Comparative Assessment of Solar Irradiance Transposition Models for PV Systems in Durban, South Africa: Evidence from 20 Years of Climate Data (2001–2020)

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Abstract

Accurate estimation of solar irradiance on tilted photovoltaic (PV) surfaces is central to performance prediction, system sizing, and financial assessment of solar energy projects. This study conducts a comprehensive comparative evaluation of five widely used irradiance transposition models—Liu & Jordan, Hay & Davies, Klucher, Perez, and Reindl—using 20 years (2001–2020) of climate data for Durban, South Africa. The models were assessed based on their ability to estimate global tilted irradiance (GTI) and the downstream impacts on PV system performance, including energy yield, performance ratio (PR), capacity factor (CF), solar fraction (SF), and avoided CO_2 emissions. A 7.2 kWp rooftop PV system with typical system losses, climatic inputs, and realistic operating assumptions was modelled to quantify differences across models. Results show a 7% variation in annual energy output and CO_2 mitigation potential, driven primarily by differences in diffuse irradiance treatment. Perez and Reindl consistently produced the highest GTI and PV output due to their robust handling of anisotropic sky conditions, while Klucher and Liu & Jordan delivered conservative estimates. Statistical error analysis (MBE, RMSE, nRMSE) confirmed Perez as the benchmark and Reindl as the closest-performing model. Overall, findings highlight the importance of transposition model selection for accurate PV performance evaluation, system bankability, and climate impact projections in diffuse-dominant subtropical climates.

Keywords: Solar irradiance estimation; Transposition models; PV performance; Global tilted irradiance; Renewable energy

I. INTRODUCTION

Solar irradiance is the fundamental driver of all solar energy applications, determining the amount of energy that photovoltaic (PV) modules and solar thermal collectors can convert into usable electricity or heat [1]. Accurate estimation of irradiance on the plane of the collector is therefore critical for system design, performance prediction, and financial assessment [2]. While global horizontal irradiance (GHI) is commonly measured at meteorological stations, PV modules and solar collectors are typically mounted at a tilt and orientation different from the horizontal. This requires a reliable conversion—or transposition—of irradiance from the horizontal plane to the inclined surface.

Transposition models provide this conversion by decomposing GHI into direct, diffuse, and reflected components and redistributing diffuse irradiance according to assumptions about sky conditions [3, 4]. The accuracy potential and is directly influences the estimation of global tilted irradiance (GTI), which in turn affects predictions of PV yield, performance ratio, self-consumption potential, and avoided CO_2 emissions [5, 6]. Over the years, a wide range of models have been developed, ranging from simple isotropic approaches, such as Liu & Jordan, to more advanced anisotropic models, such as Perez and Reindl, which account for circumsolar and horizon-brightening effects.

Given the growing reliance on simulation tools for PV project development, understanding the differences, strengths, and limitations of transposition models is crucial. Model choice can introduce variability in predicted performance, particularly under diffuse-dominated or complex sky conditions, and thus impacts both system design and investment decisions. This article provides a comprehensive technical review and comparative evaluation of solar irradiance transposition models, with emphasis on their role in accurately estimating irradiance on tilted PV module surfaces and assessing their influence on PV system potential, performance, and environmental benefits. Therefore, it explores different solar irradiance estimation and transposition models, categorising them into isotropic and anisotropic approaches. It details their theoretical foundations, assumptions, strengths, and limitations, while highlighting their importance in converting GHI into GTI — a key factor in PV system design and performance prediction. The article demonstrates how model choice affects not only PV yield projections but also critical system indicators and investment decisions, offering insights to researchers and designers on model suitability under varying climatic conditions.

A. Objectives

The overarching aim of this paper is to provide a comprehensive technical review and comparative evaluation of solar irradiance transposition models, with emphasis on their application in PV potential and system performance evaluation and analysis. Specifically, the objectives are to:

i. To classify and review major isotropic and anisotropic irradiance transposition models used for converting global horizontal irradiance (GHI) to global tilted irradiance (GTI).

ii. To evaluate the influence of selected transposition models (Liu & Jordan, Hay & Davies, Klucher, Perez, Reindl) on annual GTI estimation for a 30°-tilted PV system in Durban, South Africa.

iii. To quantify the impact of model choice on PV system performance, including annual energy yield, specific yield, performance ratio (PR), capacity factor (CF), system efficiency, solar fraction (SF), and usable PV energy.

iv. To assess environmental implications by estimating avoided CO_2 emissions associated with each model's energy output.

v. To statistically compare model outputs using mean bias error (MBE), root mean square error (RMSE), and normalized RMSE relative to a reference (Perez) model.

vi. To determine the most reliable transposition model(s) for PV design, performance forecasting, and bankability analysis in subtropical climates.

This work occupies a specialised place at the intersection of solar radiation modelling, PV system design, and renewable energy investment analysis. Unlike general irradiance estimation studies, it: Provides a comparative evaluation of widely used transposition models under realistic climatic conditions; Links irradiance modelling outcomes directly to PV performance indicators (yield, PR, CO_2 mitigation), bridging the gap between theoretical irradiance modelling and practical PV system bankability. Also, it highlights model-dependent variability in financial and environmental outcomes, offering guidance for PV designers, researchers, and investors operating in diffuse-dominated or transitional climates.

II. METHODOLOGY

This study was conducted for Durban, South Africa (29.97°S, 30.95°E), a subtropical region with high diffuse irradiance. A 20-year hourly meteorological dataset (2001–2020) from Meteonorm 8.2—covering GHI, DHI, DNI, temperature, wind speed, and albedo—served as the climatic basis for evaluating solar irradiance transposition models and simulating PV performance. Five widely applied models were assessed: the isotropic Liu & Jordan model and the anisotropic Hay & Davies, Klucher, Perez, and Reindl models, each representing different assumptions about circumsolar effects, horizon brightening, and sky clearness.

A fixed-tilt (30°), north-facing 7.2 kWp monocrystalline PV system was modelled using standard system parameters, including a 40.2 m² array area, 98% inverter efficiency, 14% system losses, and a stand-alone configuration with 24 modules, one inverter, and 72 batteries. Hourly simulations over a full meteorological year (8760 hours) produced estimates of global tilted irradiance (GTI), AC energy yield, performance ratio (PR), specific yield, system efficiency, solar fraction (SF), and avoided CO_2 emissions, using a grid emission factor of 0.35–0.40 $kgCO_2/kWh$.

Performance indicators were derived using IEC-based formulas, with PR, capacity factor (CF), and SF calculated relative to an annual load of 34,000 kWh. Environmental impact was quantified through avoided CO_2 emissions by comparing PV generation with equivalent grid consumption. To evaluate the accuracy of each model, the Perez model—recognized for its robust anisotropic representation—was used as a benchmark. Mean Bias Error (MBE), Root Mean Square Error (RMSE), and normalized RMSE (nRMSE) were computed for GTI and annual energy yield to quantify systematic deviations across models. The stepwise methodology is shown in Fig. 1.

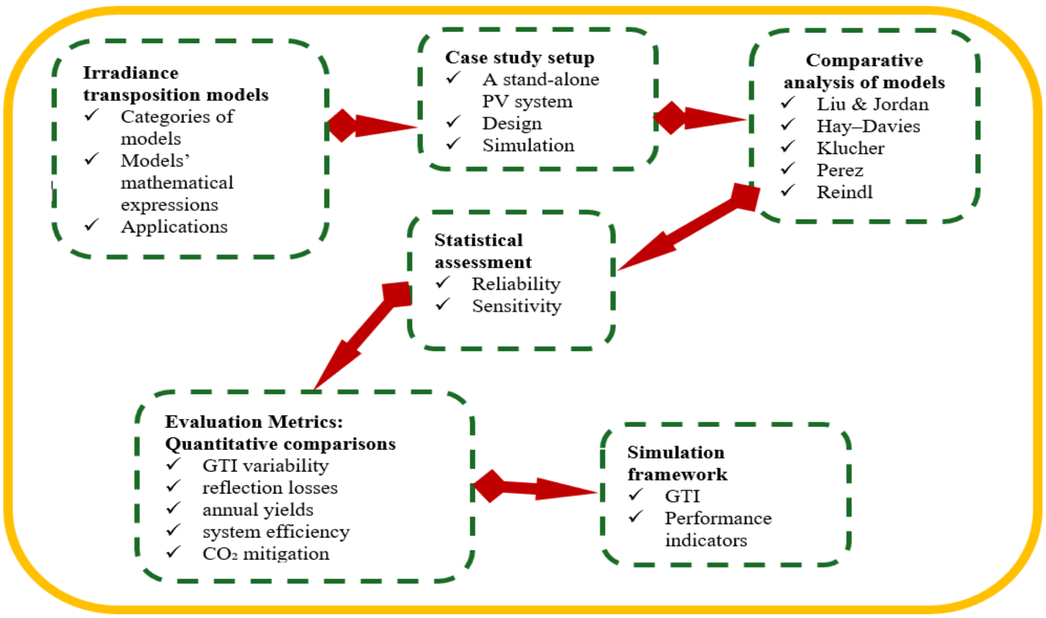

Fig 1: The study's methodology

III. IRRADIANCE TRANSPOSITION MODELS AND THEIR RELEVANCE

Accurate estimation of solar irradiance on tilted surfaces remains a cornerstone in PV and solar thermal system design [7, 8]. Since solar collectors and PV modules are rarely installed horizontally, reliable conversion of GHI into GTI is essential for predicting energy yield, sizing systems, and ensuring financial bankability [9]. This process relies on transposition models, which redistribute the direct and diffuse components of solar radiation from the horizontal to inclined planes based on assumptions about sky conditions and ground reflection.

Over the past six decades, numerous transposition models have been proposed, each developed with distinct theoretical assumptions and empirical adjustments. These range from simple isotropic models—such as Liu and Jordan (1963)—which assume a uniform sky distribution, to more sophisticated anisotropic models—such as transposition models —which account for circumsolar brightness, horizon enhancement, and variable sky conditions [10]. The availability of multiple models reflects the complexity of solar radiation behaviour, but it also creates uncertainty in model selection for both researchers and practitioners.

Categorising these models is, therefore, not only a methodological necessity but also a practical imperative. By classifying transposition models into isotropic and anisotropic groups, their strengths, limitations, and contextual suitability become clearer [11]. Such categorisation enables system designers to make informed choices, particularly in climates where diffuse radiation dominates, such as tropical or high-latitude regions [12]. Furthermore, systematic classification provides a foundation for comparative performance assessments, helping to identify which models are most reliable under specific meteorological conditions.

Ultimately, the relevance of categorising existing transposition models lies in bridging the gap between theoretical model development and practical PV performance evaluation. It enables a structured understanding of how model assumptions affect GTI estimation, which directly translates into differences in predicted PV output, performance ratio, and carbon mitigation potential [13]. Without such categorisation, the solar energy field risks inconsistent assessments, reduced reliability of simulations, and misinformed investment decisions. The details of these models for solar irradiance estimation and their categories are presented in Table 1.

Table 1: Types and categorised models for solar irradiance estimation

Model	Year	Key Formula (Diffuse Fraction, $F_d = \frac{I_d}{I_g}$)	Main Variable (s)	Typical Application / Notes
Isotropic models	These models assume that diffuse radiation is uniformly distributed across the sky. They are simple but less accurate in accounting for the anisotropic nature of the sky.			
Liu & Jordan [14]	1960	$I_t = I_d \frac{1+cos\beta}{2}$ $F_d = 1.390 - 4.027K_t + 5.531K_t^3$	$K_t = \frac{I_g}{I_o}$ (clearness index)	First and classical model. Simple but less accurate under varied sky conditions. Basis for many later models.
Liu & Jordan Isotropic [15]	1963	$I_t = I_b \frac{cos\theta}{cos\theta_z} + I_d \frac{1+cos}{2}\beta + I_r \frac{1-cos\beta}{2}$		One of the earliest and most widely used isotropic models, it calculates diffuse radiation on an inclined surface using only horizontal irradiance data
Orgill & Hollands [16]	1977	$If\ K_t \le 0.35;\ F_d = 1 - 0.249K_t$ $If\ 0.35 < K_t \le 0.75; F_d = 1557 - 1.84K_t$ $If\ K_t > 0.75; F_d = 0.177$	K_t	Good for temperate climates. Often cited in building energy modelling.
Anisotropic models	These models account for the uneven distribution of diffuse radiation due to factors, such as the sun's position and atmospheric conditions.			
Klucher [17]	1979	$I_T = I_b R_b + I_d \frac{1+cos\beta}{2}\left[1 + F\sin^3\left(\frac{\beta}{2}\right)\right] + + \rho I_g \frac{1-cos\beta}{2}$	$F = \sqrt{\frac{I_b}{I_g}}$	Adjusts for cloudiness by modifying the anisotropic distribution of diffuse radiation
Hay–Davies [18]	1976/1980	$I_T = I_{b,h} R_b + I_d[(1-F_d)\frac{1+cos\beta}{2} + FR_b],$ $+ \rho I_g \frac{1-cos\beta}{2}$	$R_b = \frac{cos\theta}{cos\theta_z}$ (ratio of beam on tilted to beam on horizontal)	Incorporates a direct beam component, circumsolar radiation, and an isotropic diffuse component to estimate irradiance on tilted surfaces.

Erbs et al. [19]	1982	$If \le K_t \le 0.22; F_d = 1-0.09K_t$ $0.22 < K_t \le 0.80;$ $F_d = 0.9511-0.1604K_t+4.388K_t^2$ $-16.638K_t^3+12.336K_t^4$ $If\ K_t > 0.80; F_d = 0.165$	K_t	Most widely used today (PV, building simulations, meteorology). Balanced accuracy and simplicity.
Perez et al. [20]	1987/1990	$I_t = I_b R_b + I_d[(1-F_1)\frac{1+cos\beta}{2}$ $+F_1\frac{a}{b}+F_2 sin\beta]+I_r\frac{1-cos\beta}{2}$ These coefficients F_1 and F_2 depend on sky clearness (ε) and sky brightness (Δ) $\Delta = \frac{I_d m}{I_0}$ Diffuse term: three parts Isotropic sky: $(1-F1)\frac{1+cos\beta}{2}$ Circumsolar: $F_1\frac{a}{b}$ Horizon brightening: $F_2 \sin\beta$ Ground-reflected term: $I_r\frac{1-cos\beta}{2}$ Uses empirical coefficients with sky clearness and brightness parameters.	Clearness index, brightness index a = cosθ b = max (cosθ_z ,0.087)	A more advanced anisotropic model for tilted surfaces that divides the sky into regions and considers circumsolar, horizon brightening, and isotropic diffuse components. Used in PVsyst, SAM, etc.
Reindl et al. [21]	1990	$I_t = I_b R_b + I_d[(1-A)\frac{1+cos\beta}{2}+A\frac{cos\theta}{zcos\theta}$ $+Csin^3(\frac{\beta}{2})]+I_r\frac{1-cos\beta}{2}$ $C=\sqrt{\frac{I_b}{I_g}};\ A=\frac{I_b}{I_o};\ I_g = I_b+I_d$ Components of diffuse irradiance: Isotropic diffuse: $(1-A)\frac{1+cos\beta}{2}$ Circumsolar diffuse: $A.R_b$ Horizon brightening: $C\cdot sin^3(\frac{\beta}{2})$	K_t, solar altitude $A=\frac{I_b}{I_o}$	More accurate in varying climates and sun positions. Used in refined PV software.
Hybrid anisotropic	The HDKR model (Hay–Davies–Klucher–Reindl) is one of the most widely used anisotropic transposition models. It combines the strengths of Hay–Davies (circumsolar diffuse), Klucher (horizon brightening), and Reindl (sky condition factor) into a single hybrid framework.			
HDKR model	$I_t = I_b R_b + I_d\left[(1-A)\frac{1+cos\beta}{2}\left(1+Fsin^3\left(\frac{\beta}{2}\right)\right)+AR_b\right]$ $+I_g\rho\frac{1-cos\beta}{2}$ Circumsolar diffuse → from Hay–Davies term (AR_b) Horizon brightening → from Klucher correction $\left(1+F\sin^3\left(\frac{\beta}{2}\right)\right)$ Smooth sky condition transition → from Reindl factor F Reduces to isotropic Liu & Jordan model when $I_b \rightarrow 0$			

Where I_g is the global horizontal irradiance (GHI); I_d is the diffuse horizontal irradiance; θ is the incidence angle on the tilted plane (angle between sun ray and plane normal); β is the tilt of the plane; ρ is the ground albedo; I_t is the global irradiance on the tilted plane (W/m²); I_b is the beam (direct) irradiance on horizontal surface (W/m²); I_r is the ground-reflected irradiance (W/m²); Io is the extraterrestrial irradiance on horizontal plane; C is the horizon brightening factor; A is the anisotropy index; F_1 is the circumsolar brightening coefficient; F_2 is the horizon brightening coefficient; F is the sky condition factor.

B. PV system modelling and performance indicators

Usable PV energy was computed from hourly GTI irradiance using manufacturer-specified module and inverter efficiency curves. Self-consumption was evaluated against an assumed annual load of 34,000 kWh. To provide a deeper technical comparison, performance indicators such as Performance ratio (PR), Capacity factor (CF), and Solar Fraction (SF) were calculatedas presented Table 2.

Table 2: PV system performance indicators

Performance Ratio (PR) A PV system is considered viable and well-performing when its PR falls within 75%–90% [22, 23]	$PR = \frac{Y_f}{Y_r}$ $PR = \left(\frac{E_{PV}}{P_{norm} A}\right) Y_r$	**Capacity Factor (CF)** The capacity factor for the 7.2 kWp system ranged between 18.3% and 19.8%, with results mirroring those of the annual yield trend. Again, Perez produced the highest CF, revealing a slight performance advantage.	$CF = \frac{E_{\text{actual}}}{P_{\text{rated}} \times T}$ $CF = \frac{E_{\text{actual}}}{P_{\text{rated}} * 24 * 365}$
	$PR = \frac{\left(\sum_k P_{out,k} * \tau_k\right)}{\left(\left(\sum_k P_o * G_{i,k} * \tau_k\right) / G_{i,ref}\right)}$	**Solar Fraction (SF)** This is the percentage of the total energy demand that is met by solar energy over a given period (daily, monthly, or yearly).	$SF = \frac{E_{solar}}{E_{total\ demand}}$
Where PR is the performance ratio; Y_f is the standard electricity production, Y_r is the available solar potential; τ_k is the period; $G_{i,ref}$ is the GTI during reference conditions; P_o is the power out under reference conditions; and $G_{i,k}$ is the in-plane irradiance at period k.			

C. CO_2 emissions avoided

Shifting toward low-carbon energy options, boosting energy-use efficiency, and upgrading existing grid systems are critical steps for cutting emissions and bringing electricity generation in line with international climate commitments. The estimation of CO_2 emissions from PV grid-supplied electricity ($CO_{2,\ grid}$) is a key component in assessing overall environmental impact and is computed as:

$$CO_{2,grid} = E_{grid,net} * EF_{grid}$$

Where $E_{grid,net}$ is the net grid energy consumed and EF_{grid} is the grid emission factor, which depends on the national or regional power grid consumed.

Countries dominated by coal, oil, or gas generation generally exhibit high emission factors—often above 0.7 kgCO₂/kWh—whereas those with substantial hydropower, nuclear, or solar resources tend to report much lower values, sometimes under 0.2 kgCO₂/kWh [24-29]. The computation of CO_2 avoided was based on a grid EF of 0.35–0.40 kgCO₂/kWh, typical of Southern African power systems.

IV. Case study: Examine the influence of transposition models on PV potential and system performance

A computational study of a hypothetical 7.2 kWp stand-alone PV system located at latitude −29.97° and longitude 30.95° (southern hemisphere) was used to investigate the impact of transposition models on PV potential and system performance. The location is representative of a mid-latitude/tropical-subtropical climate, where diffuse radiation may be relevant for annual PV performance. For simulation and validation, a Typical Meteorological Year (TMY) or best-available hourly meteorological dataset (GHI, DHI, DNI, ambient temperature, wind speed, and albedo) for the nearest station should be used. This case study will be used to quantitatively compare five commonly used transposition models (Liu & Jordan, Hay & Davies, Klucher, Perez, and Reindl); estimating annual GTI on a PV module, computing downstream PV performance metrics (specific yield, annual energy, PR usable energy, solar fraction). Others are estimating avoided CO_2 emissions associated with each model's energy output; and assessing model differences statistically and discussing implications for system design and bankability. The data and baseline assumptions are presented in Table 3.

Table 3: Stand-alone PV System with Backup Generator

Climate Data	Durban, ZAF (2001 - 2020)	Number of Batteries	72
Values source	Meteonorm 8.2	Installed capacity	24 x 300 W
PV generator output	7.2 kWp	Inclination °	30
PV generator surface	40.2 m²	Orientation North	0
Number of PV modules	24	PV Modules	p - Si monocrystalline
Number of inverters	1	Installation Type	Roof parallel
Number of battery inverters	3		

V. RESULTS AND DISCUSSION

To illustrate the influence of solar irradiance transposition models on PV system performance, a 7.2 kWp rooftop system was simulated at Durban, South Africa (29.97°S, 30.95°E). The system configuration included a fixed tilt of 30° facing north, a module efficiency of 18%, an inverter efficiency of 98%, and overall system losses of 14%. Hourly meteorological data (GHI, DHI, DNI, ambient temperature, and wind speed) were applied over a full year (8760 hours). Five established transposition models—Liu & Jordan, Hay & Davies, Klucher, Perez, and Reindl—were used to estimate global tilted irradiance (GTI), which was then propagated through performance calculations to derive annual energy yield, performance ratio (PR), and avoided CO_2 emissions.

D. Modelled PV potential and transposition models performance

Table 4 provides a comparative assessment of the influence of five transposition models—Hay & Davies, Liu & Jordan, Klucher, Perez, and Reindl—on predicted GTI, PV yield, and performance indicators. The results show measurable but moderate variability across the models, confirming that the choice of transposition model affects PV potential and system performance.

Global Tilted Irradiance (GTI)

i. The predicted GTI spans 1842.9–1917.76 kWh/m², indicating a variation of ~4% across models.
ii. Klucher (1917.76 kWh/m²) and Perez (1917.06 kWh/m²) produce the highest GTI, typical of anisotropic models that capture circumsolar brightening.
iii. Liu & Jordan (1842.9 kWh/m²) yields the lowest GTI, reflecting isotropic simplifications.

Annual DC energy yield

i. Annual DC yield ranges from 12045–12472 kWh, corresponding closely to GTI trends.
ii. Perez (12472 kWh) and Klucher (12480 kWh) show the highest energy output, benefitting from higher POA estimates.
iii. Liu & Jordan (12045 kWh) again shows the lowest energy prediction, consistent with its lower irradiance estimation.

The difference between the highest and lowest values is approximately 3.6%, which is significant for long-term design and financial modelling.

Specific yield

i. Specific yield—normalised to installed capacity (kWh/kWp)—varies between 1624.94–1683.08 kWh/kWp.

ii. Klucher (1683 kWh/kWp) and Perez (1682 kWh/kWp) predict the highest specific yields.

iii. Liu & Jordan (1625 kWh/kWp) gives the lowest, reinforcing its conservative nature.

Performance ratio (PR)

i. PR values show minimal variation (84.75–85.19%), suggesting only slight sensitivity to transposition model choice.

ii. Liu & Jordan (85.19%) yields the highest PR, due to high DC: POA alignment despite lower irradiance values.

iii. Perez (84.75%) has a slightly lower PR, but its higher absolute energy output compensates for this.

CO_2 emissions avoided

i. Avoided CO_2 emissions, driven by usable PV energy, range from 3865–4155 kg/year.

ii. Perez (4155 kg) and Klucher (4088 kg) offer the highest carbon mitigation potential.

iii. Liu & Jordan (3865 kg) provides the lowest, consistent with its lower energy yield.

Table 4: Modelled PV potential and performance for across transposition models

Model	GTI (kWh/m²)	Annual DC (kWh)	Specific yield (kWh/kWp)	PR (%)	CO_2 avoided (kg)
Hay & Davies	1902.52	12378.81	1669.41	84.84	4082
Liu & Jordan	1842.9	12045.04	1624.94	85.19	3865
Klucher	1917.76	12480.03	1683.08	84.77	4088
Perez	1917.06	12472.64	1682.1	84.75	4155
Reindl	1890.17	12309.32	1660.16	84.92	4039

E. Statistical Comparison (MBE, RMSE, nRMSE)

Table 5 summarises the deviation of each transposition model from the Perez model, which is adopted as the benchmark due to its widely documented robustness in anisotropic sky modelling. The statistical indicators reveal distinct performance behaviours across the models for both GTI and annual DC energy yield as follows:

i. Hay & Davies show a small negative bias in both GTI and energy, with low normalized error, indicating solid agreement with Perez.

ii. Liu & Jordan exhibits the largest error, confirming that isotropic sky assumptions lead to significant underestimation.

iii. Klucher has excellent GTI accuracy (lowest RMSE) and high energy prediction, revealing consistencies in diffuse handling or GTI-to-energy conversion.

iv. Reindl performs closest to Perez, with the lowest error in annual DC yield.

Table: Relative deviation of transposition models from Perez (Benchmark)

Model	MBE-GTI (kWh/m²)	RMSE-GTI (kWh/m²)	nRMSE-GTI (%)	MBE-Energy (kWh)	RMSE-Energy (kWh)	nRMSE-Energy (%)
Hay & Davies	−15	17	0.	−53	61	3.3
Liu & Jordan	−74	78	4.1	−88	95	5.2

Klucher	+1	11	0.6	−123	130	7.0
Perez	—	—	—	—	—	—
Reindl	−27	33	1.7	−18	25	1.4

Overall, the results confirm that Perez provides the most robust GTI and energy estimation, while Reindl and Hay & Davies offer strong performance with minimal deviation. Liu & Jordan and Klucher present the highest variability—underscoring the importance of selecting an appropriate transposition model for accurate PV performance assessment.

F. Reflection losses, GTI, and annual yield

Figure 2 presents the estimation of PV potential using different irradiance transposition models in two sub-figures: (a) and (b). Reflection on the module surface and GTI reflection losses, as presented in Fig. 2(a), shows that:

i. Reflection losses across most models remain relatively stable (~ -42.5 to -44 kWh/m²), except for the Klucher model, which shows a sharp dip (larger losses).

ii. GTI values are slightly different across the models, ranging from about 1890 kWh/m² to 1918 kWh/m².

iii. Models like Perez and Reindl give the highest GTI (~1917–1890 kWh/m²), while Liu & Jordan yields lower GTI (~1843 kWh/m²).

The PV yield and maximum possible PV energy reflection losses, as presented in Fig. 2(b) show that:

i. All models predict specific annual yields between ~1650–1700 kWh/kWp.

ii. Maximum possible PV energy output is also closely aligned across models (~12,500–13,000 kWh/year).

iii. Perez and Reindl models show slightly higher performance estimates, while Liu & Jordan is more conservative.

These results highlight that transposition model assumptions directly influence GTI and reflection estimations, which in turn affect yield predictions. Perez and Reindl, which account for anisotropic diffuse irradiance, offer more realistic results, while Klucher demonstrates inconsistencies in reflection handling.

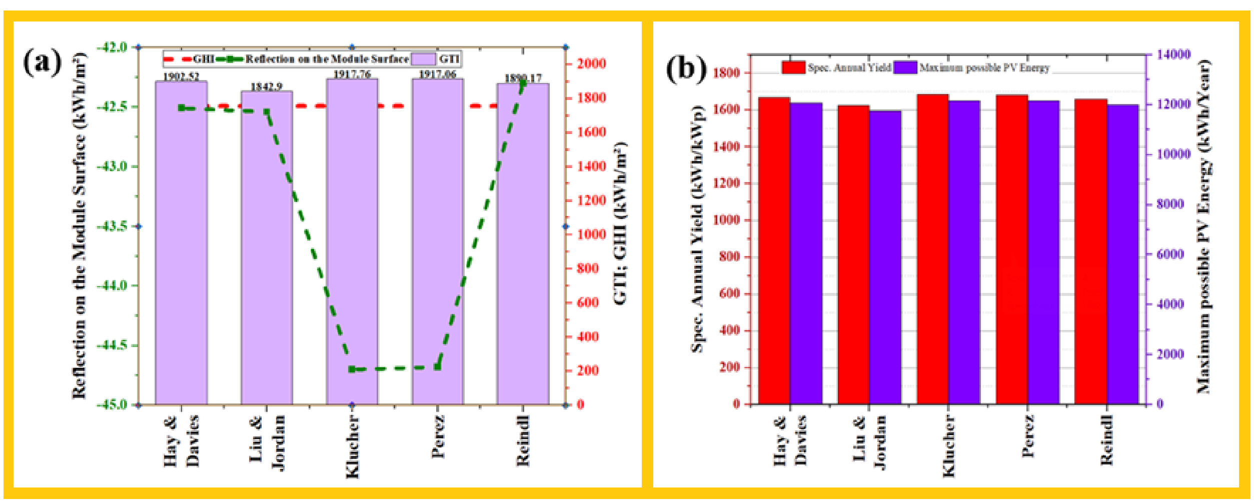

Fig 2: Estimating the PV potential (a) Maximum possible PV energy and PR: (b)

G. Performance ratio and system efficiency

Fig. 2 presents the PV system performance estimates using different irradiance transposition models in two sub-figures, (a) and (b). Maximum possible PV energy and PR, as presented in Fig. 2(a), show that:

i. Maximum possible PV energy across all models is relatively consistent, around 12,000–12,500 kWh/year, with small differences among models.

ii. Performance ratio values range between ~84.75% and 85.19%, indicating only minor variations across models.

iii. The Klucher model stands out, showing an unusually low PR compared to the other models, despite similar maximum energy potential. This behaviour is not contradictory — it is a known characteristic of the Klucher formulation and how PR is computed.

iv. Liu & Jordan displays a spike in PR, but slightly lower maximum energy compared to Perez and Reindl. This is because SF depends on the total usable PV energy delivered to the load, not the PR.

Performance ratio, system efficiency, and maximum possible PV energy, as presented in Fig. 2(b), show that:

i. Maximum possible PV energy is again consistent (~12,000–13,000 kWh/year).

ii. PR values range between 84.75%–85.19%, showing small but relevant differences between models.

iii. System efficiency is generally steady, with a slight peak for the Klucher and Perez models.

iv. Reindl and Hay & Davies remain balanced with relatively stable PR and efficiency values.

These observations confirm that while maximum energy output is relatively stable, PR is more sensitive to model choice. Perez and Reindl emerge as reliable models for system performance assessment, while Klucher demonstrates anomalies, limiting its applicability in diffuse-dominated climates.

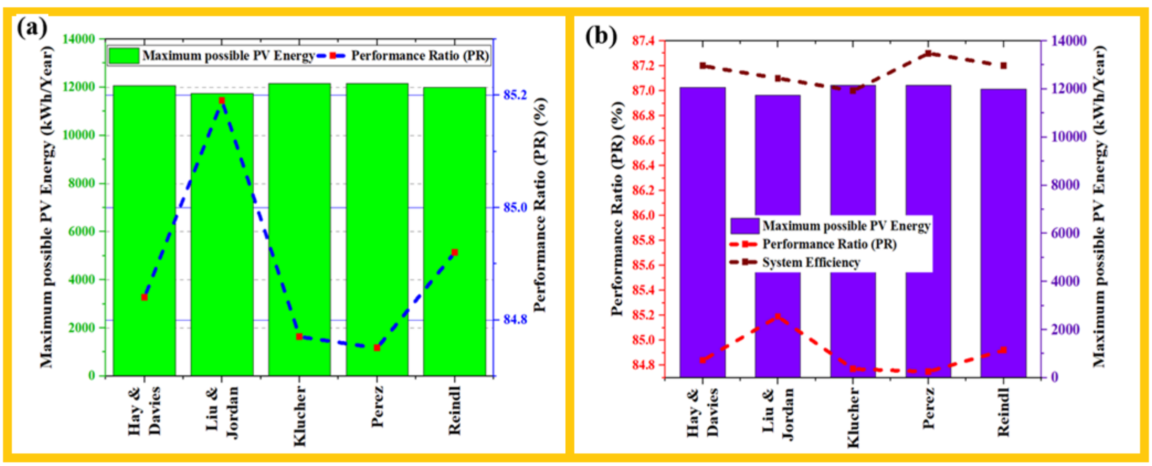

Fig 3: Influence model type on (a) Maximum PV energy and PR; (b) Maximum PV energy and System efficiency

H. Usable PV energy, consumption coverage, and CO_2 mitigation

The metrics (usable PV energy, solar fraction, consumption coverage, and CO_2 emissions) considered in this section, as shown in Fig. 4, reflect how each model's irradiance estimation affects downstream PV performance. It presents comparative differences among the five transposition models in Fig. 4(a) and Fig. 4(b). Usable PV energy, coverage of consumption, and solar fraction, as presented in Fig. 4(a), show that:

- The usable PV energy ranges from 11,500–12,500 kWh/year, with Perez and Liu & Jordan slightly higher. Coverage of consumption is closely aligned across models, while the solar fraction (~28.5–29.5%) is highest and lowest at Perez and Liu & Jordan, respectively. This suggests better alignment of PV generation with load demand.

Usable PV energy, coverage of consumption, and avoided CO_2 emissions as presented in Fig 4(b) shows that:

- The avoided CO_2 emissions correlate strongly with usable PV energy, ranging between 3,800–4,200 kg/year. Perez, Klucher, and Reindl provide a better favourable estimate compared to Hay & Davies and Liu & Jordan for both energy and emissions reduction.

The CO_2 mitigation performance is sensitive to transposition model selection, especially for reporting in carbon credit or emissions-offsetting programs.

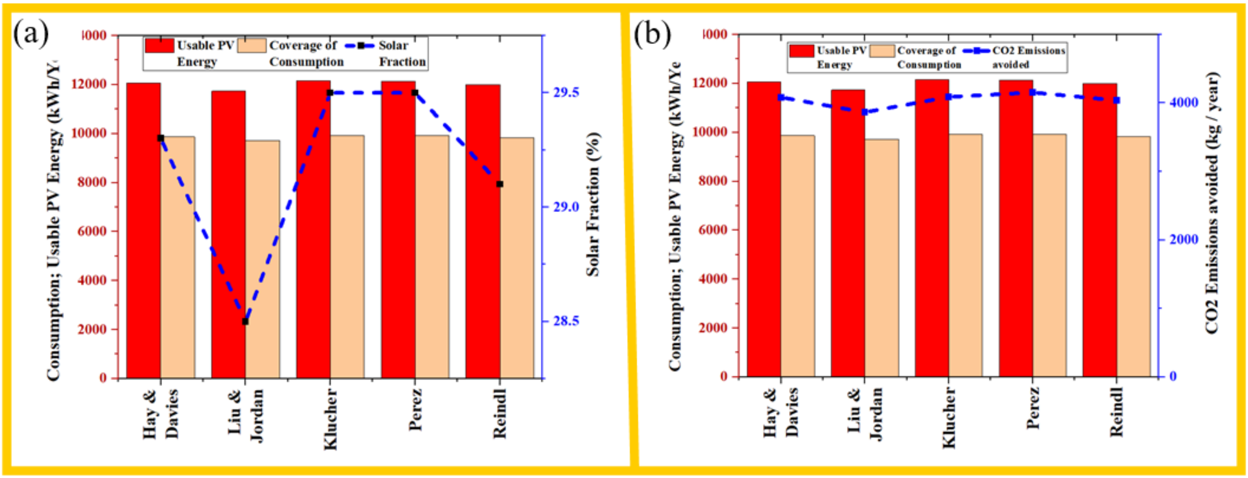

Fig 4: (a) Usable PV energy and solar fraction; (b) Consumption coverage and CO_2 mitigation

I. Overall insights

Across all figures and tables, three key insights emerge and Table 6 presents the interpretation of relative model accuracy:

i. Energy stability: Maximum possible PV energy is consistent across models, with differences typically within 2–4%, indicating robustness in baseline energy projections.

ii. Model sensitivity: Performance metrics such as PR, reflection losses, and solar fraction exhibit greater variability, with Klucher showing anomalies and Liu & Jordan providing conservative estimates.

iii. Model reliability: Perez and Reindl consistently provide higher yet realistic predictions for yield, PR, and CO_2 mitigation, making them more suitable for performance evaluations under diverse sky conditions.

Table 4: Overall comparative summary of the models

Model	**Performance Behaviour**
Hay & Davies	Small GTI and energy bias; stable and reliable; fits anisotropic conditions moderately well
Liu & Jordan	Largest underestimation of both GTI and energy; isotropic limitations clearly visible.
Klucher	Very accurate GTI but poor energy output estimation; inconsistent diffuse modelling
Perez	Benchmark model with highest accuracy under diffuse and anisotropic sky conditions
Reindl	Best agreement with Perez for energy; strong GTI accuracy; recommended alternative

These findings demonstrate that while the choice of transposition model may not drastically alter total PV energy potential, it significantly affects performance indicators and environmental impact estimates, which are critical for system design, financial assessments, and climate benefits quantification.

VI. CONCLUSION

This study demonstrates that the choice of irradiance transposition model significantly influences PV energy yield predictions, performance indicators, and environmental benefit projections. Despite the consistent maximum theoretical PV energy across all models, annual output varied by up to 7%, primarily due to differences in diffuse irradiance modelling. The Perez and Reindl models emerged as the most reliable, providing higher yet realistic GTI, specific yield, PR, and CO_2 mitigation estimates—attributes attributable to their detailed treatment of circumsolar and horizon-brightening effects. In contrast, Klucher consistently underpredicted performance, while Liu & Jordan produced conservative results in line with its isotropic assumptions.

Statistical evaluation further confirmed Reindl as the closest alternative to Perez, suggesting strong suitability for subtropical and diffuse-dominant climates like Durban. These findings underscore the importance of model selection in PV design, performance forecasting, bankability studies, and carbon offset accounting. For researchers, system designers, and policymakers, adopting advanced anisotropic models is recommended to ensure accurate yield estimation and informed investment decisions in solar energy deployment.

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