado-Moreno

SSR trends from ground-based and satellite imagery

⁸Šúri and Cebecauer (2014).

⁹https://solargis.com

¹⁰Ineichen (2013); Global Solar Atlas (2019).



Figure: SSR estimation model scheme. Source: https://dev.globalsolaratlas.info/ support/methodology.

Satellite-based dataset

Employs satellite imagery from the MFG (1994-2005) and MSG (2005 onwards).

Aerosol extinction is updated daily using AOD from various atmospheric models¹¹.

Thus, this dataset has the important **advantage** over previous studies¹²that it already **includes the aerosol impact on the SSR trend**.

¹¹MERRA-2 (1994-2002); MACC-II (2003-2012); CAMS (2013-onwards). ¹²Pfeifroth et al. (2018); Sanchez-Lorenzo et al. (2017).

Leandro Segado-Moreno

SSR trends from ground-based and satellite imagery

Other datasets

The **CMIP6** dataset (Eyring et al., 2016) involves several independent climate models that quantify the **impact** of standardized **forcing pathways on climate** variables, including SSR.

We have employed SSR average series of **6 CMIP6 different models**, composed of historical series (1994-2014) and projections (2015-2050) under 4 different SSP scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5)

In addition, SSR data from the ECMWF **ERA5** reanalysis (Hersbach et al., 2020) have been also considered.

Selected GEBA stations meet the following criteria:

Selected GEBA stations meet the following criteria:

Latitude is 60° or lower.

Selected GEBA stations meet the following criteria:

Latitude is 60° or lower.

Ominimum number of valid month data of 240 months (i.e., 20 equivalent years).

Selected GEBA stations meet the following criteria:

Latitude is 60° or lower.

- Minimum number of valid month data of 240 months (i.e., 20 equivalent years).
- Ominimum distance between stations of 50 km to prevent collinearity issues.

Selected GEBA stations meet the following criteria:

- Latitude is 60° or lower.
- Minimum number of valid month data of 240 months (i.e., 20 equivalent years).
- Ominimum distance between stations of 50 km to prevent collinearity issues.



Figure: Pre-selected GEBA sites. The color shows the coverage factor (%), i.e., the fraction of valid month data in the period 1994-2019.

Under these criteria, a total of 102 stations were originally pre-selected.



Figure: Region-wide average trend for the GEBA dataset versus minimum time series coverage factor.

- However, data gaps may lead to unrealistic average SSR series and trend values.
- The calculation of the region-wide SSR trend was performed with **3 different methods**.

- Results suggest that methods 2 and 3 are robust against coverage factor.
- A minimum coverage factor of 92% (288 months) was set.
- As a consequence, final selection of GEBA sites was reduced to **64 locations**.



Figure: Selected GEBA station sites. All stations at these sites have a coverage factor of at least 92% and the distance between them is greater than 50 km.

For the satellite and NWP datasets, the monthly SSR values are **bilinearly interpolated** from their native spatial grid to the GEBA **station locations**.

3. Methods

Trend calculation

For the calculation of the wide-area SSR trend over separate-site trend maps and average series, methods 2 and 3 have been used, respectively.

Statistical significance of the trends was asserted with the Mann-Kendall test at a 95% confidence level (Kendall, 1948)

Error metrics

Modelled datasets were compared against the GEBA observations using **MBE, SD and RMSE** metrics.

Deseasonalised anomalies

The deseasonalised time series of anomalies have been obtained by **subtracting** from each monthly value the **average of all values for the same month**.

Homogeneity test

Possible inhomogeneities in the model datasets were detected using the **PELT algorithm** (Wambui et al., 2015) and corrected before any analysis was performed.

3.1 Homogenization of modelled datasets



Figure: Mean monthly ground-observed (up), satellite derived (center) and residual (down) anomaly SSR series for the 1994-2019 period.

Trend mismatch between observations and satellite datasets is mainly related to these **bias inhomogeneities**.

Leandro Segado-Moreno

4. Validation of modelled datasets

Table: Error metrics (MBE, RMSE and SD) obtained for the satellite derived, ERA5 and average CMIP6 datasets. Units are Wm^{-2} .

Dataset	$\mathbf{MBE}\pm\sigma$	$\textbf{RMSE} \pm \sigma$	$\mathbf{SD} \pm \sigma$		
SGv2.3.0	-0.003 ± 4.187	7.657 ± 4.418	76.893 ± 7.029		
ERA5	4.699 ± 6.023	11.902 ± 4.750	77.071 ± 5.997		
CMIP6	7.618 ± 7.882	21.935 ± 5.067	82.059 ± 5.654		



Figure: Mean Bias Error (left) and Root Mean Squared Error (right) for the Solargis dataset, for all the chosen locations, in the period 1994-2019. Units are Wm^{-2}

4. Validation of modelled datasets





Figure: Scatter plot of satellite-estimated versus ground-based SSR measurements over the period 1994-2019. Huber robust regression method was used with a loss factor $\varepsilon = 4.5$.

Figure: Scatter plot of ERA5 dataset versus ground-based SSR measurements over the period 1994-2019. Huber robust regression method was used with a loss factor $\varepsilon=4.5.$

4. Validation of modelled datasets



100 W=0.0299+0.7451x R²=0.7968 10² 1

Figure: Scatter plot of satellite-estimated versus ground-based measurements of SSR deseasonalised, detrended anomalies over the period 1994-2019.

Figure: Scatter plot of ERA5 versus ground-based measurements of SSR deseasonalised, detrended anomalies over the period 1994-2019.

• Trend maps show a widespread increase in SSR during the period 1994-2019 for both GEBA and Solargis datasets.



Figure: Linear trends of the monthly ground-observed (left) and satellite-derived (right) SSR series over Europe during the period 1994-2019. Significant trends (p<0.05) have been marked with black dots.

• Wide-area average trend rates for the period 1994-2019.

Table: Average SSR trends (Wm^{-2} per decade and %) for all datasets during the period 1994-2019.

Dataset	% (Wm $^{-2}$) dec $^{-1}\pm\sigma$				
GEBA	2.48 (3.48) ± 1.98 (2.78)				
SGv2.3.0	$2.45(3.44) \pm 1.51(2.12)$				
ERA5	$1.11(1.61) \pm 0.84(1.22)$				
CMIP6	$0.89~(1.31)\pm0.40~(0.59)$				

• ERA5 and CMIP6 datasets show positive yet significantly lower average trends, as compared to those of GEBA an Solargis.

• Wide-area **average series** from satellite-based estimations **matches** the observational series accurately.



Figure: Monthly SSR deseasonalised anomaly series (dashed lines) of satellite-based (blue) and ground-measured (red) datasets, their 6-month centred moving average series (solid lines) and their trends (straight lines).

• Same plot with the ERA5 and CMIP6 datasets.



Figure: Monthly SSR deseasonalised anomaly series (dashed lines) of satellite-ground-measured (red), ERA5 reanalysis (purple) and average ensemble CMIP6 (green) datasets, their 6-month centred moving average series (solid lines) and their trends (straight lines).

• A similar analysis has been conducted for the seasonal series.



Figure: Seasonal trends of the monthly ground-observed (up) and satellite-derived (down) SSR series over Europe during the period 1994-2019. Significant trends (p<0.05) have been marked with black dots. Values are expressed as Wm^{-2} per decade.

Table: Average seasonal SSR trends (Wm $^{-2}\ {\rm per}\ {\rm decade})$ for all datasets during the period 1994-2019.

Dataset DJF		MAM	JJA	SON	
GEBA	0.84 ± 1.67	4.72 ± 3.53	5.44 ± 5.21	2.94 ± 2.94	
SGv2.3.0	1.97 ± 1.52	5.12 ± 3.30	4.03 ± 3.83	2.65 ± 2.20	
ERA5	-0.15 \pm 1.01	2.12 ± 2.43	3.00 ± 2.99	1.49 ± 1.46	
CMIP6	$\textbf{-0.14} \pm \textbf{0.35}$	1.43 ± 1.16	3.25 ± 1.29	0.73 ± 0.57	

- The highest increases in SSR are observed in spring and summer.
- Low positive trend in SSR during winter, or even negative trends in some stations.
- Satellite-based estimations use to slightly **over-predict** trends in winter and spring, and **under-predict** in summer and autumn.



Figure: Seasonal SSR deseasonalised anomaly series of satellite-based (blue) and ground-measured (red) datasets. The series are expressed as anomalies (Wm⁻²) from the 1994–2019 mean for each month separately.

6. Projected SSR trend

• All scenarios show similar average trends ($\sim 1 \text{ Wm}^{-2}$ per decade).



Figure: Monthly SSR deseasonalised anomaly series of satellite-based (blue) and ground-measured (red) for the period 1994-2019. Average CMIP6 for different CMIP6 models historical and SSP projection SSR series are plotted for the periods 1994-2014 and 2015-2050, respectively. The series are expressed as anomalies (Wm⁻²) from the 1994-2019 mean for each month separately. Color envelopes represent the standard deviation of all models for each scenario.

7. Conclusions

First, SSR from **satellite-based** estimations have been **compared** to **measures** from 64 ground-based stations across Europe. Results show that:

- There is an excellent agreement between ground observations and satellite-based SSR. Satellite-based estimations are able to reproduce approximately 94.8% of the variability of the SSR measured by ground-based observations.
- **Trend** analysis showed a widespread increase in SSR in Europe since 1994, with the highest rates of increase present in the central and southern regions of Europe.
- Trends in satellite and ground-based data overlap properly in space and have almost identical mean rates of about 2.5% (3.5 Wm⁻²) per decade.
- G Results of the seasonal trends study show that:
 - The highest increases in SSR are observed in spring and summer.
 - There was almost **no trend** in SSR during **winter**, or even a negative trend in some stations.
 - Satellite-based estimations slightly over-predict trends in winter and spring, and under-predict in summer and autumn.

7. Conclusions

Second, satellite and ground-based datasets have been compared to monthly SSR outputs from **ERA5** reanalysis and **CMIP6 model means** from different SSP's, for the same temporal period:

- All SSP scenarios show similar trends in SSR.
- Projections show a slight increase in SSR of about 1 Wm⁻² per decade until 2050, with an increasing annual variability.
- Overall, the reliability of these models is inferior to that of satellite-based data, suggesting that there are still uncertainties with regard to climate models SSR prediction.









Thanks for your attention

e-mail: leandrocristian.segadom@um.es





References I

- Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E. (2016). Overview of the coupled model intercomparison project phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, 9(5):1937–1958.
- Gilgen, H. and Ohmura, A. (1999). The global energy balance archive. Bulletin of the American Meteorological Society, 80(5):831–850.
- Gilgen, H., Wild, M., and Ohmura, A. (1998). Means and trends of shortwave irradiance at the surface estimated from global energy balance archive data. Journal of Climate, 11(8):2042–2061.
- Global Solar Atlas (2019). Validation Report for Global Solar Radiation Model. https://documents1.worldbank.org/curated/ en/507341592893487792/pdf/Global-Solar-Atlas-2-0-Validation-Report.pdf.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049.
- Ineichen, P. (2013). Long term satellite hourly, daily and monthly global, beam and diffuse irradiance validation. interannual variability analysis. Technical report. ID: unige:29606.
- Kendall, M. G. (1948). Rank correlation methods.
- Lee, J., Marotzk, J., Bala, G., Cao, L., Corti, S., Dunne, J., Engelbrecht, F., Fischer, E., Fyfe, J., and Jones, C. (2022). 2021: Future global climate: Scenario-based projections and nearterm information.
- Perez, R., Schlemmer, J., Kankiewicz, A., Dise, J., Tadese, A., and Hoff, T. (2017). Detecting calibration drift at ground truth stations a demonstration of satellite irradiance models' accuracy. In 2017 IEEE 44th Photovoltaic Specialist Conference (PVSC), pages 1104–1109. IEEE.
- Pfeifroth, U., Sanchez-Lorenzo, A., Manara, V., Trentmann, J., and Hollmann, R. (2018). Trends and variability of surface solar radiation in Europe based on surface-and satellite-based data records. *Journal of Geophysical Research: Atmospheres*, 123(3):1735–1754.
- Pinker, R., Zhang, B., and Dutton, E. (2005). Do satellites detect trends in surface solar radiation? Science, 308(5723):850-854.
- Sanchez-Lorenzo, A., Enriquez-Alonso, A., Wild, M., Trentmann, J., Vicente-Serrano, S. M., Sanchez-Romero, A., Posselt, R., and Hakuba, M. Z. (2017). Trends in downward surface solar radiation from satellites and ground observations over Europe during 1983–2010. Remote Sensing of Environment, 189:108–117.

References II

- Sanchez-Lorenzo, A., Wild, M., and Trentmann, J. (2013). Validation and stability assessment of the monthly mean CM SAF surface solar radiation dataset over europe against a homogenized surface dataset (1983–2005). *Remote sensing of* environment, 134:355–366.
- Šúri, M. and Cebecauer, T. (2014). Satellite-based solar resource data: Model validation statistics versus user's uncertainty. In ASES SOLAR 2014 Conference, San Francisco, pages 7–9.
- Wambui, G. D., Waititu, G. A., and Wanjoya, A. (2015). The power of the pruned exact linear time (pelt) test in multiple changepoint detection. American Journal of Theoretical and Applied Statistics, 4(6):581.
- Wild, M., Folini, D., Hakuba, M. Z., Schär, C., Seneviratne, S. I., Kato, S., Rutan, D., Ammann, C., Wood, E. F., and König-Langlo, G. (2015). The energy balance over land and oceans: an assessment based on direct observations and CMIP5 climate models. *Climate Dynamics*, 44:3393–3429.
- Wild, M., Ohmura, A., Schär, C., Müller, G., Folini, D., Schwarz, M., Hakuba, M. Z., and Sanchez-Lorenzo, A. (2017). The Global Energy Balance Archive (GEBA) Version 2017: A database for worldwide measured surface energy fluxes. *Earth System Science Data*, 9(2):601–613.

The calculation of the region-wide SSR trend was performed with 3 different methods:

- Method 1 First calculate the average SSR time series throughout all considered sites, then calculate the deseasonalised anomalies of the average SSR time series, and finally compute the trend by linear fitting
- Method 2 First calculate the deseasonalised anomalies site by site, then obtain the trend by linear fitting site by site, and finally obtain the average trend.
- Method 3 Calculate the deseasonalised anomalies for each site, then calculate the average anomaly throughout all considered sites and finally compute the trend by linear fitting of the averaged anomaly.

Appendix: selected CMIP6 models

Table: Selected CMIP6 models and their main features. Source: https://www.cesm.ucar.edu/community-projects/mmlea

Modeling Center	Model Version	Model Resolution (atm/ocn)	Initialization Method	Forcing (Number of Members)	Reference (*ESGF reference)
CCCma	CanESM5	${\sim}2.8^{\circ}{\times}2.8^{\circ}/{\sim}1.4^{\circ}{\times}0.9^{\circ}$	Macro	historical (50), ssp126 (50), ssp245 (50), ssp370 (50), ssp585 (50)	Swart et al. (2019)
CNRM	CNRM-CM6-1	${\sim}1.4^{\circ}{\times}1.4^{\circ}/\text{nominal}~1^{\circ}$	Macro	historical (30), ssp126 (6), ssp245 (10), ssp370 (6), ssp585 (6)	*Voldoire (2018)
EC-Earth Consortium	EC-Earth3	${\sim}0.7^{\circ}{\times}0.7^{\circ}/\text{nominal}~1^{\circ}$	Macro	historical (23), ssp126 (7), ssp245 (5), ssp370 (7), ssp585 (7)	*EC-Earth Consortium (2019)
NASA	GISS-E2-1-G	${\sim}2^\circ{\times}2.5^\circ/{\sim}1^\circ{\times}1.25^\circ$	Macro	historical (40), ssp126 (2), ssp245 (15), ssp370 (2), ssp585 (2)	*NASA GISS (2019)
Met Office	UKESM1-0-LL	${\sim}1.25^{\circ}{\times}1.9^{\circ}/\text{nominal}~1^{\circ}$	Macro	historical (17), ssp126 (5), ssp245 (5), ssp370 (5), ssp585 (5)	*Tang et al. (2019)
MIROC	MIROC6	${\sim}1.4^{\circ}{\times}1.4^{\circ}/\text{nominal}~1^{\circ}$	Macro	historical (50), ssp126 (50), ssp245 (50), ssp370 (3), ssp585 (50)	Tatebe et al. (2019)

Appendix: selected GEBA sites

No.	Station	Country	Longitude (º)	Latitude (º)	No.	Station	Country	Longitude (º)	Latitude (º)
1	Sonnblick	AT	12.95	47.05	33	Ajaccio	FR	8.80	41.92
2	Graz	AT	15.45	46.98	34	Malin Head, C.	IE	-7.33	55.37
3	Klagenfurt	AT	14.33	46.65	35	Belmullet	IE	-10.00	54.23
4	Locarno-Monti	CH	8.78	46.17	36	Dublin Airport	IE	-6.25	53.43
5	Hradec Kralove	CZ	15.85	50.25	37	Valentia	IE	-10.25	51.93
6	Ostrava-Poruba	CZ	18.15	49.82	38	Kolobrzeg	PL	15.58	54.18
7	Churanov	CZ	13.62	49.07	39	Belsk	PL	20.78	51.83
8	Kucharovice	CZ	16.08	48.88	40	Zakopane	PL	19.97	49.28
9	Braunschweig	DE	10.45	52.3	41	Stockholm	SE	17.95	59.35
10	Wuerzburg	DE	9.97	49.77	42	Kiev	UA	30.45	50.40
11	Trier	DE	6.67	49.75	43	Odessa	UA	30.63	46.48
12	Weihenstephan	DE	11.70	48.40	44	Wien-Hohe-Warte	AT	16.37	48.25
13	Hohenpeissenberg	DE	11.02	47.8	45	Praha / (Prag-Karlov)	CZ	14.43	50.07
14	Santander	ES	-3.82	43.47	46	Zuerich-Kloten	CH	8.53	47.48
15	Oviedo	ES	-5.87	43.35	47	Hamburg	DE	10.00	53.63
16	Madrid	ES	-3.72	40.45	48	Bastia	FR	9.48	42.55
17	Murcia	ES	-1.17	38.00	49	Karlstad	SE	13.47	59.37
18	Caen	FR	-0.47	49.18	50	Lund	SE	13.22	55.72
19	Strassburg	FR	7.63	48.55	51	Norrkoepping	SE	16.25	58.58
20	Rennes	FR	-1.73	48.07	52	Vaexjoe / Kronoberg	SE	14.73	56.93
21	Tours	FR	0.72	47.45	53	Visby - Aerolog. Station	SE	18.35	57.67
22	Dijon	FR	5.08	47.27	54	Basel	CH	7.58	47.55
23	Nantes	FR	-1.60	47.17	55	Brest	FR	-4.42	48.45
24	La Rochelle	FR	-1.15	46.15	56	Bourges	FR	2.37	47.07
25	Limoges	FR	1.28	45.82	57	Bregenz	AT	9.75	47.50
26	Clermont-Ferrand	FR	3.17	45.78	58	Salzburg / Freisal	AT	13.05	47.78
27	Bordeaux	FR	-0.70	44.83	59	La Coruna	ES	-8.42	43.37
28	Embrun	FR	6.50	44.57	60	Valladolid	ES	-4.77	41.65
29	Nice	FR	7.20	43.65	61	Montelimar	FR	4.73	44.58
30	Montpellier	FR	3.97	43.58	62	Zoseni	LV	25.90	57.14
31	Marignane	FR	5.22	43.43	63	Geneve-Cointrin	CH	6.12	46.24
32	Perpignan	FR	2.87	42.73	64	Payerne (BSRN)	СН	6.94	46.82

Appendix: GEBA, ERA5 and CMIP6 average series



Figure: SSR series of ground-measured (red), ERA5 (purple) and CMIP6 (green) datasets. The series are expressed as Wm^{-2} for the 1994–2019 period, together with their respective linear trends.