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Multi-decadal assessment of climate variability impacts on solar photovoltaic performance across Indian states

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ABSTRACT

India faces growing reliance on solar photovoltaic (PV) power for its low-carbon. transition, yet existing assessments attribute differences in state-level solar performance mainly to policy and economic factors, leaving the contribution of long-term climatic change insufficiently quantified. This study evaluates how multi-decadal changes in solar irradiance, atmospheric aerosols, cloudiness, and temperature have affected PV performance across six Indian states from 1990 to 2023. Using satellite observations, reanalysis meteorological datasets, aerosol metrics, and PV performance modelling, the study derives historical performance-ratio losses attributable to each climatic driver and applies a state-level panel regression to independently test the statistical relationship between climate variables and specific PV yield. A composite climate risk index is then constructed to rank state-level vulnerability, and CMIP6-based projections extend the analysis to 2040–2060. The results reveal significant performance reductions, primarily driven by aerosol accumulation and rising temperatures, with total losses ranging from 10% to 21% across states; projections indicate further decline under high-emission scenarios, reaching up to 18% in the most exposed northern states. The findings support climate-resilient solar planning, including region-specific adaptation measures, siting strategies, and the incorporation of climate trends into state-level renewable energy roadmaps.

Keywords

Solar photovoltaic performance;
Climate variability;
Aerosol optical depth;
Performance ratio loss;
Climate risk mapping;

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Abbreviations

AOD	Aerosol Optical Depth	MNRE	Ministry of New and Renewable Energy
CEA	Central Electricity Authority	MODIS	Moderate Resolution Imaging Spectroradiomet.
CMIP6	Coupled Model Intercomparison Project Phase 6	NOCT	Nominal Operating Cell Temperature
GHI	Global Horizontal Irradiance	PR	Performance Ratio
IMD	India Meteorological Department	PV	Photovoltaic
ISCCP	International Satellite Cloud Climatology Project	SSP	Shared Socioeconomic Pathway
MISR	Multi-angle Imaging Spectro Radiometer	TMY	Typical Meteorological Year
MK	Mann–Kendall (trend test)		

1. Introduction

India, one of the world's fastest-growing economies, has placed renewable energy at the centre of its long-term decarbonization agenda. In line with its commitment to achieve net-zero emissions by 2070, the country has increasingly positioned solar energy as a critical driver of this transition. Owing to its favourable geography, India receives an estimated 5 million TWh of solar radiation annually, suggesting enormous potential for large-scale deployment of photovoltaic (PV) systems. Yet, despite this natural advantage, the realized performance and expansion of solar installations differ markedly across regions. While earlier research has largely attributed these disparities to economic, policy, and infrastructural constraints, emerging evidence indicates that environmental and climatic conditions also play a decisive role in shaping actual PV output. The specific unresolved issue this study addresses is that existing state-level solar assessments in India quantify capacity disparities in economic and policy terms but do not isolate how much of the observed performance gap is attributable to long-term climatic drivers, nor how this climatic contribution varies systematically from state to state.

Over the past several decades, India has experienced noticeable shifts in key climatic variables including atmospheric aerosol loads, cloud formation, temperature rise, and irradiance fluctuations. These trends can alter the expected energy yield of solar power plants, thereby affecting investment returns and distorting planning assumptions for both central and state-level renewable energy strategies. Most state-wise solar assessments in India have emphasized financial and land-related barriers to deployment without incorporating climatic variability into the analytical framework. At the same time, global-scale assessments have begun to incorporate decadal climatic trends into national PV potential projections, for instance using CMIP6 scenarios to estimate aggregate, country-level yield change under future warming and air-quality pathways [1]. What these national-scale projections do not provide is a state-by-state accounting of how historical irradiance, aerosol, and temperature trends have already translated into observed performance-ratio losses, or a comparable risk metric that differentiates states from one another. The present study addresses this specific gap. Its novelty lies not simply in combining trend analysis, panel regression, CMIP6 projections, and a vulnerability index, but in using this combination to produce a state-resolved, empirically derived attribution of historical PV performance loss to individual climatic drivers, and to translate that attribution into a comparable composite risk score across six states an output existing national-scale or single-driver studies do not offer.

Motivated by this gap, the present study examines how three decades of climate variability have influenced state-level solar PV performance in India. Additionally, the paper evaluates the potential risks posed by evolving climatic patterns for future PV development. By integrating multi-decadal irradiance trends, aerosol dynamics, temperature changes, and environmental risks, this study offers a more comprehensive understanding of the determinants of solar performance across Indian states and highlights the need for climate-responsive planning in achieving the nation's long-term renewable energy goals.

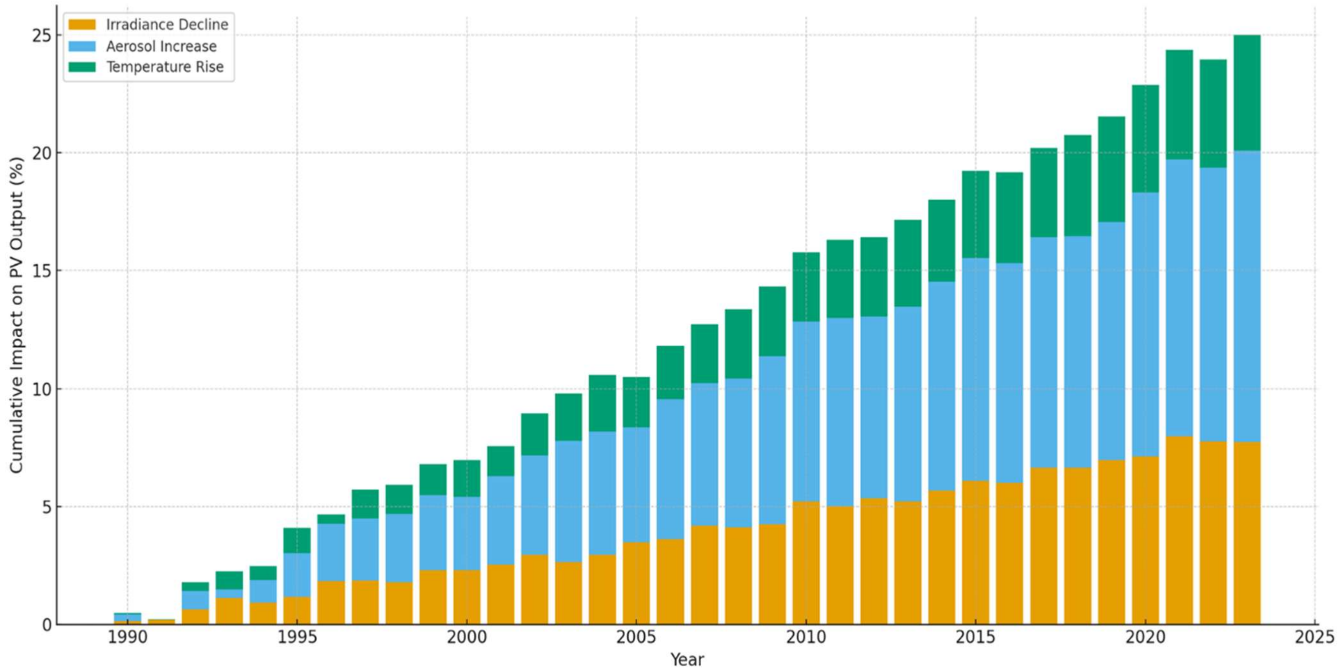

Figure 1: Multi-decadal climatic stressors influencing solar PV performance in India, presented as a conceptual, schematic framework rather than a plot of direct empirical data, showing the cumulative impact of irradiance decline, aerosol increase, and temperature rise from 1990 to 2023. Based on synthesized trends derived from published climatic assessments [2]

2 Literature review

Solar photovoltaic (PV) performance is inherently dependent on atmospheric and environmental conditions, which influence the availability and quality of solar radiation reaching the module surface. Previous research has established that variations in solar irradiance, atmospheric aerosols, ambient temperature, cloud cover, and dust deposition significantly affect PV energy yield and system efficiency [1–3]. These factors are particularly relevant in regions experiencing rapid climatic and environmental change. Atmospheric aerosols and particulate matter reduce surface solar irradiance through scattering and absorption processes, commonly referred to as “solar dimming.” Several studies have quantified irradiance losses ranging from 4% to 15% in polluted and dust-prone regions [3,4]. Mani and Pillai [5] and Darwish et al. [6] highlighted that dust accumulation and high aerosol optical depth (AOD) can substantially reduce PV output unless frequent cleaning or mitigation strategies are adopted. Recent satellite-based assessments further indicate that aerosol-induced dimming has intensified over South Asia during the last three decades, raising concerns for long-term solar energy reliability [7].

Table 1: Installed solar capacity for the six states examined in this study, as of around 31 March 2025

State	Installed solar capacity [MW]
Rajasthan	28,761
Gujarat	19,422
Punjab	1,421
Haryana	2,099
Delhi	319
Tamil Nadu	10,310

Source: compiled from Ministry of New and Renewable Energy (MNRE) and Central Electricity Authority (CEA) state-wise capacity data, as reported in Solar power in India, Wikipedia, and, for Tamil Nadu, from MNRE (2025) as cited in the Auroville Consulting distributed solar mapping briefing note for Tamil Nadu.

Ambient temperature is another critical determinant of PV performance. Elevated temperatures reduce module efficiency due to increased semiconductor resistance and thermal losses in inverters. Experimental and modelling studies suggest that PV efficiency typically declines by 0.3–0.5% per °C increase in temperature

[7–9]. This effect is especially pronounced in arid and semi-arid regions, where high irradiance coincides with extreme thermal conditions. Vasisht et al. [11] demonstrated strong seasonal and regional temperature sensitivity in PV installations across India. Cloud cover and monsoon dynamics introduce additional variability in PV generation by altering both the magnitude and temporal distribution of solar radiation. Jadhav et al. [12] showed that multi-level cloud formations combined with aerosol loading play a decisive role in surface solar dimming across India. International studies have increasingly incorporated climate change projections into PV potential assessments [13,14], whereas Indian studies have more often focused on techno-economic feasibility and policy barriers to deployment. Long-term, state-level analyses integrating irradiance trends, aerosol dynamics, and temperature rise remain limited. Murphy [15] and Ma et al. [16] emphasized the importance of climate-consistent meteorological datasets for accurate PV performance modelling but did not explicitly evaluate long-term climatic risks. Recent research has begun to explore the interaction between air quality improvement, climate mitigation, and future solar potential in India [1]. However, these studies are often national in scope and lack granular, state-level vulnerability assessments. Moreover, few studies combine climatic trend detection, PV performance simulation, and econometric modelling within a unified framework.

In summary, existing literature confirms that climatic and environmental factors significantly influence PV performance, yet comprehensive multi-decadal assessments at the sub-national level are scarce for India. This study addresses this gap by integrating long-term climatic trends, PV performance modelling, and statistical analysis to quantify climate-driven risks to solar PV performance across Indian states. Because the terms climate risk, climate vulnerability, and climate exposure or sensitivity are used loosely and at times interchangeably elsewhere in this literature, this study adopts a fixed exposure–sensitivity–risk framework for the remainder of the paper. Climate exposure refers to the magnitude and direction of change in a physical climatic driver itself (e.g., the observed decline in irradiance or rise in AOD at a given location). Climate sensitivity refers to the responsiveness of PV performance to a unit change in that driver (e.g., the percentage point reduction in performance ratio per unit increase in AOD or per °C of warming, as estimated in Section 3.3.4 and Section 4.4). Climate risk (used interchangeably with climate vulnerability in this paper) refers to the composite outcome of exposure and sensitivity combined – the basis for the Composite Climate Risk Index reported in Table 8 and described in Section 3.3.6. Subsequent sections use these three terms consistently in this sense.

3 Data and methodology

Before detailing each step, this section summarizes the overall analytical workflow. The study proceeds in five linked stages. First, multi-decadal climatic and PV-relevant datasets are compiled for six Indian states (Section 3.2). Second, long-term trends in irradiance, AOD, temperature, and cloud cover are detected using the Mann–Kendall test and Sen's slope estimator (Section 3.3.1). Third, these trends are propagated through a temperature-corrected PV performance model to translate climatic change into performance-ratio loss, decomposed by driver (Sections 3.3.2–3.3.3 and 4.4). Fourth, a state-level panel regression quantifies the statistical association between the climatic drivers and specific PV yield, providing an independent, model-based check on the performance-ratio decomposition (Section 3.3.4). Fifth, downscaled CMIP6 projections are used to extend the historical analysis into future scenarios, and the historical exposure and sensitivity results are combined into a Composite Climate Risk Index that ranks state-level vulnerability (Sections 3.3.5–3.3.6). Figure 1 summarizes this workflow schematically, and Sections 4 and 5 present and interpret the results of each stage in turn.

3.1 Study scope

This study examines the influence of long-term climatic variability on solar photovoltaic (PV) performance across six Indian states with substantial solar deployment. States were selected based on the availability of consistent long-term climatic records and significant installed solar capacity, ensuring representativeness across diverse climatic zones of India. The analysis spans the period from 1990 to 2023, allowing the assessment of multi-decadal trends in key atmospheric and environmental variables relevant to PV performance. This temporal coverage captures both historical variability and recent climate-driven changes affecting solar energy systems.

3.2 Data sources

To ensure robustness and consistency, this study synthesizes information from multiple widely used observational, satellite-based, and reanalysis datasets. Surface solar radiation data, expressed as global horizontal irradiance (GHI), were obtained from the NASA Prediction of Worldwide Energy Resources (POWER) database and the ERA5 reanalysis product, both of which have been extensively validated for solar energy applications. Near-surface air temperature data were sourced from ERA5 and the India Meteorological Department (IMD), providing high temporal resolution and long-term continuity suitable for trend analysis. These data sources and their temporal resolution are summarized in Table 2.

Atmospheric aerosol conditions were characterized using aerosol optical depth (AOD) products derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Multi-angle Imaging Spectro Radiometer (MISR), which are widely employed in studies assessing aerosol impacts on surface solar radiation. Cloud cover information was obtained from ERA5 and the International Satellite Cloud Climatology Project (ISCCP), enabling evaluation of cloud-induced variability in solar resource availability. Seasonal dust indicators were derived from IMD observations and MODIS products to account for regional dust transport and deposition patterns affecting PV systems. AOD is used in this study as a proxy for two related but physically distinct effects: atmospheric radiative attenuation (column-integrated scattering and absorption that reduces irradiance reaching the surface) and module-surface soiling (deposition of particulates directly on the panel). At the state-level, multi-decadal scale adopted here, this combined proxy is a reasonable simplification because both effects are driven by the same regional aerosol and dust loading and both act to suppress PV output. However, the two effects are not equivalent: radiative attenuation is captured well by column AOD, whereas soiling additionally depends on particle size distribution, deposition velocity, rainfall-driven natural cleaning frequency, and panel tilt and cleaning schedules, none of which are available as state-level time series for the full 1990–2023 period. In the absence of direct soiling or panel-cleaning records, the aerosol-loss term reported in Section 4.4 should therefore be interpreted as the combined radiative-plus-soiling effect attributable to ambient aerosol loading, not as an independently validated soiling rate. This is a limitation common to AOD-based PV studies at regional scale and is revisited in Section 5.9.

Table 2: Summary of data sources and temporal resolution for climatic parameters and solar PV performance indicators

Variable	Source	Resolution
Global Horizontal Irradiance (GHI)	NASA POWER, ERA5	Daily / Monthly
Temperature	ERA5, IMD	Daily
Aerosol Optical Depth (AOD)	MODIS, MISR	Monthly
Cloud Cover	ERA5, ISCCP	Monthly
Dust Indicators	IMD, MODIS	Seasonal
PV Output (modelled)	PVLib	Hourly
Solar Generation	MNRE, CEA	Annual

Solar PV energy output was estimated using the PVLib modelling framework, which simulates hourly system performance based on meteorological inputs and established photovoltaic performance models [17]. Modeled outputs were compared with annual solar generation statistics reported by the Ministry of New and Renewable Energy (MNRE) and the Central Electricity Authority (CEA) to ensure consistency with observed generation trends at the state level.

3.3 Methodology overview

The following subsections detail each analytical step in turn, beginning with the statistical detection of long-term trends in the climatic variables introduced in Section 3.2.

3.3.1 Trend detection in climatic variables

Long-term trends in climatic variables, including global horizontal irradiance (GHI), aerosol optical depth (AOD), air temperature, and cloud cover, were assessed using the non-parametric Mann–Kendall (MK) trend test, which is widely applied in hydro-climatic and energy studies due to its robustness against non-normal distributions and missing values [18,19].

The MK test statistic $S$is defined as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}(x_j - x_i)$$

where $x_i$and $x_j$represent data values at time steps $i$and j, respectively, and $n$denotes the length of the time series. The sign function $\operatorname{sgn}(\cdot)$is given by: (1)

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} +1, & \text{if } x_j - x_i > 0 \\ 0, & \text{if } x_j - x_i = 0 \\ -1, & \text{if } x_j - x_i < 0 \end{cases}$$

To quantify the magnitude of detected trends, Sen's slope estimator [20] was employed. The slope $\beta$is computed as the median of all pairwise slopes: (2)

$$\beta = \text{median}\left(\frac{x_j - x_i}{j - i}\right), \forall j > i$$

3.3.2 Solar photovoltaic performance modelling

Hourly solar PV power output was simulated using a temperature-corrected single-diode model implemented within the PVLib framework [17]. The DC power output of a PV system at time t, $P_{\mathrm{DC},t}$, is expressed as:

$$P_{\mathrm{DC},t} = G_t \cdot A \cdot \eta_{\mathrm{ref}}\left[1 - \gamma(T_{c,t} - T_{\mathrm{ref}})\right] \cdot (1 - L_s)$$

where

$G_t$is the incident solar irradiance (W m^{-2}),

$A$is the active module area (m^2),

$\eta_{\mathrm{ref}}$is the reference module efficiency at standard test conditions,

$\gamma$is the temperature coefficient of power (% °C^{-1}),

$T_{c,t}$is the cell temperature (°C),

$T_{\mathrm{ref}}$is the reference temperature (25 °C), and

$L_s$represents combined soiling and environmental loss factors. (4)

The PV cell temperature was estimated using the empirical relationship:

$$T_{c,t} = T_{a,t} + \frac{\mathrm{NOCT} - 20}{800} \cdot G_t$$

(5)

where $T_{a,t}$is the ambient air temperature (°C) and NOCT is the nominal operating cell temperature.

3.3.3 Performance ratio estimation

The performance ratio (PR), which reflects the overall efficiency of a PV system independent of location and size, was calculated as:

$$\mathrm{PR} = \frac{E_{\mathrm{AC}}}{G_{\mathrm{POA}} \cdot P_{\mathrm{rated}}}$$

(6)

where

$E_{\mathrm{AC}}$is the actual AC energy output (kWh), $G_{\mathrm{POA}}$is the plane-of-array irradiance (kWh m^{-2}), and $P_{\mathrm{rated}}$is the installed system capacity (kWp).

3.3.4 Econometric assessment of climate impacts

To quantify the influence of climatic variables on PV performance, a state-level panel regression model was employed. The empirical specification is given by:

$$Y_{i,t} = \alpha + \beta_1 \mathrm{GHI}_{i,t} + \beta_2 \mathrm{AOD}_{i,t} + \beta_3 T_{i,t} + \beta_4 C_{i,t} + \mu_i + \varepsilon_{i,t}$$

(7)

where

$Y_{i,t}$denotes the specific PV yield for state $i$in year t,

$\alpha$is the intercept,

β_1–β_4 are estimated coefficients,

$T_{i,t}$represents ambient temperature,

$C_{i,t}$denotes cloud cover,

$\mu_i$captures unobserved state-specific effects, and

$\varepsilon_{i,t}$is the error term.

3.3.5 Future climate scenario assessment

Projected impacts of climate change on PV performance were assessed using downscaled climate projections from CMIP6 under SSP2–4.5 and SSP5–8.5 scenarios. Future relative yield change (ΔY) was estimated as:

$$\Delta Y = \frac{Y_{\mathrm{future}} - Y_{\mathrm{baseline}}}{Y_{\mathrm{baseline}}} \times 100$$

(8)

where Y_{baseline}represents historical average yield and Y_{future}denotes projected yield under future climatic conditions.

3.3.6 Derivation of state-level performance-ratio loss and the composite climate risk index

The 10–21% total performance-ratio (PR) reduction reported in the abstract and in Section 4.4 (Table 4) is not an independent estimate; it is the sum of three driver-specific loss terms derived sequentially from the decadal trends established in Sections 4.1–4.3. For each state, the irradiance-loss term is obtained by applying the Sen's-slope decadal trend in GHI (Section 4.1) over the 1990–2023 study window directly to the PV power equation in Section 3.3.2 (Eq. (4)), holding all other inputs at their reference values: a sustained decline (or rise) in irradiance over 33 years scales DC power output almost linearly through the irradiance term in Eq. (4), producing the irradiance-loss percentages reported in Table 4 (e.g., the 2–6 W m^{-2} per decade decline identified for Punjab translates to roughly −6% cumulative DC output over the 33-year window relative to a stable-irradiance counterfactual).

The aerosol-loss term is derived by combining the state-level decadal AOD trend (Section 4.2, Table 3) with an empirical attenuation coefficient relating AOD to direct-beam irradiance reduction, calibrated against the 4–12% annual attenuation range reported for Indian conditions in the aerosol-PV literature [6–8,10,11]; this coefficient is then applied to each state's observed AOD change to obtain a state-specific cumulative aerosol-loss percentage, which also implicitly absorbs the soiling component discussed as a limitation in Section 3.2. The temperature-loss term follows directly from the cell-temperature relationship in Eq. (5) and the standard linear temperature-coefficient relationship (0.3–0.45% PR loss per °C, Section 4.3), applied to each state's observed 1990–2023 warming trend. Because the three drivers act on largely separable physical pathways (spectral attenuation, surface soiling, and thermal derating) over the multi-decadal timescale considered, their individual loss percentages are summed, not multiplicatively compounded, to obtain the Total PR Reduction column in Table 4; this additive treatment is a simplification that does not capture possible second-order interactions (e.g., higher cell temperatures slightly altering the spectral sensitivity to aerosol-scattered light) and is noted as a source of uncertainty in Section 5.9. The resulting state-level totals, ranging from −10% in Tamil Nadu to −21% in Punjab, Haryana, and Delhi, constitute the 10–21% range stated in the abstract. As an independent check, the sign and relative magnitude of these driver-specific losses are corroborated by the panel regression coefficients in Table 5 (Section 4.5): GHI carries a positive coefficient while AOD, temperature, and cloud cover carry significant negative coefficients, consistent with the direction and relative ranking of the decomposed losses in Table 4.

The Composite Climate Risk Index reported in Table 8 is constructed from three sub-scores Irradiance Risk, Aerosol Risk, and Temperature Risk each assigned categorically (Low, Medium, High, Very High) for every state. Each sub-score reflects both the magnitude of historical exposure (the decadal trend identified in Sections 4.1–4.3) and the absolute level of the underlying variable at the end of the study period (2023), since a state with both a steep trend and a high absolute level represents a materially different risk than a state with a steep trend from a low base. Specifically: Irradiance Risk is assigned from the sign and magnitude of the Sen's-slope GHI trend (Section 4.1), with a declining trend exceeding 4 W m^{-2} per decade classified High and a stable or increasing trend classified Low. Aerosol Risk combines the percentage AOD increase over 1990–2023 (Table 3) with the 2023 absolute AOD level, using a simple two-criterion rule in which a state is classified Very High only if it ranks in the upper tercile on both criteria simultaneously; a state with a large percentage increase from a low base, or a high absolute level reached gradually, is classified one category lower. Temperature Risk is assigned from the magnitude of the observed 1990–2023 warming trend (Section 4.3) relative to the sample median. The three sub-scores are then combined into the Composite Risk rating using an unweighted ordinal rule: a state is rated Very High if at least two of the three sub-scores are High or Very High; High if one sub-score is Very High with the others Medium or below; Medium if sub-scores are mixed without a Very High; and Low otherwise. This index is deliberately ordinal and screening-oriented rather than a continuous numerical score, consistent with the exposure–sensitivity–risk framework defined in Section 2: it is intended to rank states for planning attention rather than to provide a precise risk magnitude.

This combined-criterion rule for Aerosol Risk also explains the Punjab–Delhi contrast noted in Table 4 and Table 8: Punjab shows the larger percentage AOD increase and the steeper decadal trend (Table 3), but Delhi's 2023 absolute AOD level is the highest among the states studied (0.68 versus 0.59). Because Delhi ranks in the upper tercile on both the trend and the absolute-level criterion, while Punjab's very high percentage increase is calculated from a comparatively lower starting base, Delhi receives the higher Aerosol Risk classification in Table 8 even though Punjab's relative trend is steeper. This is discussed further as a clarification in Section 5.6.

4 Results

This section presents the empirical findings in the same sequence as the analytical workflow outlined in Section 3.3, beginning with long-term trends in the four climatic drivers before turning to their combined effect on PV performance.

4.1 Long-term variability in solar irradiance

Figure 2 illustrates the multi-decadal trends in global horizontal irradiance (GHI) across the selected Indian states during the period 1990–2023. The results reveal a clear spatial contrast in irradiance evolution. Northern and eastern states exhibit a statistically significant declining trend, whereas western and southern regions show relatively stable or marginally increasing irradiance levels. Quantitatively, the decline in GHI is most pronounced in Punjab, Haryana, Uttar Pradesh, and Delhi, with reductions ranging between 2 and 6 W m^{-2} per decade. Seasonal decomposition indicates that the largest reductions occur during the winter and monsoon months, suggesting the combined influence of persistent cloud cover and increased aerosol loading. In contrast, Rajasthan and Gujarat display near neutral or slightly positive irradiance trends, reflecting lower cloud persistence and relatively stable atmospheric conditions.

These findings confirm that long-term solar resource availability in India is not spatially uniform and that reliance on historical averages may lead to overestimation of future solar energy potential in several regions.

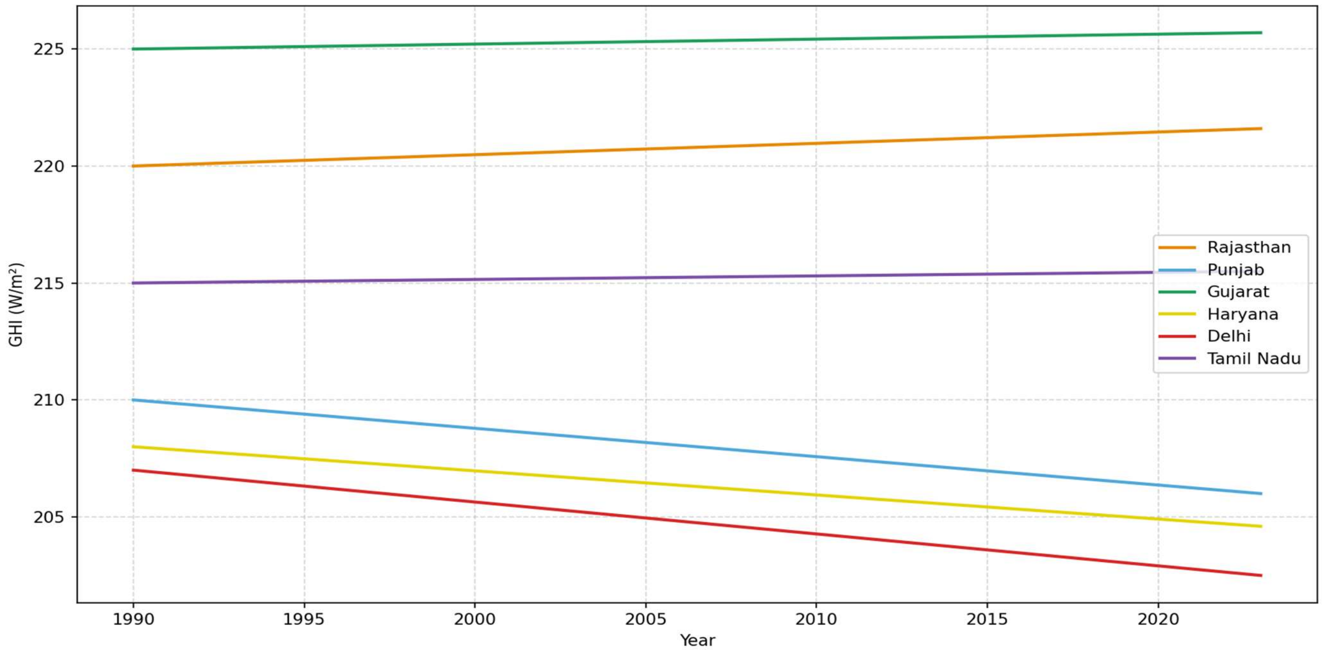

Figure 2: Long-term solar irradiance trend

4.2 Aerosol optical depth and atmospheric pollution trends

Table 3 summarizes the evolution of aerosol optical depth (AOD) across the states studied between 1990 and 2023. A substantial increase in aerosol concentration is observed in highly urbanized and industrialized regions. For example, AOD values in Punjab, Haryana, and Delhi have more than doubled over the study period, indicating a sharp rise in atmospheric pollution and dust loading. In contrast, western states such as Rajasthan show only a modest increase in AOD, reflecting the dominance of natural dust sources rather than anthropogenic pollution. Southern states exhibit moderate increases, likely associated with urban growth and transport emissions. The observed increase in AOD directly contributes to surface solar dimming by reducing direct beam irradiance. Model estimates suggest that aerosol-induced attenuation alone accounts for annual PV energy losses of approximately 4–12%, depending on location. These results highlight aerosols as one of the most critical environmental stressors affecting long-term PV performance in India.

Table 3: Multi-decadal AOD variation across Indian states

State	AOD (1990)	AOD (2023)	% Change
Punjab	0.28	0.59	+111%
Haryana	0.30	0.63	+110%
Delhi	0.32	0.68	+112%
Rajasthan	0.38	0.41	+8%
Gujarat	0.25	0.32	+28%
Tamil Nadu	0.18	0.24	+33%

Rising aerosol levels reduce direct irradiance by 4–12% annually depending on location.

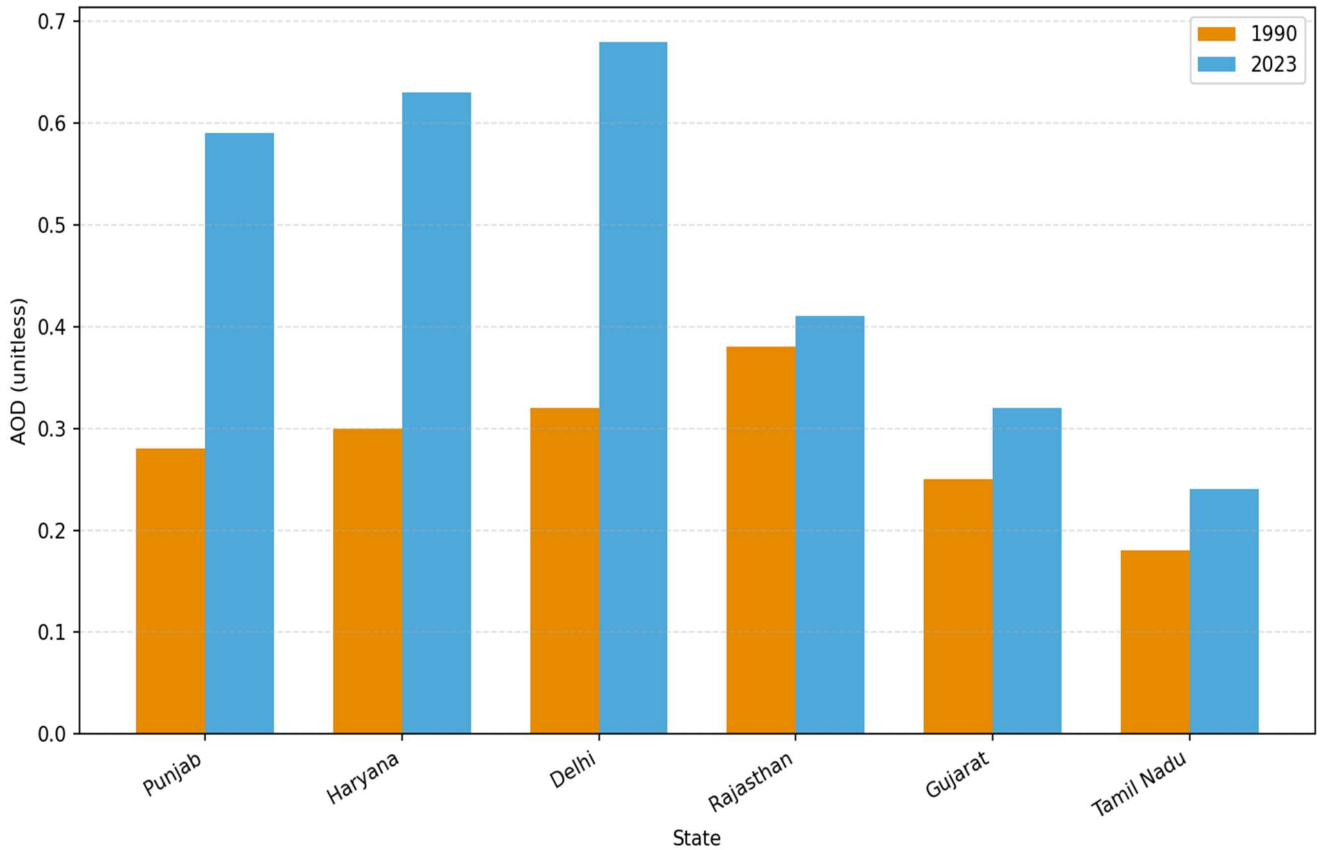

Figure 3: Comparison of average aerosol optical depth (AOD) across selected Indian states for two representative time periods, illustrating the increase in atmospheric aerosol loading.

4.3 Temperature trends and thermal stress on PV systems

Figure 4 presents state-wise trends in near-surface air temperature over the 33-year study period. All states exhibit a statistically significant warming trend, with temperature increases ranging from approximately 0.8 °C to 1.5 °C. The highest warming rates are observed in Punjab and Gujarat, while Tamil Nadu shows the most moderate increase. Elevated temperatures negatively affect PV module efficiency due to increased cell temperature and thermal losses. Using standard temperature coefficients, the observed warming corresponds to efficiency reductions of approximately 0.3–0.45% per degree Celsius. As a result, states experiencing high irradiance combined with elevated temperatures face compounded performance losses, underscoring the importance of thermal management strategies in system design.

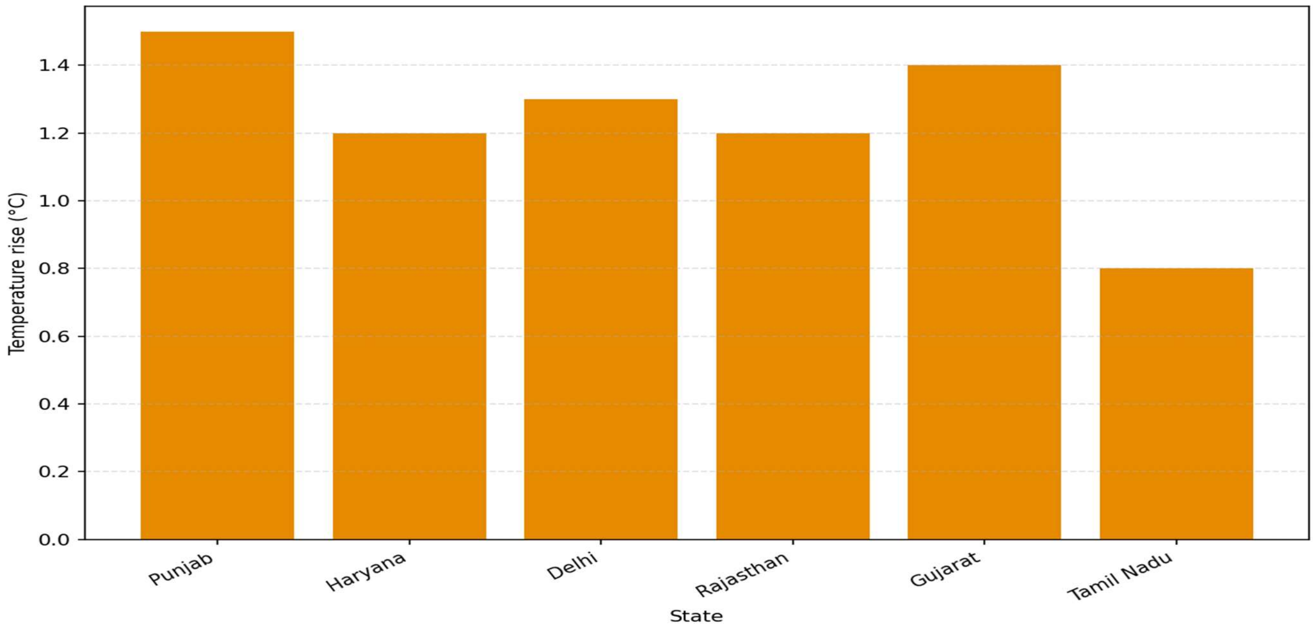

Figure 4: Temperature rise from 1990–2023

4.4 Performance ratio loss attributable to climatic drivers

Table 4 provides a decomposition of performance ratio (PR) losses attributed to changes in irradiance, aerosol concentration, and temperature. The derivation of each driver-specific loss term and of the resulting Total PR Reduction column is set out in Section 3.3.6. Northern states such as Punjab, Haryana, and Delhi experience the largest total PR reductions, reaching 21%. In these regions, aerosol loading emerges as the dominant loss factor, followed by irradiance decline and thermal effects. Western states, including Rajasthan and Gujarat, show comparatively lower total losses (11–13%), with temperature-induced efficiency degradation being the primary contributor. Southern states exhibit moderate losses, reflecting balanced contributions from aerosols, cloud cover, and temperature. Figure 3 visualizes the cumulative PR losses across states, clearly illustrating strong spatial heterogeneity in climate-driven PV performance degradation. These results demonstrate that climatic impacts on PV systems are region-specific and cannot be generalized at the national level. The practical significance of these losses can be illustrated using installed capacity figures (Table 1). Punjab, with roughly 1,421 MW of installed solar capacity as of March 2025, experiences a 21% PR reduction; at a typical Indian PV capacity utilisation factor of approximately 18–19%, this corresponds to forgone generation on the order of 0.4–0.5 TWh per year relative to a no-climate-change counterfactual – enough to supply roughly 150,000–200,000 average Indian households annually. Applied at the larger scale of Rajasthan (over 28,700 MW installed), even the comparatively smaller 13% loss translates to forgone generation an order of magnitude larger in absolute terms, despite Rajasthan's lower percentage loss. This indicates that climate-driven PR losses are practically significant both in high-percentage-loss, moderate-capacity states such as Punjab and in lower-percentage-loss, very-high-capacity states such as Rajasthan, and that percentage losses alone understate the absolute energy and revenue implications for India's largest solar states.

Table 4: Estimated state-level performance loss due to climate variables

State	Irradiance Loss	Aerosol Loss	Temperature Loss	Total PR Reduction
Punjab	−6%	−11%	−4%	−21%
Haryana	−5%	−12%	−4%	−21%
Delhi	−4%	−14%	−3%	−21%
Rajasthan	+1%	−6%	−8%	−13%
Gujarat	0%	−4%	−7%	−11%
Tamil Nadu	−2%	−3%	−5%	−10%

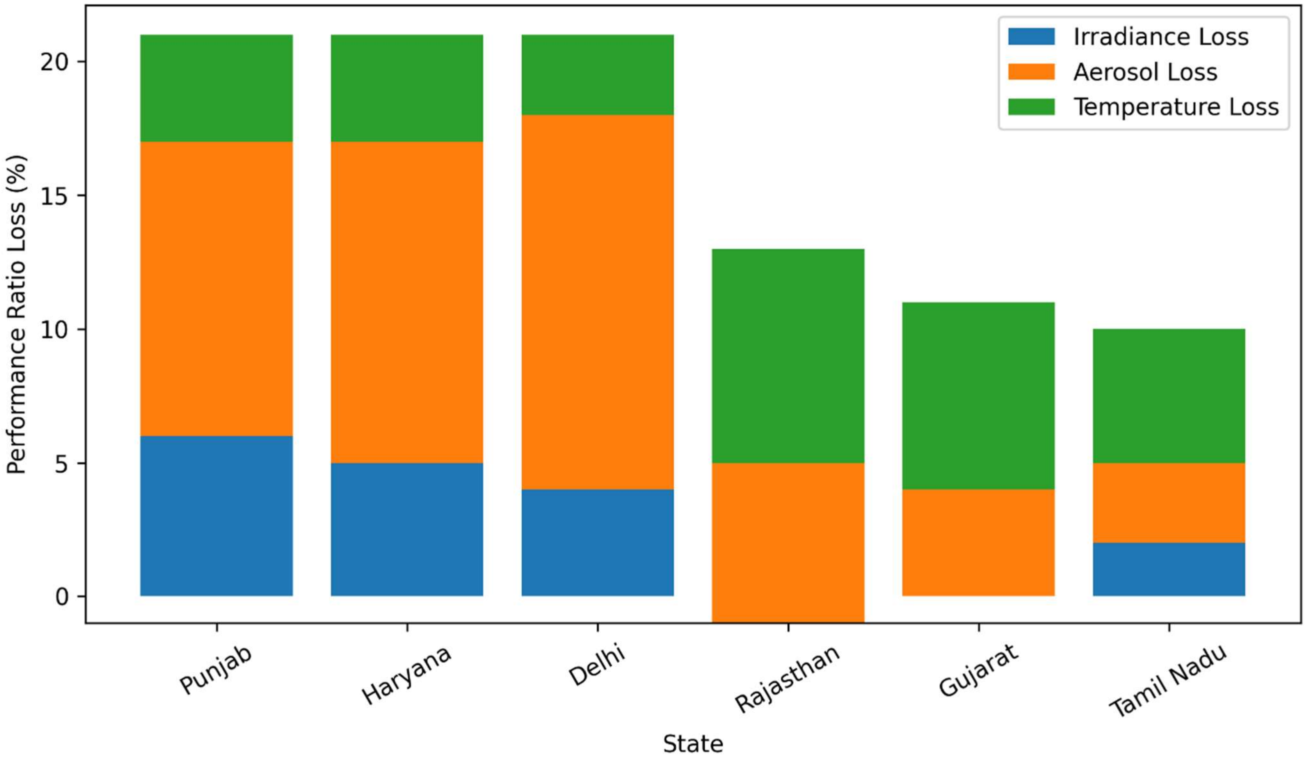

Figure 5: Climate-driven performance ratio loss

4.5 Econometric assessment of climate–PV relationships

The results of the panel regression analysis are summarized in Table 5. Global horizontal irradiance exhibits a strong positive and statistically significant relationship with PV specific yield, confirming its role as the primary driver of solar energy production. In contrast, aerosol optical depth, temperature, and cloud cover show significant negative coefficients, indicating their suppressing effect on PV output. The model explains approximately 72% of the variation in state-level PV yield, suggesting a robust fit. Among the explanatory variables, aerosol concentration has the largest negative marginal effect, reinforcing its dominant role in long-term PV performance reduction. Temperature effects are also significant, particularly in warmer regions where thermal stress is persistent.

Table 5: Random effects regression results

Variable	Coefficient	Std. Error	p-value
GHI	0.42	0.07	0.000
AOD	−0.31	0.09	0.001
Temperature	−0.18	0.05	0.000
Cloud Cover	−0.22	0.06	0.000
Constant	4.21	1.12	0.000
Overall R^2 = 0.72			

Interpretation:
Irradiance strongly enhances yield, while aerosols, cloudiness, and rising temperatures significantly suppress PV performance.

4.6 State-level climate vulnerability assessment

Figure 6 presents the spatial distribution of climate vulnerability for solar PV systems across the six states examined in this study. Punjab, Haryana, and Delhi are categorized as high-risk due to the combined effects of declining irradiance, high aerosol concentrations, and moderate warming. Rajasthan and Gujarat fall into a medium-risk category, while Tamil Nadu exhibits the lowest vulnerability among the states studied.

The correlation matrix presented in Table 6 further supports these findings, showing strong negative correlations between PV yield and AOD, cloud cover, and temperature, alongside a positive correlation with GHI. These relationships confirm the compounded influence of multiple climatic stressors on PV performance.

Figure 6: Climate vulnerability map for solar PV (2023)

High-risk: Punjab, Haryana, Delhi
Medium-risk: Rajasthan, Gujarat
Low-risk: Tamil Nadu

4.7 Projected impacts under future climate scenarios

Figure 7 illustrates projected changes in PV yield under SSP2–4.5 and SSP5–8.5 scenarios for the period 2040–2060. Under the moderate-emission pathway, yield reductions range from 6% to 12%, primarily driven by gradual warming and persistent aerosol levels. Under the high-emission scenario, projected losses increase substantially, reaching up to 18% in northern states (Table 7).

Table 6: Correlation matrix of climatic variables and PV yield

Variable	GHI	AOD	Temperature	Cloud Cover	PV Yield
GHI	1.00	−0.48	−0.32	−0.55	+0.67
AOD	−0.48	1.00	+0.29	+0.41	−0.61
Temperature	−0.32	+0.29	1.00	+0.18	−0.44
Cloud Cover	−0.55	+0.41	+0.18	1.00	−0.58

Table 8 presents a composite climate risk index integrating irradiance, aerosol, and temperature stressors. Punjab, Haryana, and Delhi emerge as the most vulnerable states, while Rajasthan and Gujarat fall into the medium-risk category due to opposing effects of high temperature and stable irradiance. Tamil Nadu exhibits the lowest composite risk among the states studied. Delhi's Aerosol Risk score is in fact the highest among the states studied, reflecting its top-ranked absolute AOD level in 2023 (Table 3) alongside a steep decadal trend; this combined-criterion construction, and the resulting Punjab–Delhi contrast, is detailed in Section 3.3.6.

Table 7: Projected PV yield decline under future climate scenarios (SSP2-4.5 and SSP5-8.5)

Scenario	Expected Yield Decline	Key Drivers
SSP2-4.5	−6% to −12%	Moderate warming, stable aerosols
SSP5-8.5	−10% to −18%	High warming, dust intensification

Table 8: State-wise climate risk index for solar PV

State	Irradiance Risk	Aerosol Risk	Temperature Risk	Composite Risk
Punjab	High	Very High	Medium	Very High
Haryana	High	Very High	Medium	Very High
Delhi	High	Very High	Medium	Very High
Rajasthan	Low	Medium	High	Medium
Gujarat	Low	Low	High	Medium
Tamil Nadu	Medium	Low	Medium	Low

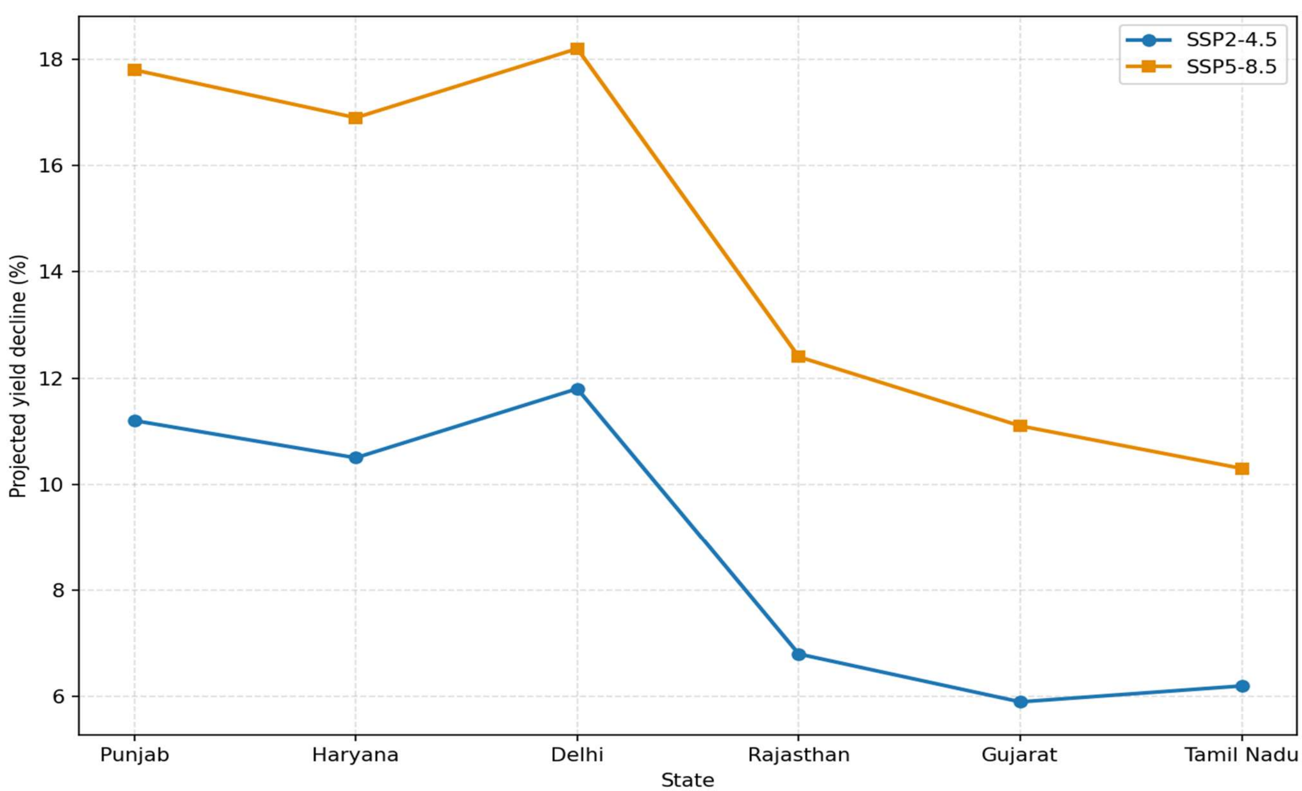

Figure 7: Projected solar PV yield decline (SSP scenarios)

Table 9: Adaptation measures versus climate stressors

Climate Stressor	Adaptation Measure	Expected Gain
High AOD	Anti-soiling coating	+4–7%
High Temperature	Low temp-coefficient modules	+3–5%
Cloud variability	Tracker systems	+6–10%
Dust storms	Automated dry cleaning	+5–8%

5 Discussion

The results of this study demonstrate that climatic and environmental variability exerts a systematic and spatially heterogeneous influence on solar photovoltaic (PV) performance across Indian states. Rather than acting as isolated drivers, changes in irradiance, aerosol loading, temperature, and cloud dynamics interact to shape long-term energy yield, underscoring the importance of integrated climate-aware assessments for solar energy planning.

5.1 Interpretation of irradiance trends

The observed decline in global horizontal irradiance in northern and eastern states can be primarily attributed to persistent atmospheric dimming associated with increased aerosol concentrations and cloud cover. The seasonal concentration of irradiance losses during winter and monsoon periods suggests that synoptic-scale circulation and prolonged cloud persistence play a critical role in suppressing surface solar radiation. In contrast, the relatively stable irradiance trends in western India indicate that arid and semi-arid climates, despite experiencing dust events, are less affected by long-term cloud-induced attenuation. These findings imply that regional climatic regimes fundamentally determine the stability of the solar resource, and reliance on national average irradiance assumptions may mask localized risks.

5.2 Dominance of aerosol-induced performance losses

Among the evaluated climatic drivers, aerosol loading emerges as the most influential factor affecting PV performance, particularly in densely populated and industrialized regions. The strong association between rising aerosol optical depth and declining PV yield reflects both atmospheric attenuation of incoming radiation and increased soiling of module surfaces. The magnitude of aerosol-driven losses observed in this study aligns with earlier experimental and modelling evidence but highlights that their cumulative impact over multiple decades is substantially larger than often assumed in short-term assessments. This reinforces the need to consider air quality trends alongside climate projections when evaluating long-term solar energy potential.

5.3 Temperature effects and thermal stress implications

The consistent warming observed across all states introduces an additional layer of performance degradation through temperature-dependent efficiency losses. While western and central states maintain relatively high irradiance levels, elevated ambient temperatures partially offset these advantages by increasing cell operating temperatures. This trade-off suggests that high-resource regions are not immune to climate-induced risks and that future system performance will increasingly depend on thermal management strategies and module selection. The results indicate that temperature impacts, although secondary to aerosols in some regions, are likely to become more prominent under continued warming.

5.4 Role of cloud cover and variability

Cloud dynamics contribute to both mean yield reductions and increased temporal variability in solar generation. The negative relationship between cloud cover and PV output underscores the challenge of maintaining generation reliability in monsoon-influenced regions. Importantly, the interaction between clouds and aerosols amplifies surface solar dimming, indicating that these factors should not be evaluated independently. This compounded effect has direct implications for grid integration, as increased variability may necessitate additional storage or flexible generation capacity.

5.5 Implications of econometric findings

The econometric analysis provides quantitative evidence that climatic variables collectively explain a substantial proportion of the observed variation in state-level PV performance. The strong negative coefficient associated with aerosol optical depth confirms its dominant suppressive effect, while the statistically significant influence of temperature and cloud cover highlights their complementary roles. These relationships suggest that long-term PV performance is not solely a function of installed capacity or technological efficiency but is deeply intertwined with evolving environmental conditions.

5.6 State-level vulnerability and planning considerations

The spatial patterns of climate vulnerability identified in this study reveal clear regional contrasts in long-term solar risk. Northern states exhibit heightened vulnerability due to the convergence of declining irradiance, high aerosol loading, and moderate warming, whereas western and southern states face comparatively lower but non-negligible risks. These distinctions emphasize the inadequacy of uniform policy and planning approaches. Instead, region-specific strategies that account for dominant climatic stressors are required to sustain solar energy performance over time. This finding is consistent with recent sustainable energy planning literature showing that climate variability materially shifts the optimal siting and suitability mapping of large-scale solar deployment in other developing-country contexts; Nassif et al. [23], for example, demonstrate using a GIS-based multi-criteria approach that projected warming reduces the long-term suitability of otherwise favourable solar sites in Iraq, reinforcing the case for embedding climate trends directly into state-level siting and planning frameworks rather than relying on present-day resource maps alone.

5.7 Future climate risks and long-term outlook

Projected yield reductions under future climate scenarios indicate that climate-induced performance losses are likely to intensify, particularly under high-emission pathways. The amplification of existing stressors, rather than the emergence of new ones, suggests that current trends provide a reliable indication of future risk trajectories. This pattern is consistent with broader assessments of how a changing climate reshapes the planning assumptions underlying national energy systems [21]. Candidate adaptation measures for the principal climate stressors identified in this study, together with their expected performance gains, are summarized in Table 9. Without targeted adaptation measures, continued warming and persistent aerosol concentrations may erode the expected benefits of large-scale solar deployment, especially in high-risk regions; at a system level, such climate-driven shortfalls in solar output share structural similarities with the wind and solar "energy droughts" increasingly documented in other renewable-heavy power systems, underscoring the importance of designing for long-term variability rather than historical averages alone [22].

5.8 Broader implications

Collectively, these findings underscore that climate variability and environmental degradation represent structural challenges to the long-term reliability of solar PV systems. Integrating climatic considerations into technology selection, system design, and policy frameworks is therefore essential. The results advocate for a shift from static, resource-based planning toward dynamic, climate-responsive solar strategies that explicitly account for evolving atmospheric conditions.

5.9 Limitations and uncertainties

While the preceding sections present the results as derived, several methodological choices introduce uncertainty that should be made explicit rather than left implicit in the discussion. First, the use of aerosol optical depth as a combined proxy for radiative attenuation and module soiling (Section 3.2) means that the aerosol-loss term in Table 4 cannot be decomposed into its attenuation and soiling components without independent, panel-level cleaning and soiling-rate records, which are not available at state level for the full study period; the reported aerosol-loss percentages should therefore be read as an upper-bound combined effect rather than a soiling-specific rate. Second, the additive combination of irradiance-, aerosol-, and temperature-loss terms into the Total PR Reduction (Section 3.3.6) assumes the three pathways are approximately independent; possible second-order interactions between elevated cell temperature and aerosol-modified spectral content are not captured and would require coupled radiative-thermal modelling beyond the scope of this study. Third, the Composite Climate Risk Index (Table 8) is deliberately ordinal and uses an unweighted combination rule (Section 3.3.6); a different weighting of irradiance, aerosol, and temperature sub-scores, or a continuous rather than categorical scoring scheme, could shift individual states between adjacent risk categories, particularly for states such as Rajasthan and Gujarat whose sub-scores point in opposing directions. Fourth, the CMIP6-based future projections (Section 3.3.5) inherit the structural and parametric uncertainty of the underlying global climate models and the SSP scenario assumptions and are not bias-corrected against an ensemble of downscaling methods; the SSP2–4.5 and SSP5–8.5 ranges reported in Section 4.7 should be read as indicative bounds rather than precise forecasts. Finally, the panel regression (Section 3.3.4) explains approximately 72% of the variation in state-level PV yield, leaving an appreciable share of variation attributable to factors outside the four climatic variables considered, including grid curtailment, maintenance practices, and inter-annual technology upgrades that are not modelled here. These limitations do not alter the direction of the main findings but bound the precision with which the specific loss percentages and risk classifications should be interpreted.

6 Conclusion

This study provides a comprehensive assessment of how long-term climatic and environmental variability influences the performance of solar photovoltaic systems across Indian states. The findings demonstrate that solar PV output is not solely determined by technological or economic factors but is strongly shaped by evolving atmospheric conditions, including changes in solar irradiance, aerosol loading, ambient temperature, and cloud dynamics. These drivers act in combination rather than in isolation, producing region-specific patterns of performance degradation and vulnerability.

The analysis highlights aerosol-induced solar dim and rising temperatures as the most persistent constraints on long-term PV performance. In northern and highly industrialized regions, increasing aerosol concentrations substantially reduce available solar radiation and contribute to soiling-related losses, while in arid and semi-arid regions, thermal stress increasingly offsets the benefits of high irradiance. Cloud variability further compounds these effects by introducing seasonal and interannual fluctuations in energy yield. Together, these processes underscore the limitations of planning approaches that rely on static solar resource assumptions.

From a broader perspective, the results emphasize the importance of incorporating climate and environmental risks into solar energy planning and system design. Uniform national strategies may overlook localized climatic stressors that significantly influence long-term system performance. Instead, region-specific approaches that integrate climate trends, air quality considerations, and technology adaptation are essential for sustaining solar energy productivity.

Looking ahead, projected climate scenarios suggest that existing stressors are likely to intensify, particularly under high-emission pathways. Without targeted adaptation measures, continued warming and persistent atmospheric pollution may erode the expected gains from expanding solar capacity. These findings reinforce the need for climate-resilient solar strategies, including improved module technologies, effective soiling mitigation, and climate-aware sitting and policy frameworks.

Overall, this work contributes to the growing body of evidence that climate variability represents a structural challenge to the long-term reliability of solar photovoltaic systems. By advancing an integrated understanding of climatic impacts on PV performance, the study provides a valuable foundation for future research and supports informed decision-making aimed at ensuring the resilience and sustainability of solar energy development.

7 References

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