

Article

Assessing the Impact of Solar Spectral Variability on the Performance of Photovoltaic Technologies Across European Climates

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Abstract

Precise photovoltaic (PV) performance modeling is essential for optimizing system design, operational monitoring, and reliable power forecasting—yet spectral correction is often overlooked, despite its significant impact on energy yield uncertainty. This study employs the FARMS-NIT model to assess the impact of spectral irradiance on eight PV technologies across 79 European sites, grouped by Köppen–Geiger climate classification. Unlike previous studies limited to clear-sky or single-site analysis, this work integrates satellite-derived spectral data for both all-sky and clear-sky scenarios, enabling hourly, tilt-optimized simulations that reflect real-world operating conditions. Spectral analyses reveal European climates exhibit blue-shifted spectra versus AM1.5 reference, only 2–5% resembling standard conditions. Thin-film technologies demonstrate superior spectral gains under all-sky conditions, though the underlying drivers vary significantly across climatic regions—a distinction that becomes particularly evident in the clear-sky analysis. Crystalline silicon exhibits minimal spectral sensitivity (<1.6% variations), with PERC/PERT providing highest stability. CZTSSe shows latitude-dependent performance with ≤0.7% variation: small gains at high latitudes and losses at low latitudes. Atmospheric parameters were analyzed in detail, revealing that air mass (AM), clearness index (K_t), precipitable water (W), and aerosol optical depth (AOD) play key roles in shaping spectral effects, with different parameters dominating in distinct climate groups.

Keywords: spectral irradiance; photovoltaic performance; PV modeling; FARMS-NIT; spectral effects; crystalline silicon; thin-film



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1. Introduction

Atmospheric carbon dioxide (CO₂) levels have been rising at an alarming rate, reaching unprecedented concentrations in recent years. At the Mauna Loa Observatory in Hawaii, widely regarded as a benchmark for global CO₂ trends, measurements recorded a jump to 427 parts per million (ppm) in 2024, marking the largest annual increase since records began in 1958 [1]. Renewable energy sources, led by solar photovoltaics (PV), offer a promising solution to mitigate rising CO₂ emissions by displacing fossil fuel-based electricity generation. Solar PV systems, which produce electricity with significantly lower carbon intensity, ranging from 15 to 38 gCO₂/kWh compared to the 500 gCO₂/kWh typical

of fossil fuel grids, can make a substantial contribution to reducing global greenhouse gas emissions [2]. Over the past two decades, the PV industry has achieved notable gains in energy conversion efficiency and dramatic reductions in solar panel costs [3]. Global PV deployment is accelerating rapidly, with the European Union targeting over 320 GW of installed solar capacity by 2025 and nearly 600 GW by 2030 under the REPowerEU plan [4]. In the United States, 32.5 GW of new utility-scale solar capacity is projected to be added in 2025, accounting for more than half of all planned capacity additions that year [5]. The rapid expansion of solar PV underscores its critical role in clean energy transitions, necessitating enhanced power system flexibility and advanced performance modeling to optimize generation, ensure reliability, and maintain grid security throughout system lifecycles. High-precision PV performance modeling enables precise design-phase simulations, real-time operational monitoring, and reliable power forecasts, thereby enhancing grid integration and supporting energy trading strategies. Large-scale initiatives like the Sandia National Laboratories PV Performance Modeling Project [6] have shown that robust modeling and thorough validation are essential for advancing PV system performance and reducing uncertainty. For instance, a recent intercomparison study of the IEC 61853 standard [7], involving 10 research institutions, demonstrated how collaborative validation of energy rating algorithms can reduce discrepancies in Climate-Specific Energy Rating (CSER) calculations from 14.7% to under 0.1%, establishing best practices for spectral correction and power matrix extrapolation to ensure consistency across modeling frameworks [8].

To ensure precise PV performance modeling, it is essential to account for the three primary factors that govern PV cell efficiency: irradiance, temperature, and the solar spectrum. While temperature and broadband irradiance are routinely measured and incorporated into both research and field modeling, the spectral composition of sunlight is often overlooked. This is largely because standardized testing and power ratings rely on a single reference spectrum (AM1.5), defined in IEC 60904-3 standard [9], which simplifies comparisons but fails to capture the real-world spectral variability caused by atmospheric conditions, geographic location, and time of day. High-resolution spectral measurements, though most accurate, remain rare outside specialized laboratories due to the cost and complexity of spectroradiometers. Measurement campaigns and research on how the solar spectrum affects PV performance are often limited in duration and only cover part of the full wavelength range. They also tend to use different types of equipment and methods, which makes it difficult to compare results between studies or to accurately estimate uncertainty. As a result, most PV models treat spectrum effects as secondary, even though recent studies have shown that spectral mismatches can cause significant variations in energy yield, especially for advanced and multi-junction cell technologies. The study [10] evaluated annual energy yield across nine PV technologies under real-world spectral conditions. Single-junction silicon showed smaller efficiency deviation (± 1 –5%) from the AM1.5 spectrum, while multi-junction designs exhibited larger losses: III-V 6-junction cells had 12–25% lower annual efficiencies, and perovskite-based tandems (CIGS/Si) varied by 8–18% depending on geographic spectral conditions. The authors of [11] analyzed spectral irradiance in Lima, Peru, revealing annual average photon energy (APE) of 1.923 eV and spectral gains of +6.8% (amorphous silicon, a-Si), +4.8% (perovskite), and +2.1% (cadmium telluride, CdTe), with losses of up to -2.3% (monocrystalline silicon, mono-Si). The study highlights minimal seasonal spectral variation, emphasizing the advantage of high-bandgap technologies in blue-rich, low-latitude climates. In [12], a PV model incorporating spectral and angular irradiance details was developed, validated against SIRTa measurements [13], and found that neglecting spectral resolution introduces errors up to 15% in power simulations. Clouds increase crystalline silicon performance by 5% via near-infrared (NIR) filtering, with a further 18% gains when considering only useful spectral

ranges. The study underscores the necessity of spectral/angular-refined irradiance inputs, particularly under variable cloud cover. Another study [14] evaluated spectral irradiance impacts on mono-Si and perovskite cells using optical filters, revealing mono-Si's 7–13% current gains under high-pass filters (515–550 nm) and perovskite's dual-peak response (visible/infrared). Simulations showed copper indium selenide (CIS) outperformed CdTe in NIR, producing 50% of CdTe's visible-zone energy. The study validates a spectral factor model for HP-filtered conditions, emphasizing technology-specific spectral adaptability. Ref. [15] analyzed the performance of various PV technologies under real-world spectral conditions, demonstrating that thin-film modules like a-Si and copper indium gallium selenide (CIGS) outperform crystalline silicon in environments with significant temperature fluctuations due to their spectral adaptability and lower temperature coefficients. Their study, incorporating SMARTS2 modeling and global case analyses, emphasizes the critical role of site-specific spectral and climatic factors in optimizing PV energy yield. The findings highlight the necessity of tailored technology selection to maximize efficiency in diverse geographical settings.

Incorporating spectral effects-alongside irradiance and temperature-into modeling frameworks is therefore increasingly recognized as vital for reducing uncertainty and optimizing PV system performance under actual operating conditions. The limitations of spectral modeling in widely used PV simulation tools such as PV*SOL and PVsyst are evident in their current frameworks. In some cases, spectral effects are entirely omitted during simulations, as demonstrated in [16] to standardize comparisons between tools. Alternatively, PVsyst utilizes simplified methods, as described in [17], that rely on variables such as air mass (AM), clearness index (K_t), and precipitable water content (W) to approximate the effects of spectral mismatch. Although more accurate models based on additional variables, as in the research by [18], or based on direct spectral measurements [19,20], have been developed, current simulation tools do not support their integration.

While existing research has advanced our understanding of spectral impacts on PV performance, critical methodological and practical limitations persist across studies. Software constraints remain a primary concern, as widely used tools are restricted to clear-sky modeling, neglecting spectral behavior under overcast conditions where cloud cover alters irradiance composition through scattering and absorption effects. Geographical limitations further constrain generalizability, with many studies focusing on single locations or narrow climatic zones, limiting insights into latitudinal or microclimate-driven spectral variations. Measurement practices introduce additional biases: spectroradiometer data are frequently collected on horizontal surfaces rather than the tilt angles that maximize PV yield for specific latitudes, distorting the spectral profiles incident on operational panels. Furthermore, temporal restrictions plague the field, with most campaigns spanning days to months—insufficient to capture seasonal spectral shifts or interannual variability. These gaps collectively hinder the development of universally applicable spectral correction models.

This article presents comprehensive research on the impact of spectral irradiance on PV performance across eight different PV technologies. A total of 79 European locations were analyzed and categorized into four groups based on the Köppen–Geiger climate classification [21,22], similar to the approach taken in the study [23]; however, in that work, only irradiance and temperature were considered as inputs for PV tool comparison against real data, with spectral effects neglected. This study utilized the Fast All-sky Radiation Model for Solar applications with Narrowband Irradiances on Tilted surfaces (FARMS-NIT) to compute one-year solar spectral irradiance data at an hourly scale, providing a detailed understanding of the interplay between spectral conditions and PV efficiency across diverse climatic regions for both all-sky and clear-sky conditions. The results are evaluated to

quantify how each technology's spectral sensitivity interacts with atmospheric drivers such as AM, K_t , W, and aerosol optical depth (AOD). This study further investigates intra-climate spectral variability. While climate zones broadly correlate with spectral behavior, the research reveals significant deviations in spectral mismatch losses (up to 6%) among locations sharing the same climate type, driven by divergent atmospheric parameters. These findings challenge the sufficiency of climate-based categorization alone for spectral optimization, underscoring the need for a revised classification framework. Such a model, building on FARMS-NIT's parameterized spectral simulations, could enable finer spatial resolution (sub-climate microzones) and improve energy yield predictions.

2. Materials and Methods

2.1. Modeling Site-Specific Spectral Irradiance Using FARMS-NIT and Satellite Data

Satellite-based spectral irradiances for all locations in this study were derived using the National Renewable Energy Laboratory's National Solar Radiation Database Spectral On-Demand service [24], which employs the Fast All-sky Radiation Model for Solar Applications with Narrowband Irradiances on Tilted Surfaces (FARMS-NIT) [25,26] to generate synthetic spectra based on site-specific atmospheric and cloud conditions. FARMS-NIT is a radiative transfer model developed by NREL to compute spectral irradiance for PV applications, efficiently producing 2002 narrowband wavelengths (280–4000 nm) for both clear and cloudy skies. The NSRDB Spectral On-Demand tool leverages FARMS-NIT's capabilities to provide synthetic spectra tailored to specific locations, time intervals, and PV orientations, functioning as an interface that integrates FARMS-NIT outputs with user-defined inputs [27]. To achieve accurate modeling, the tool combines atmospheric data from the MERRA-2 reanalysis (including aerosols, ozone, and water vapor), satellite-derived cloud properties, and MODIS albedo (land surface albedo values derived from the Moderate Resolution Imaging Spectroradiometer on NASA's Terra and Aqua satellites). For Europe and Africa, the NSRDB Spectral On-Demand service uses cloud property retrievals from Meteosat satellites [28] (specifically Meteosat-10 and Meteosat-11), ensuring high spatial and temporal resolution for these regions. This approach, whose physical solar model workflow is shown in Figure 1 [29], ensures that the synthetic spectra accurately reflect local atmospheric and cloud conditions, making the NSRDB Spectral On-Demand service a robust and versatile tool for advanced PV performance modeling and spectral mismatch analysis. The NSRDB Spectral On-Demand service was recently validated by studies [30,31], who compared its synthetic spectral irradiance data to high-quality ground-based measurements at multiple sites. Both studies found that the service delivers reliable and accurate spectral data for PV modeling, achieving mean bias errors within 5% for most wavelengths and significantly improving spectral mismatch predictions compared to non-spectral models. While minor biases were noted—particularly in aerosol treatment and visible/NIR irradiance under specific cloud conditions, the service provides robust, globally applicable spectral data, making it highly valuable for advanced PV performance analysis and energy yield optimization. In [32], the author employed the FARMS-NIT model via NREL's NSRDB Spectral On-Demand tool to generate synthetic spectral irradiance data for specific locations in North and South America. While the study aimed to analyze global spectral impacts on PV technologies, the NSRDB tool's implementation of FARMS-NIT at the time was primarily configured for the Americas, leveraging GOES satellite data for cloud properties and MERRA-2 reanalysis for aerosols, ozone, and water vapor. The analysis focused on fixed-tilt (latitude-angle) PV configurations, generating hourly spectral irradiance (280–4000 nm) for selected sites across these regions. However, the reliance on latitude-based tilt angles introduces significant limitations, particularly in higher latitudes where deviations between latitude-derived angles and true optimal tilts exceed 10–15°. For

example, at a 50° latitude, PVGIS-optimized angles typically range from 35 to 40° for annual yield maximization—a 20–30% reduction from the latitude-angle approach—resulting in spectral irradiance distortions of 5–8% due to suboptimal incidence angles. However, this regional application highlighted FARMS-NIT’s capability to model site-specific spectral variability under diverse atmospheric conditions, particularly in climates with high aerosol loads (coastal areas) or significant cloud cover. In [33], the authors investigated spectral mismatch correction for CdTe and c-Si PV modules using FARMS-NIT-derived spectral data, developing the Spectral 3.0 model to account for cloud cover via clear-sky index, which reduced irradiance-weighted prediction errors by 21–31% compared to prior methods. Ref. [34] investigated PV module performance across the contiguous United States using the FARMS-NIT model to simulate spectral irradiance and quantify climatic effects on energy yield. The study revealed that CdTe modules achieved the highest climate-specific efficiency (CSER) due to spectral gains and low temperature sensitivity, outperforming silicon technologies by up to 4.9% in spectral mismatch. Temperature emerged as the dominant performance driver, causing efficiency losses up to 13.1% in hot climates. The authors critiqued the IEC 61853 reference datasets for overestimating CSER and proposed revised representative locations. This work highlights the important role of spectral and thermal modeling (via FARMS-NIT) in optimizing PV technology deployment for diverse climates. Ref. [35] investigated spectral mismatch losses in 11 commercial PV modules, focusing on intramodule external quantum efficiency (EQE) variation by measuring EQE of every individual cell within each module. Using FARMS-NIT-simulated spectra across the contiguous USA, the study found annual energy losses of 0.1–0.2% due to cell-level EQE differences, primarily driven by wavelength-dependent variations in poly-Si modules. Seasonal fluctuations reached $\pm 0.5\%$, with humid climates exacerbating losses.

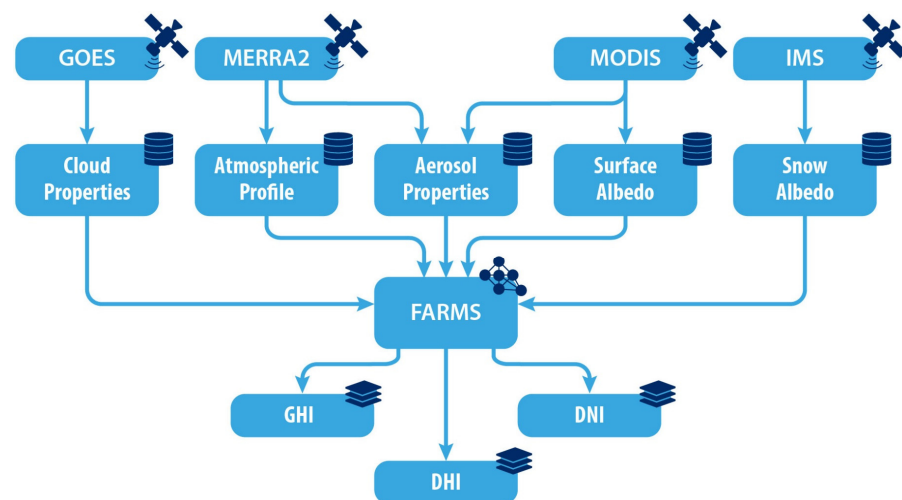


Figure 1. NSRDB: physical solar model workflow [29].

2.2. Methodology and Data

To systematically assess the leading PV technologies currently at the forefront of research and commercial deployment, eight representative types of PV cells were selected for comparative analysis. The selection encompasses both established and emerging cell architectures, ensuring a comprehensive overview of the technological landscape. To capture the diversity and technological progression of crystalline silicon (c-Si), four representative types were selected: mono-Si PERC, mono-Si N-type PERT, mono-Si HIT, and poly-Si Al-BSF, whose external quantum efficiency profiles were documented through standardized characterization protocols in [36]. Mono-Si PERC, now the industry standard, employ a passivated rear surface to boost efficiency and are included as the benchmark for

modern commercial modules. Mono-Si N-type PERT, featuring an n-type substrate and fully diffused rear, are analyzed for their improved efficiency and growing prominence among next-generation silicon technologies. Mono-Si HIT, which integrate crystalline silicon wafers with thin amorphous silicon layers, exemplify the highest performance currently achievable in commercial silicon PV, while poly-Si Al-BSF, representing the previous generation of mass-produced modules, is included to illustrate the rapid evolution and ongoing replacement of older designs. CZTSSe (copper zinc tin sulfide selenide) was included in this analysis as a representative of emerging thin-film PV technologies, owing to its potential for low-cost, earth-abundant, and non-toxic material composition, as well as its ongoing development toward higher efficiencies and commercial viability [37]. Cadmium telluride (CdTe) and amorphous silicon (a-Si) technologies were also included in this analysis, broadening the comparison to encompass key thin-film PV technologies with distinct spectral responses. The spectral response measurements for both a-Si and CdTe were conducted at the Photovoltaic Research Laboratory of the Materials Science and Renewable Energy Group (MatER-PUCP) at Pontificia Universidad Católica del Perú [38]. Additionally, perovskite was included to reflect the most recent advances in high-efficiency PV technologies. The spectral and efficiency data for this state-of-the-art PV technology were provided by author of [39], based on the most up-to-date, independently confirmed measurements, representing the current best confirmed efficiency in its class.

To facilitate direct comparison across diverse PV technologies, these spectral responses were normalized to unity. The resulting normalized spectral response curves for all eight PV technologies are presented in Figure 2, providing a clear visualization of their respective sensitivities to different regions of the solar spectrum. The spectral responses (A/W) of these technologies can be derived from official EQE measurements, using the following relationship:

$$SR(\lambda) = EQE(\lambda) \cdot \frac{q\lambda}{hc}, \quad (1)$$

where h represents the Planck's constant ($J \cdot s$), c is the speed of light in vacuum ($m \cdot s^{-1}$), q is the elementary charge, and λ is the wavelength (nm). The normalization of spectral response to unity serves two critical purposes in PV analysis: visual clarity when comparing the spectral sensitivities of different technologies and computational simplicity for calculating spectral mismatch factors. This process removes absolute magnitude differences between technologies, allowing researchers to focus on relative performance across wavelengths. To achieve this, the spectral response is normalized using the following relationship:

$$SR_{norm}(\lambda) = \frac{SR(\lambda)}{\max[SR(\lambda)]} = \frac{EQE(\lambda) \cdot \frac{q\lambda}{hc}}{\max\left[EQE(\lambda) \cdot \frac{q\lambda}{hc}\right]} = \frac{EQE(\lambda) \cdot \lambda}{\max[EQE(\lambda) \cdot \lambda]}, \quad (2)$$

For this analysis, hourly spectral irradiance values were obtained for the entire year of 2019, as this is one of the years available for Europe (with coverage for 2017–2019). Prior to analysis, the dataset was thoroughly cleaned by removing all hourly values containing negative or missing entries to ensure data quality and reliability. For each location, the optimal tilt angle, also referred to as the optimal inclination angle, was first determined using PVGIS [40], and this site-specific angle was then applied in the spectral simulation. This approach was selected as the logical standard because maximizing annual energy yield is the primary goal in real-world PV system deployment, and the optimal tilt angle ensures the highest possible solar energy capture for each specific location. PVGIS determines this angle by simulating the solar irradiation received at various tilt angles and selecting the one that produces the maximum annual output, using high-resolution meteorological data

and advanced transposition models. PVGIS achieves high accuracy through its anisotropic Hay–Davis–Klucher–Reindl (HDKR) sky model, which precisely models diffuse radiation by accounting for directional brightness variations rather than assuming uniform distribution. The system integrates satellite-derived meteorological data like PVGIS-SARAH-3 and ERA-5 to dynamically adjust for localized cloud patterns and temperature-dependent efficiency losses. Finally, 90 m-resolution digital elevation models enable terrain-aware optimization by resolving shading effects and albedo variations. Research [41] emphasized PVGIS’s integration of anisotropic sky models and terrain-aware simulations, with multi-regional validation confirming <5% uncertainty in irradiation estimates, solidifying its role in global solar resource assessment. PVGIS outperformed the Hottel–Woertz method in [42], showing <5% deviation from experimental data and up to 17.16% energy gains with monthly tilt adjustments, validating its precision in high-latitude continental climates. Experimental validation in South-South/South-East Nigeria [43] confirmed PVGIS-optimized tilt angles align with equatorial solar geometry, achieving annual energy yield improvements consistent with spectral and climatic variability patterns. The study demonstrated optimal angles between 10 and 12° maximized photon capture efficiency during dominant clear-sky periods while mitigating spectral losses from high aerosol optical depths characteristic of West Africa’s harmattan season. In contrast, international standards such as IEC 61853-3, described and evaluated through an interlaboratory comparison study [44], specify a fixed tilt angle of 20° for all climates during spectral and performance testing to provide a uniform, reproducible basis for comparing module performance across different products and laboratories, regardless of local climate or latitude. This standardized approach is not intended to reflect real-world optimal installation but rather to ensure consistency and comparability in laboratory measurements and certification processes.

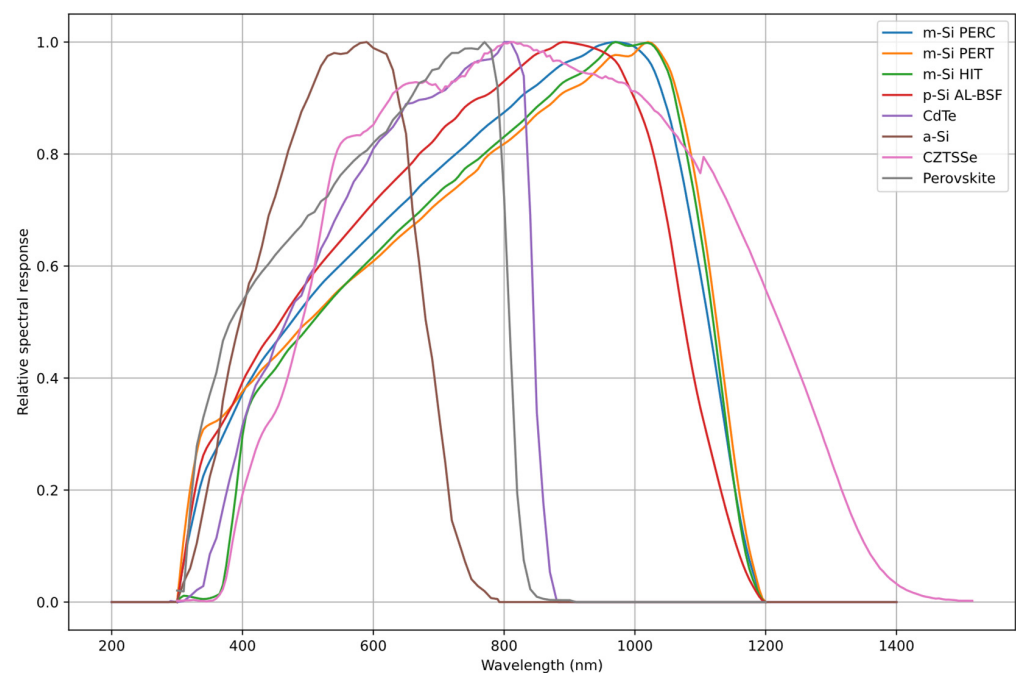


Figure 2. Normalized spectral responses of eight single-junction PV technologies.

To assess the influence of climatic variations on simulation outcomes, 79 locations across Europe were selected based on the Köppen–Geiger climate classification to encompass a broad geographic and climatic diversity (Figure 3). For countries spanning multiple zones, one representative site per climate category was included to ensure comprehensive coverage of regional meteorological conditions. However, notable exceptions were made for larger countries with extensive latitudinal ranges, where multiple locations within the

same climate zone were strategically selected to capture intra-climate variability across latitudes. Sites were grouped into four representative clusters: arid steppe climates (BSH and BSk), temperate zones with seasonal precipitation contrasts (Cfa, Csa and Csb), maritime temperate climates (Cfb), and humid continental climates (Dfb), as detailed in Table 1. This grouping captures key spectral influencers: aridity, Mediterranean seasonality, oceanic cloud regimes, and continental temperature extremes—to systematically evaluate PV performance across Europe’s dominant climate regimes. To evaluate how the climatic diversity across these sites influences PV performance, the analysis shifts to quantifying spectral effects through spectra synthesized from key atmospheric parameters and de-vice-specific responses. First, the average photon energy (APE) is used as a PV-device in-dependent index that quantifies the spectral distribution of solar irradiance by calculating the mean energy per photon, making it particularly useful for comparing spectral variations across different environmental conditions and locations. Its strength lies in providing a single-value metric to assess blue or red shifts in sunlight spectra, enabling straight-forward analysis of spectral impacts on PV performance without requiring technology-specific parameters. It can be written as follows:

$$APE = \frac{\int E(\lambda) d\lambda}{q \int \Phi(\lambda) d\lambda}, \quad (3)$$

where $E(\lambda)$ is the solar irradiance distribution across wavelengths incident on the PV device ($\text{W} \cdot \text{m}^{-2} \cdot \text{nm}^{-1}$), q is a conversion factor equivalent to the electron charge. APE has units of electronvolts (eV). $\Phi(\lambda)$ represents the photon flux density that can be calculated as follows:

$$\Phi = \frac{E(\lambda)}{hc/\lambda}, \quad (4)$$

where h represents the Planck’s constant and c is the speed of light in vacuum.

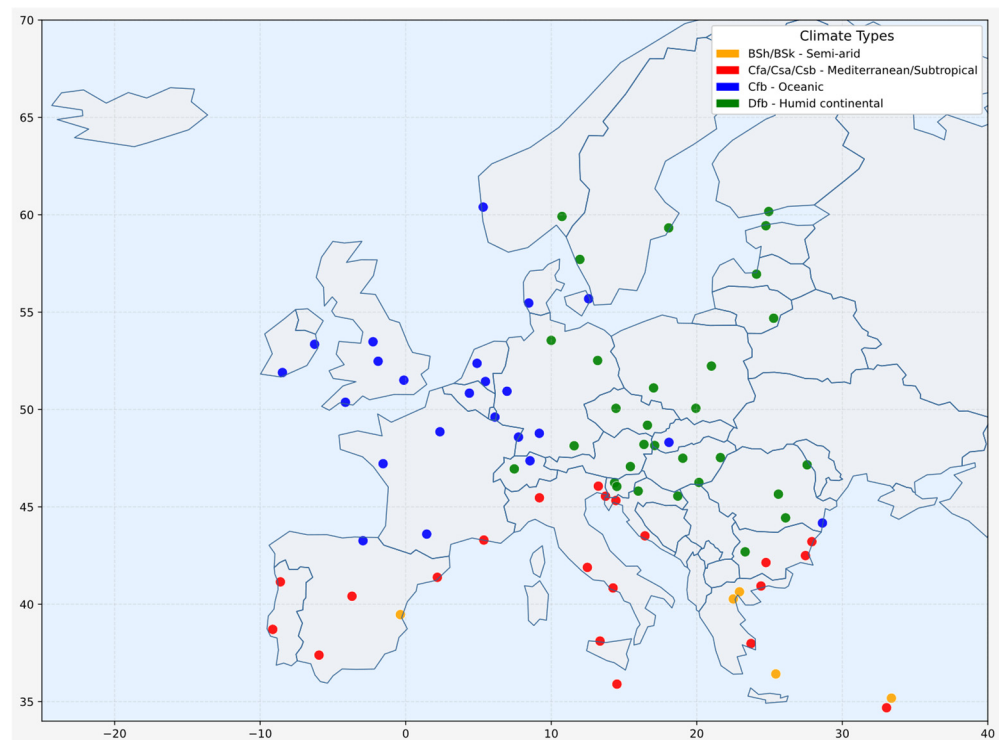


Figure 3. Climate classification of study sites in Europe.

Table 1. Classification of sites according to the climate type.

Group No.	Climate Types	No. of Locations
1	BSh, BSk	5
2	Cfa, Csa, Csb	21
3	Cfb	23
4	Dfb	30

The spectral mismatch factor (MM) and its simplified derivative, the spectral factor (SF), are PV device-dependent indexes that provide a framework for assessing deviations caused by variations in solar spectral irradiance and PV module characteristics. The spectral mismatch factor is an index that quantifies the relative spectral impact between a sample PV device and a reference PV device. It accounts for differences in their spectral responses under varying solar spectra and is critical for correcting measurements when the reference device's spectral sensitivity differs from the sample. This relationship is expressed as follows:

$$MM = \frac{\int E(\lambda)SR(\lambda)d\lambda}{\int E^*(\lambda)SR(\lambda)d\lambda} \times \frac{\int E^*(\lambda)SR_{ref}(\lambda)d\lambda}{\int E(\lambda)SR_{ref}(\lambda)d\lambda}, \quad (5)$$

where $E(\lambda)$ characterizes the solar power distribution across wavelengths incident on the PV device, and $E^*(\lambda)$ refers to the corresponding standard reference spectrum. The absolute or relative spectral response (SR) quantifies the PV device's wavelength-dependent current generation efficiency, while SR_{ref} characterizes the analogous response of the reference device. Using an ideal PV device with flat spectral response across all solar wavelengths as the reference simplifies the spectral mismatch factor to the spectral factor (SF). The spectral factor is mathematically expressed as follows:

$$SF = \frac{\int E(\lambda)SR(\lambda)d\lambda}{\int E^*(\lambda)SR(\lambda)d\lambda} \times \frac{\int E^*(\lambda)d\lambda}{\int E(\lambda)d\lambda}, \quad (6)$$

where integrals of the reference spectrum and incident spectrum correspond to the broadband irradiance (G^* and G , respectively) under reference and actual conditions, representing the total solar power per unit area across the full-range spectral distribution (280–4000 nm). The integral of the product of the incident spectral irradiance and the spectral response of the solar cell over the relevant wavelength range represents the normalized or absolute short-circuit current density (J_{sc}) generated by the device under those spectral conditions ($A \cdot m^{-2}$). If the absolute spectral response is available, this integral directly yields the absolute current density, calculated as follows:

$$J_{sc} = \int E(\lambda)SR_a(\lambda)d\lambda = [SR_a(\lambda)]_{max} \int E(\lambda)SR_{norm}(\lambda)d\lambda. \quad (7)$$

This integral quantifies the total charge carrier flux produced when the cell's spectral response interacts with the wavelength-dependent irradiance, effectively summing contributions across the solar spectrum to yield the current per unit area. The lower and upper limits of the integral correspond to the wavelength range within which the PV device's semiconductor material exhibits significant photon absorption, typically bounded by its bandgap energy and spectral response cutoff. The short-circuit current of a PV device can be determined by integrating its spectral response with the incident spectral irradiance $E(\lambda)$ across the wavelength range where the device exhibits sensitivity. The corresponding equation is as follows:

$$I_{sc} = A \int E(\lambda)SR_a(\lambda)d\lambda = A[SR_a(\lambda)]_{max} \int E(\lambda)SR_{norm}(\lambda)d\lambda = A \cdot J_{sc}, \quad (8)$$

where A is the effective area of the PV module. By unifying the formulations presented in Equations (5) and (6) through algebraic synthesis, Equation (4) condenses to

$$SF = \frac{J(\lambda)}{J(\lambda)^*} \cdot \frac{G^*}{G} = \frac{A \cdot [SR_a(\lambda)]_{max} \int E(\lambda) SR_{norm}(\lambda) d\lambda}{A \cdot [SR_a(\lambda)]_{max} \int E(\lambda)^* SR_{norm}(\lambda) d\lambda} \cdot \frac{G^*}{G} = \frac{I_{sc} \cdot G^*}{I_{sc}^* \cdot G} \quad (9)$$

In this study, the monthly and yearly irradiance-weighted spectral factor (SF_t) was calculated for all locations to quantify spectral gains/losses over these periods, using the formula

$$SF_t = \frac{\sum_i G_i \cdot SF_i}{\sum_i G_i} \quad (10)$$

where G_i is the broadband irradiance and SF_i is the instantaneous spectral factor at time i . This metric quantifies the energy-weighted spectral influence relative to the reference spectrum across the device's operational wavelength range, with values exceeding unity signifying net spectral gains and those below unity indicating losses.

3. Results and Discussion

As mentioned earlier, this study conducts a dual analysis of spectral impacts on PV performance through all-sky and clear-sky simulations to address distinct atmospheric regimes and their energy yield implications. The all-sky assessment captures real-world spectral variability across diverse weather conditions—including cloud scattering, aerosol interactions, and seasonal atmospheric composition shifts—enabling annualized quantification of spectral gains/losses under operational environments. Concurrently, the clear-sky analysis isolates spectral behavior during peak production periods, where minimal cloud interference allows direct evaluation of baseline atmospheric drivers (AM, W, AOD) and their technology-specific spectral modulation. This combined approach resolves limitations of prior studies constrained to single-scenario modeling. By integrating both regimes, the analysis advances spectral correction frameworks for energy forecasting. The analysis leverages global spectral data from the National Solar Radiation Database (NSRDB), with Figure 4 demonstrating that annual global irradiance-weighted spectra across all four climate types show enhanced power density in the visible spectrum (400–700 nm) compared to the standard AM1.5 spectrum. All spectra were normalized to the AM1.5 reference at 1050 nm to enable direct comparison of spectral shape variations.

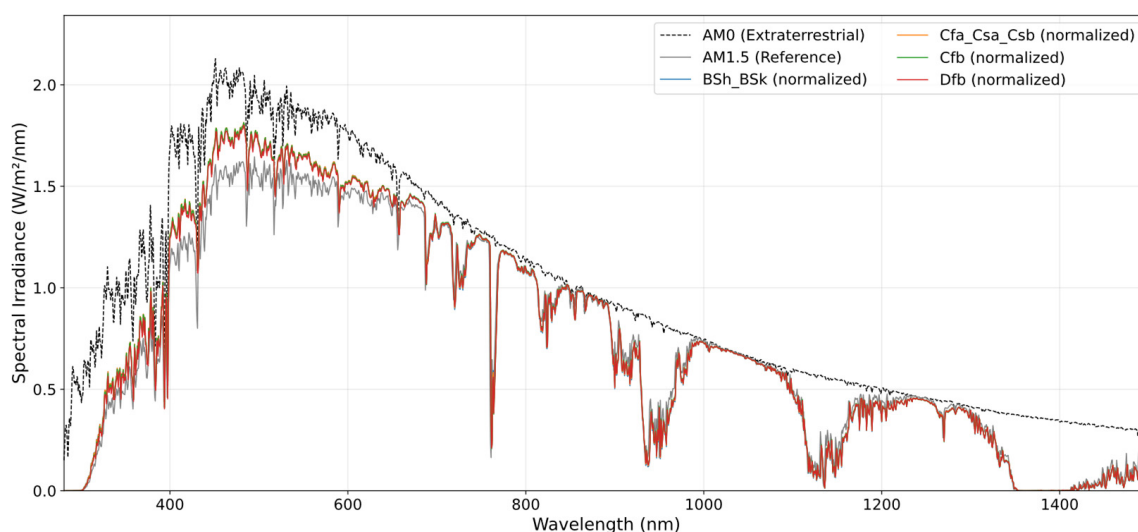


Figure 4. Irradiance-weighted average spectra for four climate groups, scaled to match AM1.5 at 1050 nm for direct comparison with standard AM1.5 and extraterrestrial AM0 spectrum.

3.1. Spectral Variability on a Yearly Scale: APE and SF Analysis

The spectral characteristics of solar radiation, quantified through average photon energy (APE), exhibit distinct patterns across climate groups, with significant implications for PV technology performance. Figures 5 and 6 present the distributions of hourly APE (350–1050 nm) under all-sky and clear-sky conditions for the four climate groups, respectively. The red dashed line marks the reference AM1.5 spectrum (1.88 eV), while the blue dashed line indicates each climate's mean APE, revealing consistent spectral blue shifts across all regions for all-sky conditions. Analysis of hourly APE distributions reveals that spectra resembling the standard AM1.5 reference (1.88 eV) are exceptionally rare in real-world conditions. Across all four climate groups, only 2–5% of hourly APE values fall within that range. The analysis reveals notable parallels in spectral characteristics between arid (BSh and BSk) and temperate (Cfa, Csa and Csb) climates. Both groups exhibit sharp APE distribution peaks at 1.91–1.92 eV (BSh and BSk: 15.77%; Cfa, Csa, and Csb: 14.33%) and nearly identical averages (BSh and BSk: 1.917 eV; Cfa, Csa, and Csb: 1.918 eV), indicating comparable spectral blue shifts relative to the AM1.5 reference ($\Delta + 0.037$ – 0.038 eV). The Cfb group demonstrates the highest average APE (1.929 eV), a significant blue shift of $\Delta + 0.049$ eV relative to AM1.5. Its APE distribution spans mostly in area 1.90–1.98 eV with a flat profile ($\sigma = 0.031$ eV). Similarly, the Dfb group also exhibits a pronounced blue shift, with an average APE of 1.925 eV ($\Delta + 0.045$ eV above AM1.5). The Dfb distribution is comparably broad and flat, covering the range from 1.90 to 1.98 eV, and features its main peak at 1.93–1.94 eV (9.59% occurrence). This broad and relatively even spread of APE values in both Cfb and Dfb climates highlights a persistent dominance of higher-energy photons throughout the year, reflecting the influence of frequent cloud cover, atmospheric scattering, and regional climatic variability. As a result, spectra closely resembling the standard AM1.5 reference are rare, while blue-shifted conditions prevail in these mid- and high-latitude environments. Under clear-sky conditions, all four climate groups exhibit reduced average photon energy (APE) compared to all-sky scenarios, though with distinct patterns. The maritime temperate (Cfb) and humid continental (Dfb) climates show the most pronounced reductions: Cfb drops from 1.929 eV (all-sky) to 1.879 eV (clear-sky), while Dfb decreases from 1.925 eV to 1.877 eV—even shifting to a red-shifted spectrum relative to AM1.5 (1.88 eV). In contrast, arid (BSh and BSk) and temperate seasonal (Cfa, Csa, and Csb) climates display smaller deviations (BSh and BSk: 1.917 eV $\rightarrow$ 1.897 eV; Cfa, Csa, and Csb: 1.918 eV $\rightarrow$ 1.891 eV). This divergence arises from fundamental atmospheric drivers: BSh and BSk and Cfa, Csa, and Csb experience fewer overcast days (<25% annual occurrence), making air mass (AM) and precipitable water (W) the dominant spectral modulators. Coastal sites with high W sustain blue shifts via near-infrared absorption, even under clear skies. Cfb and Dfb locations face frequent overcast conditions (>60% cloudy days), where all-sky spectra are blue-shifted by cloud scattering. However, clear-sky analysis reveals their higher-latitude positioning: elevated AM red-shifts spectra due to increased atmospheric path length, counteracting diffuse-light effects.

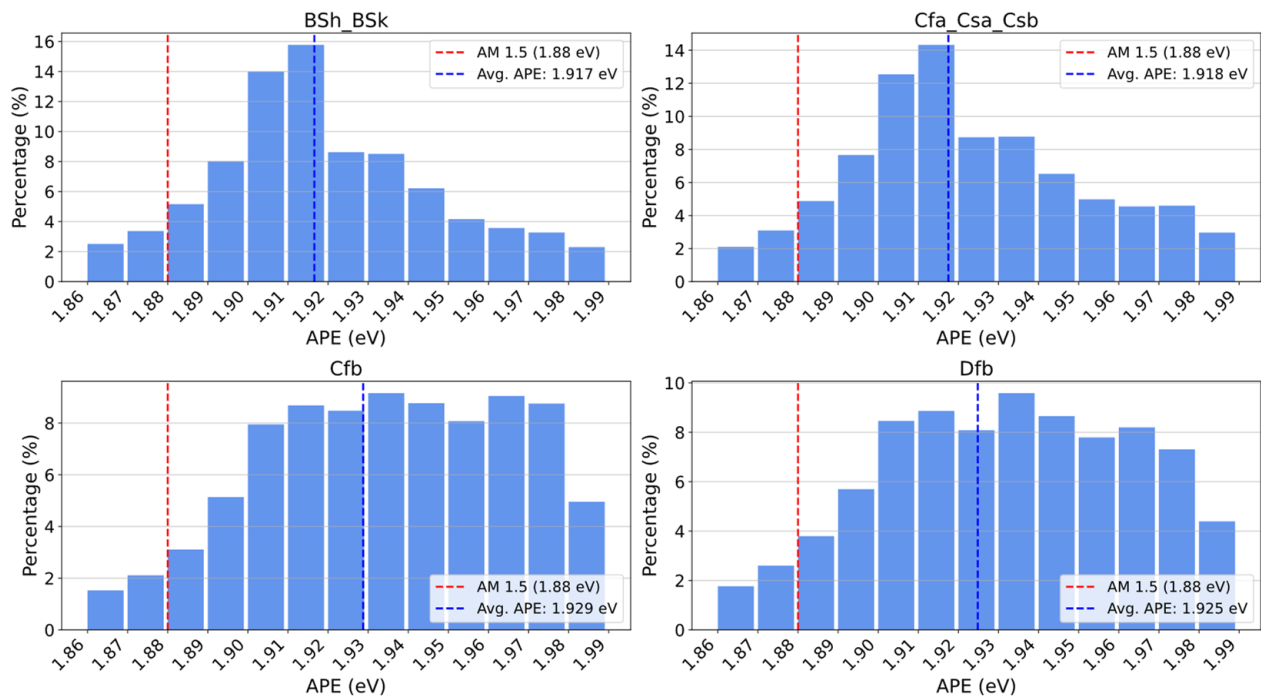


Figure 5. Hourly APE values distribution for all-sky conditions for four climate groups.

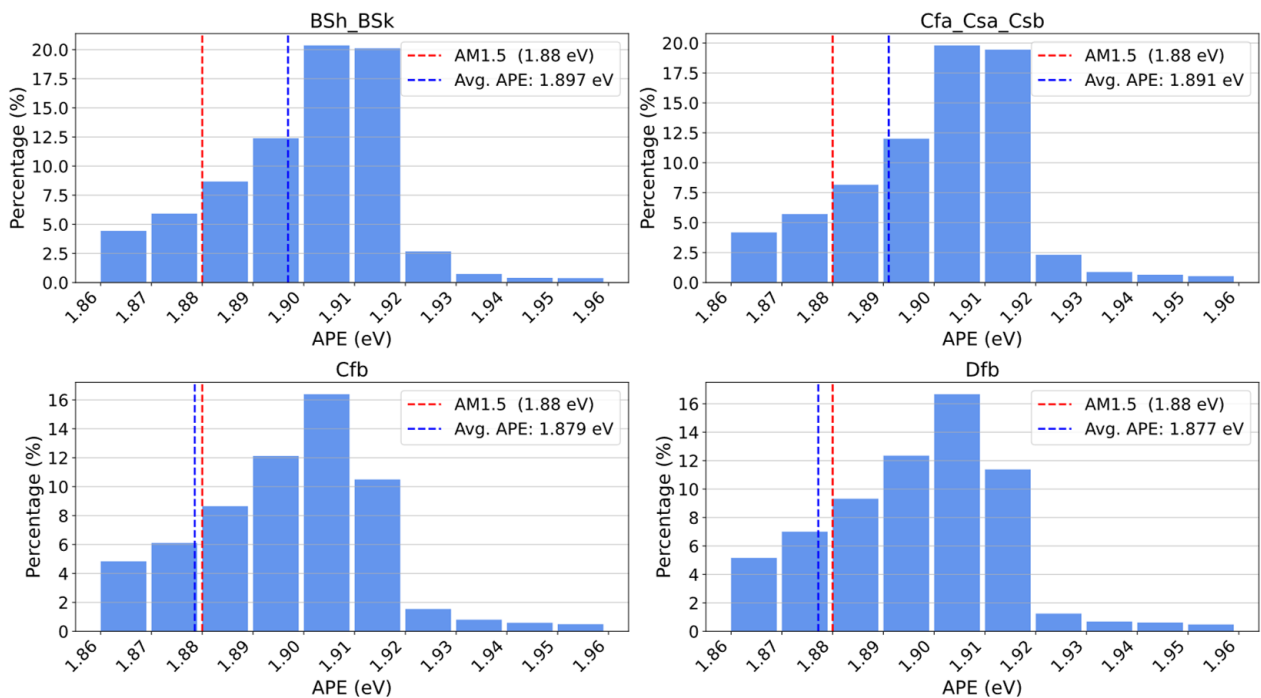


Figure 6. Hourly APE values distribution for clear-sky conditions for four climate groups.

Amorphous silicon (a-Si), with its wide bandgap (~1.7 eV), emerges as the strongest performer under high-APE conditions, achieving significant spectral gains across all climate groups: $SF = 1.059$ in Cfb (5.9% gain), 1.051–1.056 in BSh and BSk, 1.045–1.050 in Cfa, Csa and Csb, and 1.052–1.055 in Dfb. This advantage stems from its alignment with blue-rich spectra prevalent in diffuse-dominated environments and low-latitude regions, where elevated precipitable water (W) and aerosol-driven scattering enhance shorter-wavelength irradiance. However, a-Si's performance diminishes under clear skies, particularly in maritime (Cfb) and humid continental (Dfb) climates, where SF drops to 1.006 and 1.008, respectively. This reduction occurs because direct irradiance

reduces the proportion of high-energy photons critical to its efficiency. In contrast, arid and temperate seasonal climates exhibit smaller clear-sky declines ($SF \approx 1.028\text{--}1.035$), attributable to two factors that will be discussed in detail in next chapter: lower latitudes in these groups reduce AM variability, maintaining spectral stability. Coastal locations leverage high W to sustain blue-shifted spectra even under clear skies, minimizing performance gaps between all-sky and clear-sky conditions. Cadmium telluride (CdTe) and perovskite, both thin-film PV technologies, exhibit spectral performance patterns similar to a-Si but with moderately lower gains across European climates. CdTe achieves consistent spectral advantages, with 3.2% gains ($SF = 1.032$) in Cfb and 2.9% gains ($SF = 1.029$) in Dfb climates, demonstrating resilience to moderate blue shifts through balanced photon utilization and reduced thermalization losses. Perovskite follows closely, delivering 4.2% gains ($SF = 1.042$) in Cfb and 2.9% gains ($SF = 1.029$) in Dfb, though its hybrid structure shows heightened sensitivity to direct irradiance under clear skies. This performance alignment stems from their intermediate bandgaps (CdTe: ~ 1.45 eV; perovskite: ~ 1.5 eV), which optimize photon capture in blue-shifted spectra while minimizing thermalization losses—a critical advantage in diffuse-rich environments. Notably, both technologies outperform crystalline silicon in cloud-dominated regions but remain less spectrally adaptive than a-Si due to narrower absorption bandwidths. Crystalline silicon technologies exhibit minimal spectral sensitivity, with SF variations under 1.6% across climates. Monocrystalline PERC shows a modest SF increase to 1.016 in Cfb, attributable to reduced thermalization losses under blue-rich spectra. PERT technology demonstrates nearly identical spectral performance to PERC ($SF \approx 1.015\text{--}1.017$ in Cfb), owing to shared rear-passivation architectures that optimize long-wavelength response while maintaining spectral stability. Polycrystalline silicon, while similar, faces efficiency limitations from grain boundary losses, achieving a 1.8% SF gain in Cfb (1.018). Mono-Si PERT variants show marginal improvements ($SF = 1.015$ in Cfb), constrained by inherent spectral response boundaries. HIT (Heterojunction with Intrinsic Thin-layer) technology, combining c-Si absorption with thin-film passivation, achieves a SF of 1.012 in Cfb (1.2% gain), leveraging its hybrid design for enhanced short-wavelength response under diffuse light. However, its spectral stability remains high ($SF \approx 1.00\text{--}1.02$ across climates), as amorphous passivation layers mitigate recombination losses without compromising broadband utilization. Copper–zinc–tin–sulfide–selenide (CZTSSe) exhibits the lowest spectral gains among all studied PV technologies, with marginal improvements limited to Cfb and Dfb climates under all-sky conditions. In arid zones (BSh and BSk), it consistently shows spectral losses ($SF < 1$), while clear-sky scenarios yield slight losses across all climate groups. This performance pattern arises from CZTSSe's broad spectral response (380–1400 nm)—the widest among analyzed technologies—which reduces sensitivity to overcast conditions and W but diminishes utilization of blue photons due to attenuated short-wavelength sensitivity. Crucially, AM dominates its spectral behavior: elevated AM at higher latitudes shifts spectra toward red/NIR wavelengths, aligning with CZTSSe's peak quantum efficiency.

The distributions of APE depicted in Figures 5 and 6 align well with the spectral factor trends and performance conclusions drawn from Figures 7 and 8, reinforcing the observed climatic influences on PV technologies. Figure 9 further elucidates these spectral effects discussed thus far by presenting a detailed correlation between SF and APE, contrasting a-Si as a representative thin-film technology with mono-Si PERC exemplifying broader spectral response characteristics. It is distinctly illustrated that all-sky conditions consistently yield higher APE values (1.90–2.00 eV) compared to clear-sky scenarios. This elevation arises from cloud-induced scattering, which amplifies diffuse irradiance rich in shorter wavelengths (blue/UV), thereby shifting spectra toward higher photon energies. The

phenomenon is particularly pronounced in Cfb and Dfb climates, where frequent overcast conditions drive APE elevations of 0.04–0.05 eV above clear-sky baselines. The APE-*SF* graph validates that spectral gains in thin-film technologies are intrinsically linked to higher APE values, while crystalline silicon and CZTSSe achieve stability through spectral bandwidth.

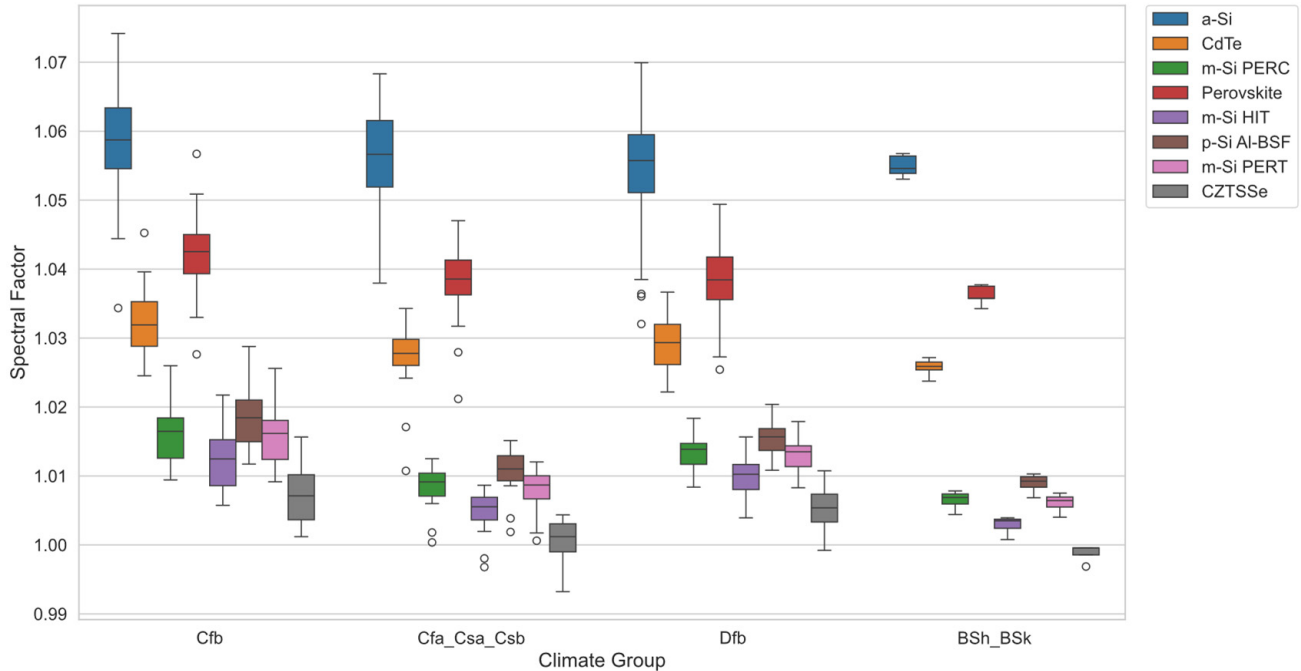


Figure 7. Yearly all-sky irradiance weighted *SF* values for PV technologies under study.

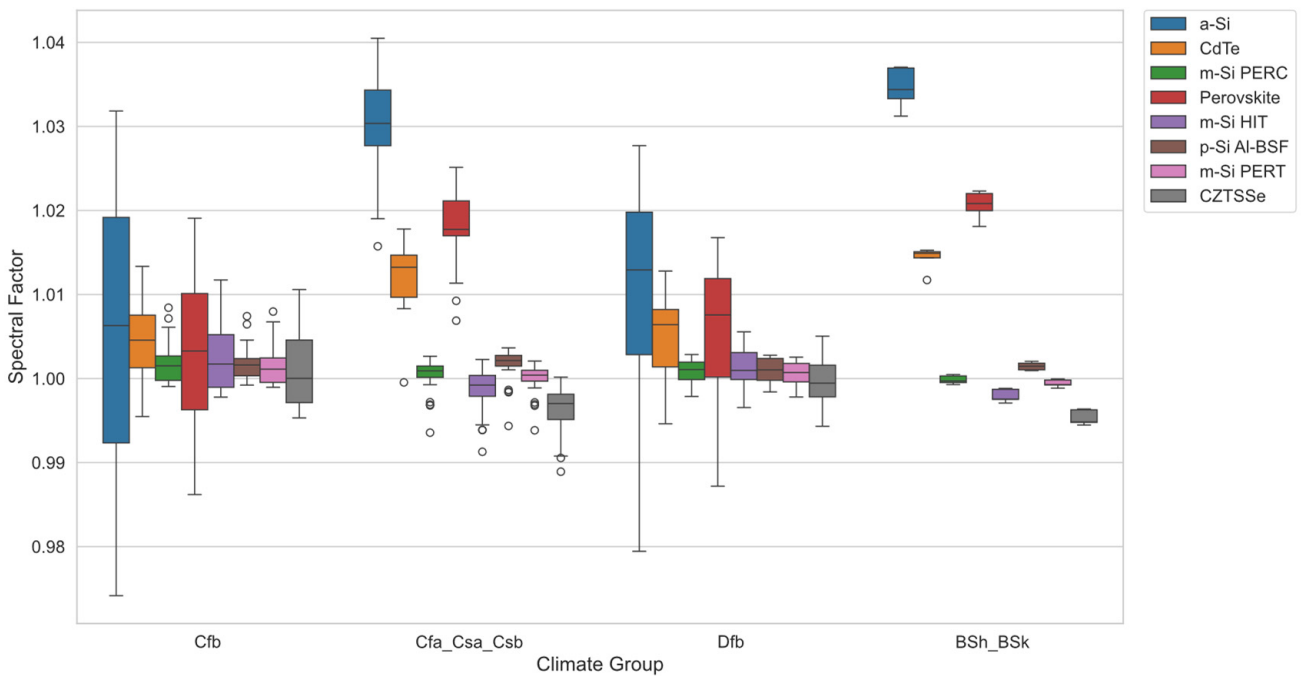


Figure 8. Yearly clear-sky irradiance-weighted *SF* values for PV technologies under study.

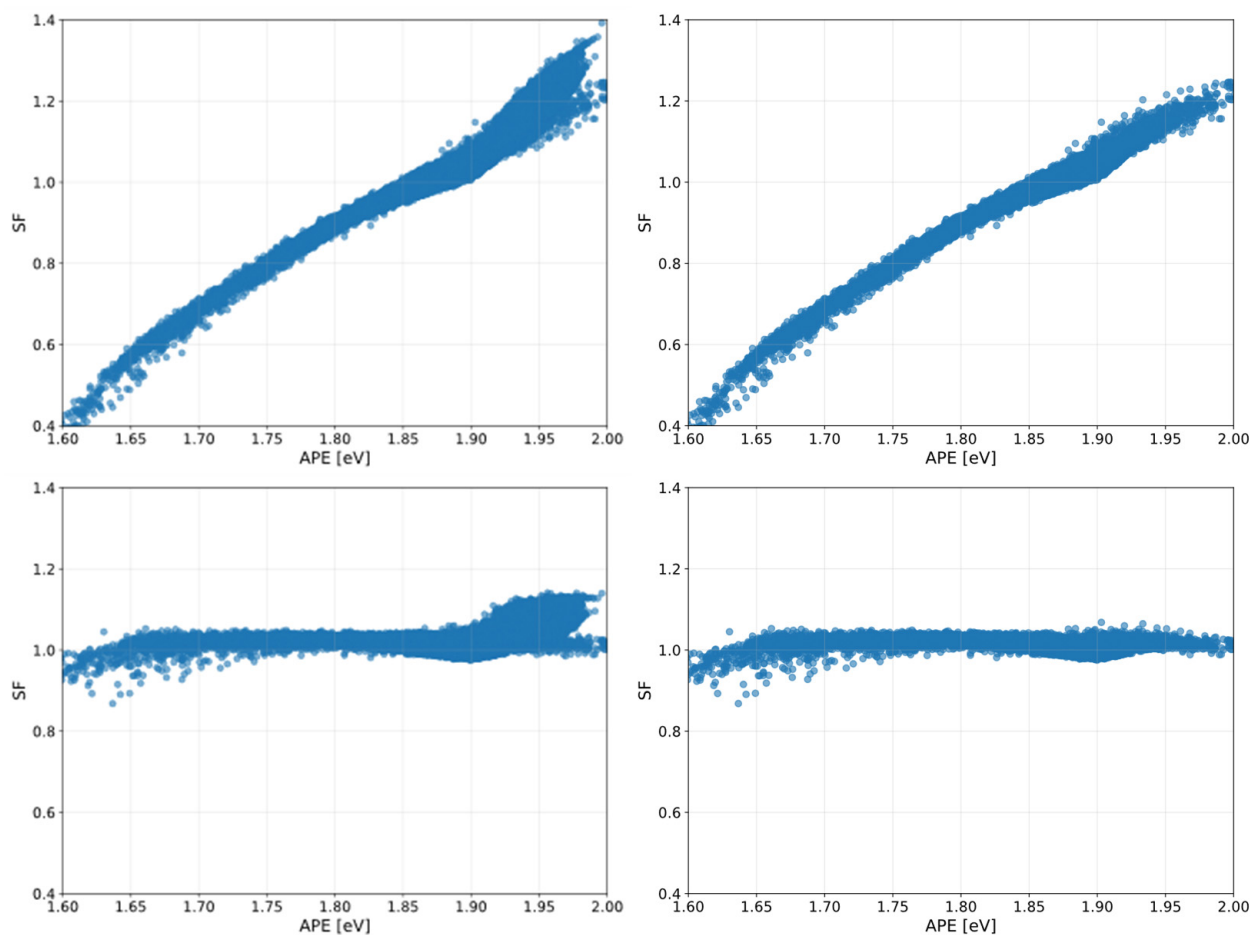


Figure 9. APE versus SF for a-Si (**upper** panel) and mono-Si PERC (**lower** panel) for all-sky (**left**) and clear-sky (**right**) conditions.

3.2. Monthly Spectral Factor Variations

To systematically evaluate irradiance-weighted monthly SF variations across PV technologies, whisker diagrams were selected for two representative types that capture key spectral response characteristics and performance trends. A-Si was selected as the primary thin-film technology for visual representation, with its whisker diagram explicitly shown to illustrate seasonal spectral dynamics. This choice reflects a-Si's pronounced sensitivity to atmospheric variability, which exemplifies broader thin-film spectral behavior. Perovskite and CdTe technologies exhibit monthly spectral trends closely aligned with a-Si, characterized by similar whisker diagram shapes. However, their whisker diagrams were omitted from visual presentation to avoid redundancy. For crystalline silicon technologies, mono-Si PERC served as the primary representative due to its widespread deployment and spectral stability, with other variants (p-Si, HIT, PERT) discussed textually to highlight minor performance deviations. CZTSSe, which exhibits a monthly whisker diagram shape closely resembling that of crystalline silicon, was also discussed textually rather than shown graphically. The all-sky and clear-sky monthly whisker plots for a-Si across all four climate groups are presented in Figure 10, while mono-Si PERC whisker plots are detailed in Figure 11.

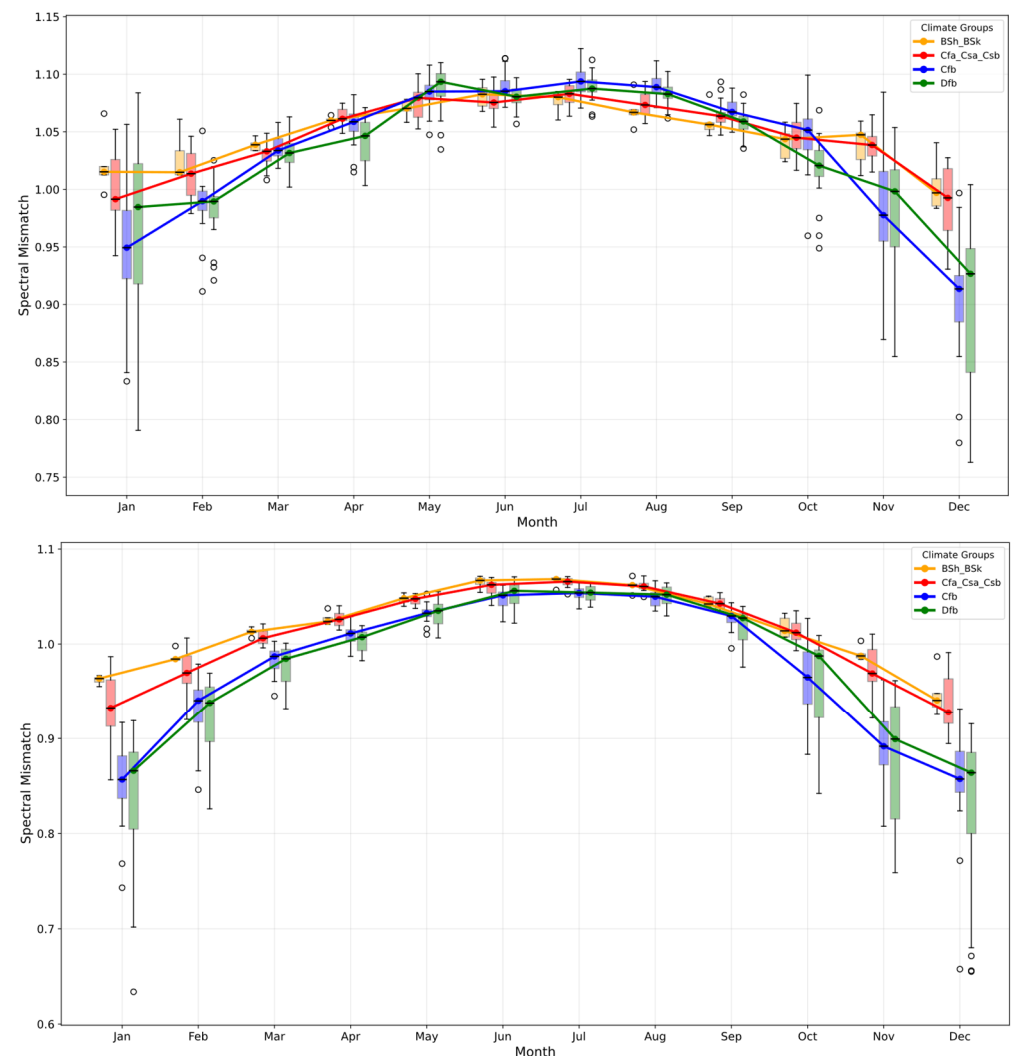


Figure 10. Monthly SF distribution for a-Si under all-sky (**upper** panel) and clear-sky (**lower** panel) conditions across four climate groups.

A clear distinction emerges in the monthly SF behavior between thin-film PV technologies and crystalline silicon as well as CZTSSe. For thin-film devices, the lowest SF values consistently occur during the late autumn and winter months, increase through spring and early autumn, and reach their maximum during the summer. This pattern is primarily driven by the strong influence of AM, which rises exponentially during autumn and winter, while remaining low and relatively flat during spring and summer, which is much more pronounced in high-latitude climates and less in lower-latitude climates, as illustrated in Figure 12. Higher AM values shift the solar spectrum toward the red, moving much of the irradiance outside the optimal spectral response range of thin-film devices, which are more sensitive to blue and visible wavelengths. This seasonal modulation is significantly more pronounced in higher-latitude climates (Cfb and Dfb), where AM variations between summer and winter exceed 1.5–2.0 units due to extreme solar elevation changes. In contrast, arid and temperate climates at lower latitudes exhibit minimal seasonal AM fluctuations ($\Delta AM < 0.5$ units), resulting in substantially smaller SF variations between winter and summer months. A clear distinction emerges in the monthly SF behavior between thin-film PV technologies and crystalline silicon as well as CZTSSe.

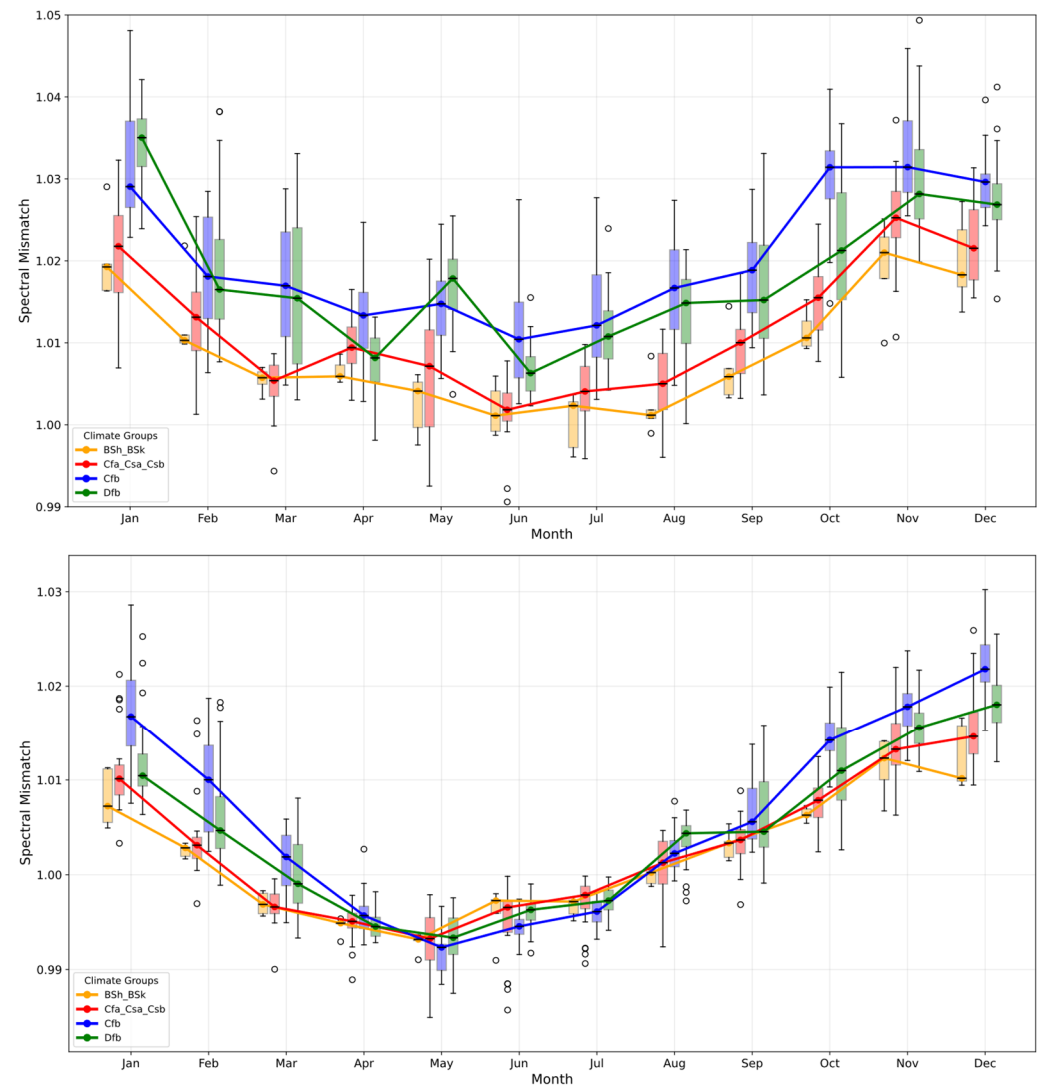


Figure 11. Monthly SF distribution for mono-Si PERC under all-sky (**upper** panel) and clear-sky (**lower** panel) conditions across four climate groups.

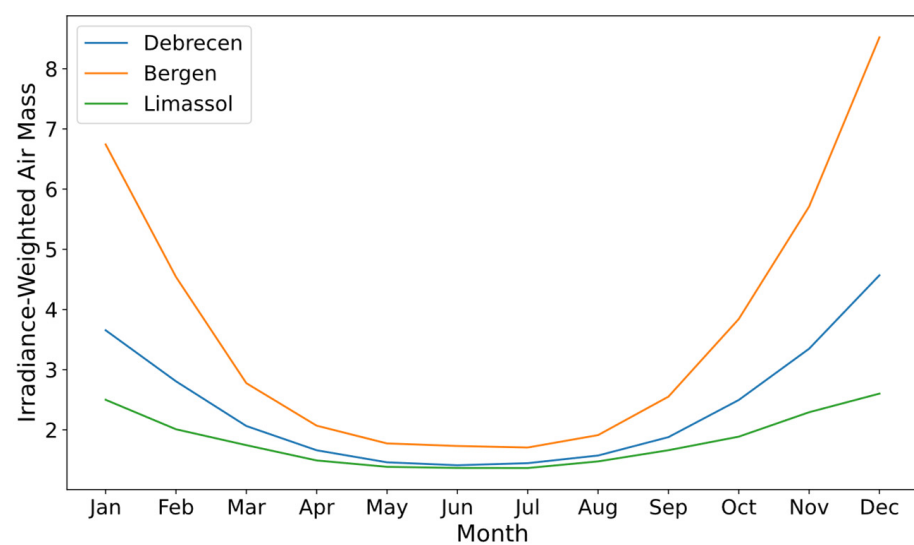


Figure 12. Irradiance-weighted AM for locations with minimum (Limassol, Cyprus), maximum (Bergen, Norway), and median latitudes (Debrecen, Hungary).

In contrast, crystalline silicon and CZTSSe technologies display the opposite trend: their SF values peak during the winter and autumn months and are lowest during spring and summer. This is because higher AM levels during the colder months shift the spectrum toward the red and near-infrared regions, where crystalline silicon and CZTSSe have stronger spectral response. Thus, these technologies are better able to utilize the red-shifted spectrum prevalent in high-AM conditions, resulting in higher SF values during periods of elevated AM. This means that AM exerts its most significant spectral influence during periods when overall energy production is lowest, namely in the winter and autumn, although it is obvious that AM impacts these technologies far less severely than thin-film technologies.

Consequently, while monthly SF graphs show pronounced seasonal dips, the annual impact of AM is less pronounced because winter and autumn contribute less to total yearly energy yield. As a result, these monthly trends can be somewhat misleading if interpreted without considering their relative contribution to annual production.

3.3. Influence of Atmospheric Variables on Spectral Factor

To quantify the influence of atmospheric variables on spectral variability, 12 representative locations were analyzed—three sites from each climate group. For all-sky conditions, the clearness index (K_t), defined as the ratio of surface horizontal irradiance to theoretical clear-sky surface horizontal irradiance, and precipitable water (W) were prioritized. K_t captures cloud modulation of spectral distribution, while W governs atmospheric absorption in near-infrared bands (900–1100 nm). Under clear-sky conditions, aerosol optical depth (AOD) and W are taken as dominant variables, as AOD dictates scattering-induced spectral shifts in the visible range (400–700 nm) and W maintains its infrared absorption role. The 3D scatter plots of hourly values of SF compared to atmospheric parameters in Figure 13 (a-Si) and Figure 14 (mono-Si PERC) quantitatively contrast spectral sensitivity between thin-film and crystalline silicon technologies. For a-Si, the plots reveal a wide dispersion of spectral factor (SF) values across the atmospheric parameter space—clearness index (K_t and W for all-sky conditions, and AOD and W for clear-sky conditions). This broad distribution underscores a-Si's heightened sensitivity to atmospheric variability. Conversely, mono-Si PERC exhibits minimal SF fluctuations across identical atmospheric gradients, forming tightly clustered data points in Figure 14. This stability persists under both all-sky and clear-sky regimes due to PERC's broadband spectral response (350–1200 nm), which dilutes the impact of variables K_t , W , and AOD.

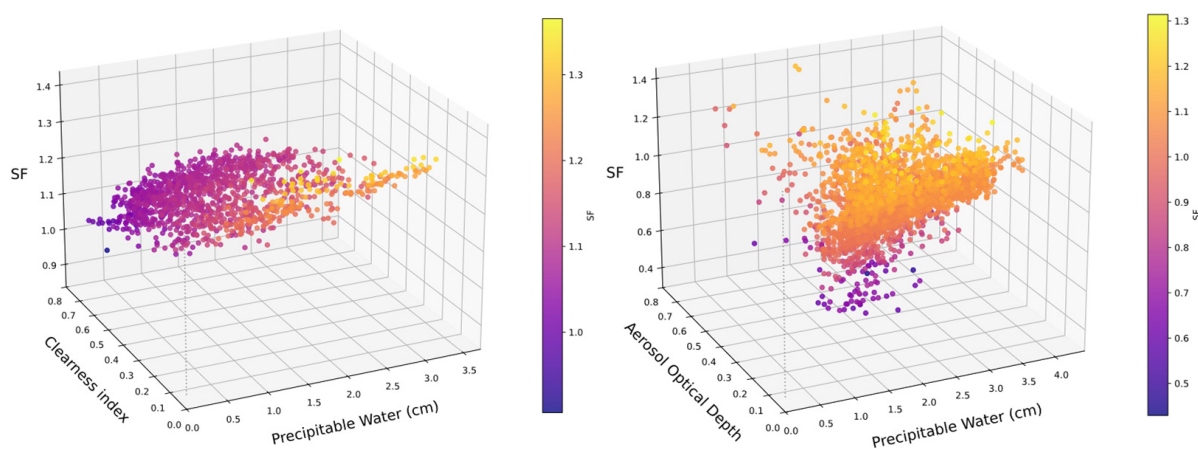


Figure 13. All-sky (left) and clear-sky (right) 3D scatter plot SF versus atmospheric parameters for a-Si.

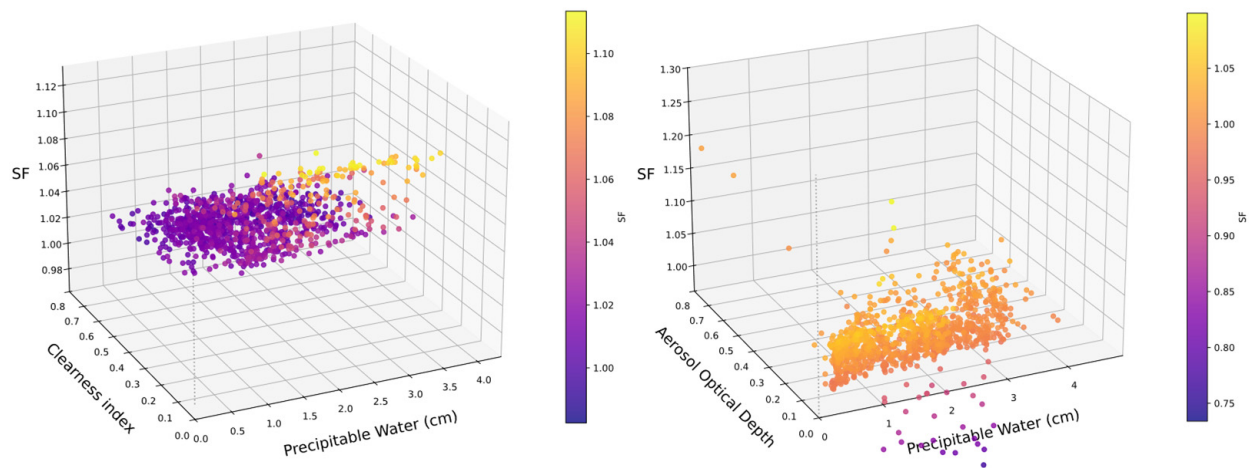


Figure 14. All-sky (left) and clear-sky (right) 3D scatter plot of SF versus atmospheric parameters for mono-Si PERC.

Table 2 (all-sky) and Table 3 (clear-sky) present annual spectral factors (SF) and average atmospheric parameters for the 12 analyzed locations, providing quantitative context for the observed climate-technology interactions. Elevated W correlates strongly with $SF > 1$, particularly for thin-film technologies. Coastal sites like Valencia and Palermo—despite high clearness index ($K_t \approx 0.75$ – 0.82)—achieve substantial thin-film gains (5.6–6.1% SF) due to synergistic effects of high W and lower latitudes. The latter reduces annual AM, enhancing blue-shifted spectra critical for thin-film photon utilization. Conversely, inland locations like Madrid exhibit smaller thin-film gains ($SF \approx 1.02$ – 1.038) and crystalline silicon losses ($SF \approx 0.95$ – 0.98) under similarly high K_t but low W , as reduced NIR backscattering limits photon harvesting. Maritime temperate (Cfb) and humid continental (Dfb) climates demonstrate substantial spectral gains for thin-film PV technologies, attributable to their distinctive atmospheric conditions that favor spectral enhancement mechanisms. Even in locations where precipitable water (W) values remain moderate, the characteristically low clearness index (K_t) values in these climate zones generate favorable spectral conditions for thin-film performance. This effect is particularly pronounced in lower-latitude sites within the same climate group, such as Sofia, where reduced AM intensifies blue-rich spectra while persistent cloud cover ($K_t \approx 0.65$) maximizes diffuse light availability. The reduced K_t reflects frequent cloud cover and diffuse light conditions, which thin-film technologies exploit more effectively than crystalline silicon due to their superior low-light performance and enhanced shade tolerance. Bergen represents a notable exception within this pattern, combining high latitude (60.39°N) with exceptionally low annual precipitable water content, which produces the smallest spectral gains among selected locations for thin-film technologies. Dublin exemplifies optimal atmospheric conditions for thin-film spectral enhancement, with elevated precipitable water content and consistently low clearness index values. Dublin’s oceanic position maintains high atmospheric humidity and frequent cloud cover, where elevated W and reduced K_t synergistically maximize spectral factor gains for thin-film technologies within the analyzed dataset.

Crystalline silicon PV technologies demonstrate significantly smaller yearly deviations from the reference spectrum compared to thin-film alternatives, exhibiting enhanced spectral stability across diverse climatic conditions. This reduced sensitivity stems from crystalline silicon’s broadband spectral response spanning approximately 350–1100 nm, with peak quantum efficiency occurring around 590–890 nm. The narrow bandgap of 1.12 eV ensures consistent photon utilization across most of the visible and near-infrared spectrum, minimizing spectral mismatch effects under varying atmospheric conditions.

Under all-sky conditions, crystalline silicon modules exhibit distinct latitude-dependent spectral performance patterns. At lower latitudes, spectral bandgap of 1.12 eV ensures consistent photon utilization across most of the visible and near-infrared spectrum, minimizing spectral mismatch effects under varying atmospheric conditions.

Table 2. Annual *SF* and average yearly values of different atmospheric parameters for all-sky conditions.

Location	Climate	Latitude	AM	W	AOD	K _t	a-Si	CdTe	Pvsk	PERC	HIT	p-Si	PERT	CZTSSe
Nicosia	BSh	35.18	2.62	2.12	0.21	0.82	5.3	2.3	3.4	0.4	0.0	0.6	0.4	−0.3
Thira	BSh	36.42	2.70	2.10	0.2	0.78	5.4	2.5	3.6	0.6	0.2	0.8	0.5	−0.2
Valencia	Bsk	39.47	2.74	2.05	0.15	0.75	5.6	2.6	3.7	0.8	0.4	1.0	0.7	−0.1
Madrid	Csa	40.41	2.76	1.47	0.10	0.77	3.8	1.0	2.1	−0.1	−0.3	0.1	0.0	−0.7
Rijeka	Cfa	45.33	2.96	2.10	0.20	0.61	5.7	2.9	3.9	1.1	0.8	1.3	1.0	0.3
Palermo	Csa	38.11	2.69	2.20	0.19	0.75	6.1	3.0	4.1	0.8	0.4	1.1	0.8	0.0
Dublin	Cfb	53.37	3.32	1.95	0.09	0.44	7.4	4.5	5.7	2.6	2.1	2.9	2.5	1.5
Bergen	Cfb	60.39	3.76	1.54	0.13	0.45	3.4	2.4	2.7	1.7	1.6	1.8	1.7	1.2
Eindhoven	Cfb	51.44	3.20	1.74	0.16	0.52	5.8	3.3	4.2	1.7	1.3	1.9	1.6	0.8
Sofia	Dfb	42.69	2.79	1.69	0.19	0.65	5.8	2.6	3.8	0.8	0.4	1.1	0.8	−0.1
Talinn	Dfb	59.44	3.69	1.45	0.14	0.48	5.0	2.8	3.6	1.4	1.2	1.6	1.4	0.7
Krakow	Dfb	50.06	3.16	1.80	0.19	0.54	5.8	3.2	4.2	1.5	1.1	1.7	1.4	0.6

Table 3. Annual *SF* and average yearly values of different atmospheric parameters for clear-sky conditions.

Location	Climate	Latitude	AM	W	AOD	K _t	a-Si	CdTe	Pvsk	PERC	HIT	p-Si	PERT	CZTSSe
Nicosia	BSh	35.18	2.69	2.21	0.2	1	3.7	1.5	2.2	0.0	0.0	0.1	0.0	−0.5
Thira	BSh	36.42	2.76	2.25	0.23	1	3.7	1.5	2.2	0.1	0.3	0.1	0.1	−0.6
Valencia	Bsk	39.47	2.97	2.03	0.14	1	3.1	1.1	1.8	−0.1	−0.3	0.0	−0.1	−0.5
Madrid	Csa	40.41	2.76	1.39	0.09	1	2	−0.1	0.7	−0.7	−0.9	−0.6	−0.6	−1.1
Rijeka	Cfa	45.33	2.96	2.24	0.18	1	2.8	1.3	1.7	0.1	0.0	0.2	0.0	−0.2
Palermo	Csa	38.11	2.79	2.31	0.18	1	4.0	1.8	2.5	0.0	−0.1	0.3	0.0	−0.4
Dublin	Cfb	53.37	4.10	1.63	0.08	1	2.5	1.0	1.4	0.0	−0.1	0.0	0.0	−0.4
Bergen	Cfb	60.39	3.78	1.45	0.13	1	−2.0	−0.5	−1.2	0.3	0.6	0.2	0.3	0.5
Eindhoven	Cfb	51.44	3.56	1.62	0.14	1	−0.1	0.2	−0.1	0.2	0.4	0.2	0.2	0.3
Sofia	Dfb	42.69	2.91	1.80	0.16	1	2.4	0.7	1.3	−0.2	−0.4	−0.1	−0.1	−0.6
Talinn	Dfb	59.44	3.42	1.61	0.14	1	0.9	0.2	0.3	−0.2	−0.2	−0.2	−0.2	−0.4
Krakow	Dfb	50.06	3.27	1.94	0.17	1	1.2	0.8	0.7	0.2	0.3	0.3	0.2	0.1

Under all-sky conditions, crystalline silicon modules exhibit distinct latitude-dependent spectral performance patterns. At lower latitudes, spectral gains remain minimal due to high solar elevation angles that concentrate irradiance in ultraviolet and visible wavelengths. The abundant direct normal irradiance in these regions provides conditions close to the AM1.5G reference spectrum, resulting in spectral factors near unity. Conversely, higher latitudes generate enhanced spectral gains for crystalline silicon technologies due to elevated AM conditions (≈ 1.5 – 2.0) that shift the solar spectrum toward red and near-infrared wavelengths. This spectral redistribution aligns favorably with crystalline silicon's extended response beyond 800 nm, enabling improved photon capture despite reduced total irradiance. Precipitable water (W) content also modulates these latitude effects, with higher W values amplifying spectral gains across all locations. Madrid exemplifies spectral losses among analyzed locations, combining low latitude (40.42°N) with minimal precipitable water content. This dual limitation restricts both AM-induced spectral shifting and water vapor enhancement effects, yielding spectral factors of 0.93–0.99 for crystalline silicon modules. Dublin represents optimal conditions for crystalline silicon spectral enhancement, combining moderate latitude (53.35°N) with substantial atmospheric water content. The synergistic effects of elevated AM and enhanced water vapor absorption produce spectral factors reaching 2.5–2.9% gains, representing the highest gains observed among maritime

temperate climates. Under clear-sky conditions, crystalline silicon spectral performance demonstrates minimal sensitivity to atmospheric variables. Lower latitudes with higher precipitable water exhibit spectral factors near zero percent gains, as the absence of cloud-induced spectral modification limits enhancement mechanisms to water vapor absorption effects alone. Madrid's clear-sky conditions produce the most pronounced spectral losses for crystalline silicon, reaching up to -0.9% due to the combination of low latitude and minimal water vapor content. Aerosol optical depth values of $0.1\text{--}0.2$ in this Mediterranean environment preferentially scatter shorter wavelengths ($400\text{--}600\text{ nm}$), reducing photon availability in crystalline silicon's peak response range without compensatory near-infrared enhancement. Higher latitudes with elevated water vapor content demonstrate small spectral gains up to 0.3% percent, as AM-induced spectral shifting partially compensates for direct irradiance reduction. The enhanced near-infrared component under these conditions aligns with crystalline silicon's extended response beyond 800 nm . Higher latitudes with lower water vapor exhibit small losses of up to -0.2% percent. PERC and PERT technologies exhibit nearly identical spectral responses and demonstrate the smallest sensitivity to spectral variations in clear-sky conditions among all crystalline silicon variants. Both architectures maintain spectral factors within $\pm 0.5\%$ of reference conditions across diverse climatic zones, attributed to their optimized rear passivation structures that minimize recombination losses while preserving broadband spectral response. Polycrystalline silicon demonstrates moderately larger spectral gains compared to PERC/PERT variants under all-sky conditions, resulting in $0.2\text{--}0.4\%$ higher spectral factors due to grain boundary effects that slightly modify spectral response characteristics. HIT technology, however, does not show consistent gains above PERC/PERT; instead, it exhibits the highest stability in all-sky conditions, particularly at lower latitudes, where its amorphous silicon passivation layers enhance short-wavelength response without compromising near-infrared sensitivity. Notably, the spectral gains observed for all crystalline silicon technologies in higher latitudes under all-sky conditions (up to 2.9% for polycrystalline silicon in Dublin) vanish during clear-sky periods, as direct irradiance reduces diffuse-light enhancement effects.

CZTSSe exhibit distinct latitude-dependent spectral performance, with losses ($SF < 1$) prevalent at lower latitudes and gains ($SF > 1$) at higher latitudes. At lower latitudes, such as Nicosia (35.18°N), high solar elevation ($AM \approx 1.0\text{--}1.2$) concentrates irradiance in ultraviolet and visible wavelengths ($300\text{--}600\text{ nm}$), which CZTSSe underutilizes due to limited sensitivity below 500 nm . Compounded by aerosol scattering ($AOD \approx 0.2\text{--}0.3$) attenuating photons in its primary response range ($600\text{--}1000\text{ nm}$), these regions yield spectral losses ($SF \approx -0.3$). Conversely, at higher latitudes like Tallinn (59.44°N), elevated AM shifts the spectrum toward red/NIR wavelengths ($700\text{--}1300\text{ nm}$), aligning with CZTSSe's extended response beyond 800 nm . This spectral redistribution enhances photon capture despite reduced total irradiance, generating gains ($SF \approx 0.7$).

4. Conclusions

This comprehensive analysis of spectral irradiance impacts on PV technologies across 79 European locations reveals critical insights for optimizing solar energy deployment strategies.

1. Real-world solar spectra rarely match laboratory standards and exhibit systematic blue shifts. Only $2\text{--}5\%$ of hourly spectra resemble the AM1.5 reference used for testing, with all European regions receiving higher-energy (shorter-wavelength) sunlight than the AM1.5 benchmark and the largest shifts occurring in maritime and continental areas.
2. Thin-film and crystalline silicon technologies respond differently to real-world spectral conditions in Europe. Thin-film modules—including amorphous silicon (a-Si), cadmium telluride (CdTe), and perovskite—demonstrate significant energy gains

under blue-shifted spectra, with a-Si achieving up to 5.9% improvement in oceanic climates, CdTe up to 3.2%, and perovskite up to 4.2%. In contrast, crystalline silicon modules (PERC, PERT, HIT, and poly-Si) remain highly stable, showing less than $\pm 1.6\%$ variation across different climates. Meanwhile, CZTSSe technology exhibits latitude-dependent performance, losing efficiency at lower latitudes but gaining at higher latitudes due to spectral shifts primarily influenced by air mass.

3. Spectral effects on PV performance are driven by different atmospheric factors depending on sky conditions—clearness index and precipitable water under all-sky conditions, and aerosol optical depth and water vapor under clear skies. Air mass becomes especially important in winter and at high latitudes. Notably, even within the same climate zone, spectral effects can vary by up to 6%, highlighting the necessity for detailed, site-specific assessments rather than relying on broad climate averages.
4. Optimizing PV system design requires site-specific, climate-aware strategies. Achieving maximum energy yield from photovoltaic (PV) systems depends on both climate-aware deployment and detailed, site-specific spectral analysis. Relying solely on broad climate classifications is insufficient; optimal PV system design requires precise, location-level spectral evaluation to match the most suitable technology to the unique conditions of each site.

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