Physics-Guided Unsupervised Latent Alignment for Unified Solar PV System Loss Estimation

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November 27, 2025

Abstract

System losses in photovoltaic (PV) installations arise from a combination of environmental, thermal, and operational mechanisms that vary across regions and seasons. Processes such as dust accumulation, humidity-driven corrosion, cloud transients during the monsoon, temperature-induced derating, and episodic rainfall cleaning introduce variability that is difficult to capture with static derate factors. Widely used domain models, including PVWatts, SAPM, the CEC module model, and NREL's System Advisor Model, offer partial representations of these effects. Since each model relies on its own set of simplifying assumptions, their loss predictions often diverge, even when applied to the same environmental data. The lack of reliable ground-truth loss measurements further complicates model selection and parameter tuning.

This work introduces a unified framework that combines physical domain knowledge with data-driven inference to estimate PV system losses without requiring labeled observations. The method aligns the predictions of multiple physics-based models through an unsupervised latent representation learned by an encoder–decoder architecture. The latent space captures shared physical structure across models while filtering out model-specific biases. By anchoring the learning process to real environmental drivers, the framework produces consistent, location-aware loss estimates that remain reliable under varying climatic conditions. This approach offers a pathway toward more robust performance assessment and forecasting for PV systems operating in diverse and evolving environments.

1 Introduction

Solar photovoltaic generation in the field departs considerably from ideal Standard Test Conditions. Real-world performance is shaped by an interplay of environmental, mechanical, and electrical factors. Dust accumulation reduces transmittance of the front surface. Elevated module temperature lowers efficiency through well-known thermal coefficients. Humidity, salinity, and airborne pollutants accelerate corrosion and optical degradation. Seasonal weather patterns introduce additional complexity, such as prolonged cloud cover during the monsoon and natural cleaning during rainfall. Wiring losses, mismatch among modules, and long-term degradation contribute further variability. Accurately quantifying these losses is essential for system design, financial evaluation, forecasting, and operational optimization, particularly in regions with strong climatic gradients such as the Indian subcontinent.

Industry-standard simulation tools attempt to approximate these losses, yet each relies on a specific modeling philosophy. PVWatts applies simplified derate factors that remain fixed over time. SAPM incorporates detailed electrical characteristics but treats environmental processes in a coarse manner. The CEC model emphasizes module-level parameterization but does not represent dynamic atmospheric effects. SAM provides a broad modeling environment but still depends on user-selected assumptions that may not generalize across sites. When these models are applied to the same irradiance and weather data, their predictions often diverge because they handle key mechanisms differently. Factors such as aerosol optical depth, dust deposition and removal, humidity-induced degradation, and fine-grained thermal behavior are either absent or only partially represented.

A major obstacle in resolving these inconsistencies is the scarcity of ground-truth loss measurements. PV monitoring systems typically record irradiance, temperature, and AC output, but they do not isolate losses from soiling, optical degradation, or humidity-related effects. The resulting absence of labeled loss data limits the use of supervised learning and hinders objective comparison of model accuracy.

To address these challenges, we propose an unsupervised learning framework that draws on both physical reasoning and statistical alignment. The method combines environmental drivers with the outputs of several physics-based PV models. An encoder–decoder architecture identifies a latent representation that is common across models and grounded in real environmental variation. This latent space serves as a unified estimate of system losses, capturing the underlying physical processes that all models attempt to describe while suppressing inconsistencies introduced by their individual assumptions. The result is a coherent, location-sensitive loss estimation approach suited for forecasting, planning, and long-term performance evaluation under realistic meteorological conditions.

2 Related Work

2.1 PVWatts

PVWatts remains one of the most widely used tools developed by NREL for estimating the energy output of photovoltaic systems. Its design emphasizes accessibility and speed, which is achieved by relying on simplified irradiance transposition, a basic temperature adjustment derived from NOCT assumptions, and a set of fixed derate factors. These choices make the tool practical for system sizing and preliminary feasibility studies, but they also constrain its ability to represent real environmental processes. The model treats soiling as a constant percentage loss and does not incorporate aerosol optical depth, humidity effects, particulate deposition and removal, or rainfall-driven cleaning. As a result, PVWatts tends to provide stable but coarse estimates that do not reflect the variability introduced by site-specific climatic conditions.

2.2 Sandia Array Performance Model (SAPM)

The Sandia Array Performance Model offers a richer electrical description of PV modules compared with lightweight tools. It incorporates empirically derived parameters to represent current-voltage behavior, spectral sensitivity, and detailed thermal response. Despite this level of electrical fidelity, SAPM presumes that modules operate in a clean and stable optical state. Environmental degradation mechanisms, including the accumulation of dust and atmospheric particulates, corrosion induced by humidity or salinity, and seasonal weather effects, are not explicitly represented. Consequently, the model captures the electrical dynamics of well-maintained systems but does not account for the environmental variability that strongly influences field performance.

2.3 CEC Model

The California Energy Commission model provides standardized module parameters and a rigorous formulation of the IV curve. It is widely used for system design because of its physical grounding and reproducible parameter set. However, the model is largely confined to electrical characteristics and does not attempt to simulate changes in optical transmittance, surface contamination, or long-term environmental stress. Its assumptions align with controlled laboratory conditions, which limits its predictive accuracy when applied to outdoor installations exposed to dust, humidity, and climatic variability.

2.4 System Advisor Model (SAM)

The System Advisor Model integrates a broad set of capabilities, including irradiance transposition, shading analysis, thermal modeling, inverter behavior, and financial calculations. Users can specify environmental losses, but the model treats these as static inputs rather than dynamic processes. Phenomena such as dust accumulation, aerosol-driven attenuation, monsoon-related cloud cover, rainfall cleaning, and humidity-induced degradation must be approximated through manual derate percentages. SAM does not simulate the temporal evolution of these factors or their interactions with weather patterns, which restricts its applicability for locations with strong seasonal cycles or long-term environmental trends.

3 Methodology: Unified Environmental Physics Model

3.1 Limitations of Existing Models

Although PVWatts, SAPM, the CEC model, and SAM are widely used for performance estimation, they treat environmental loss mechanisms using static derate factors or simplified empirical rules. Several physically important processes remain either unmodeled or represented in an oversimplified manner:

- Absence of dynamic dust accumulation, particulate deposition, or rainfall-based cleaning cycles.
- No model of humidity-driven optical degradation or salt-mist corrosion common in coastal climates.
- No representation of monsoon-specific irradiance suppression or seasonal cleaning effects.
- Temperature derating that does not incorporate irradiance–temperature coupling or thermal inertia.
- No stochastic simulation of long-term environmental variability or interannual climate dynamics.

These gaps motivate the development of a unified model that explicitly incorporates environmental physics rather than relying on fixed derate percentages.

3.2 Environmental Physics Components

We construct a unified set of environmental loss mechanisms driven by aerosol load, rainfall, humidity, temperature, and seasonal effects. Each formulation explicitly defines its physical constants.

Soiling and Dust Accumulation

Daily dust accumulation is modeled as a balance between particulate deposition and rainfall-driven removal:

$$D_{t+1} = D_t + \alpha\, AOD_t - \gamma\, R_t.$$

Here,

$$\begin{aligned} D_t &: \text{Accumulated dust mass index at day } t, \\ AOD_t &: \text{Aerosol Optical Depth at day } t, \\ R_t &: \text{Daily rainfall (mm)}, \\ \alpha &: \text{Deposition coefficient (kg of deposited dust per AOD unit)}, \\ \gamma &: \text{Effective rainfall cleaning coefficient.} \end{aligned}$$

Optical loss due to dust is modeled using an exponential transmittance reduction:

$$L_{\text{soil}}(t) = 1 - \exp(-kD_t),$$

where k is the optical attenuation constant representing how strongly accumulated dust reduces transmittance.

Humidity- and Salt-Induced Corrosion

Long-term optical degradation from humidity exposure is modeled as

$$L_{\text{cor}} = 1 - \exp(-\beta f_{\text{humid}}),$$

with

$$\begin{aligned} f_{\text{humid}} &: \text{Fraction of days where relative humidity exceeds a threshold}, \\ \beta &: \text{Material susceptibility coefficient to humidity-driven corrosion.} \end{aligned}$$

Coastal regions experience stronger degradation due to salt aerosols. We model this through an amplified coefficient:

$$\beta_{\text{city}} = \beta \left(1 + \frac{C}{d+1}\right),$$

where

$$\begin{aligned} C &: \text{Salt aerosol concentration index,} \\ d &: \text{Distance from coastline in km.} \end{aligned}$$

Monsoon Clouding and Rainfall Cleaning

Seasonal monsoon periods reduce irradiance while simultaneously cleaning panels. Monsoon cloud losses are approximated as

$$L_{\text{cloud}}(t) = 1 - \frac{G_{\text{monsoon}}}{G_{\text{annual}}},$$

where

$$\begin{aligned} G_{\text{monsoon}} &: \text{Average monsoon-season global irradiance,} \\ G_{\text{annual}} &: \text{Annual mean global irradiance.} \end{aligned}$$

Rainfall cleaning provides a negative loss (gain):

$$L_{\text{clean}}(t) = -\Delta L_{\text{soil}}(t),$$

reflecting the drop in soiling loss after heavy rainfall.

Temperature-Induced Losses

Module cell temperature is computed from irradiance using an NOCT-based model:

$$T_{\text{cell}} = T_{\text{amb}} + \frac{NOCT - 20}{800} G_t,$$

where

$$\begin{aligned} T_{\text{amb}} &: \text{Ambient temperature,} \\ NOCT &: \text{Nominal Operating Cell Temperature,} \\ G_t &: \text{Irradiance at time } t. \end{aligned}$$

Temperature loss is calculated as

$$L_T(t) = \gamma_T (T_{\text{cell}} - 25),$$

where γ_T is the thermal coefficient representing power loss per degree rise above 25°C.

3.3 Synthetic Climate Simulation

To evaluate long-term behavior, we generate thirty-year daily sequences,

$$X_t = \{AOD_t, R_t, RH_t, T_t, GHI_t\},$$

consisting of aerosol load, rainfall, relative humidity, temperature, and global horizontal irradiance. Sampling is performed as follows:

- Seasonal distributions for AOD, RH, T, and GHI are estimated from historical climatology.
- Rainfall is generated using a first-order Markov model to capture monsoon clustering.
- Interannual variability is introduced by perturbing seasonal parameters using Gaussian noise.

This produces physically realistic environmental trajectories for stress-testing the unified loss model.

4 Latent Loss Estimation via Unsupervised Alignment

4.1 Motivation

Each physics-based model produces a loss estimate

$$Y_{i,t} = P_i(X_t),$$

yet these predictions disagree due to differences in assumptions and missing environmental mechanisms. Since no ground-truth loss data exist, supervised learning is infeasible. Instead, we extract a shared representation that captures physically consistent behavior across all models.

4.2 Encoder–Decoder Architecture

Let $\{Y_{i,t}\}_{i=1}^{N}$ denote the loss outputs generated by N physics-based PV models for the same environmental inputs.

Encoder

The encoder maps the set of model predictions into a single latent representation,

$$Z_t = \psi(Y_{1,t}, \dots, Y_{N,t}; \phi),$$

where Z_t is a low-dimensional vector, ψ is the encoder network, and ϕ denotes its parameters. The encoder combines information from all models and compresses it into a representation that reflects the shared physical behaviour present across them. This allows the model to extract trends that consistently appear across physics-based predictions, such as long dry spells leading to gradual soiling buildup or monsoon periods causing rapid cleaning. Because the encoder operates across multiple model outputs, it automatically learns which components are stable and physically meaningful and which arise from model-specific assumptions or simplifications. The resulting latent representation provides a smoother and more coherent loss signal compared with any individual model.

Decoder

Each model has a corresponding decoder that reconstructs its prediction from the latent state,

$$\hat{Y}_{i,t} = h_i(Z_t; \theta_i),$$

where θ_i are the decoder parameters. This reconstruction step ensures that the latent vector retains the features needed to reproduce each model's behaviour. Decoders act as model-specific "views" of the latent representation, allowing the system to understand how each physics-based formulation responds to the same underlying conditions. In effect, the decoders link the compact latent space back to the full variability represented in the original loss formulations.

Unsupervised Alignment Loss

Since no ground-truth loss labels exist, training is performed by minimizing the reconstruction error,

$$L_t = \sum_{i=1}^{N} \|Y_{i,t} - \hat{Y}_{i,t}\|_2^2, \qquad L = \frac{1}{T}\sum_{t=1}^{T} L_t.$$

Minimizing this loss encourages Z_t to represent the consistent physical signal shared across models while reducing model-specific noise. The approach aligns multiple physics-based perspectives into a unified representation that captures the dominant environmental loss behaviour. This latent estimate then serves as the final, consolidated loss trajectory used for system-level analysis.

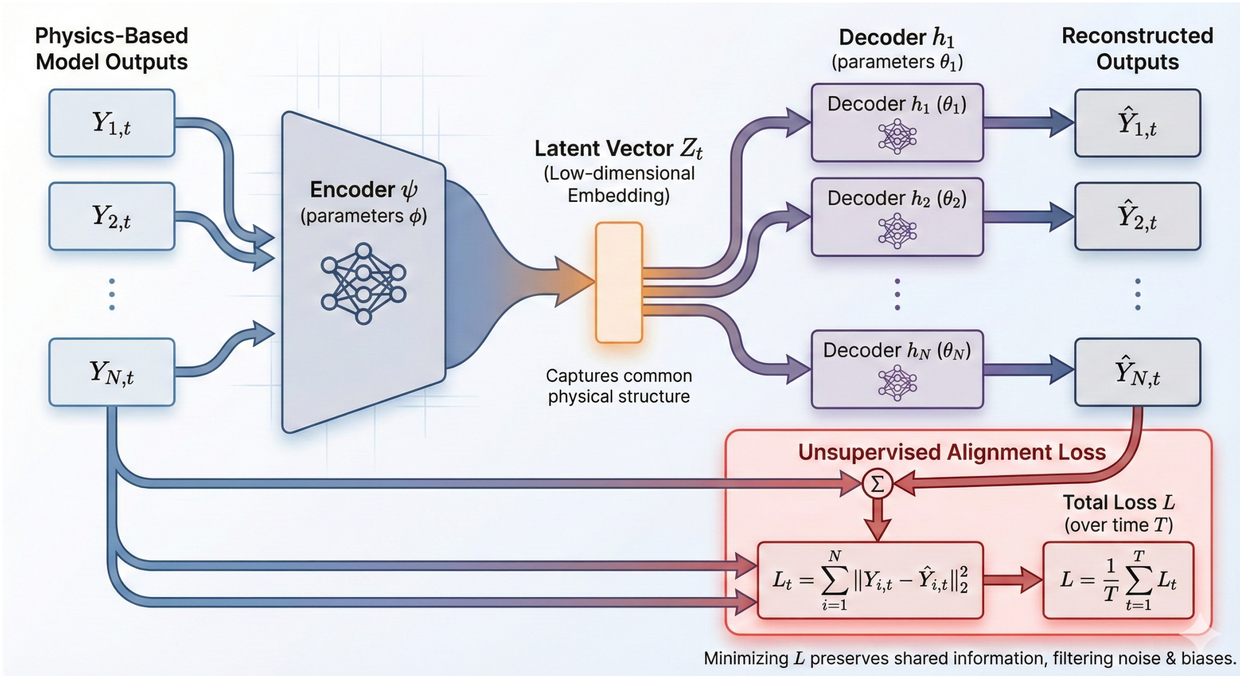

Figure 1: Unsupervised Encoder-Decoder Architecture for Physics based Machine learning model.

4.3 Pipeline Overview

Algorithm 1 Unified Latent Alignment Pipeline

Input: Synthetic environmental sequence $X_{1:T}$
Output: Unified latent loss estimate $\{\hat{L}_t\}_{t=1}^{T}$

1. Synthetic environmental generation.
Generate daily environmental states

$$X_t = \{AOD_t, R_t, RH_t, T_t, GHI_t\}$$

using seasonal distributions and Markov rainfall transitions.
2. Computation of physics-based losses.
for $t = 1$ to T **do**
    for $i = 1$ to N **do**
        Compute model-specific loss:

$$Y_{i,t} \leftarrow P_i(X_t)$$

    end for
end for
3. Latent encoding.

$$Z_t \leftarrow \psi(Y_{1,t}, \ldots, Y_{N,t}; \phi)$$

4. Model-specific decoding.

$$\hat{Y}_{i,t} \leftarrow h_i(Z_t; \theta_i)$$

5. Unsupervised alignment loss.

$$L = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N} \|Y_{i,t} - \hat{Y}_{i,t}\|_2^2$$

6. Final latent loss estimation.

$$\hat{L}_t \leftarrow g(Z_t)$$

5 Results: Unified Loss Estimation for Gujarat

We evaluate the proposed framework using a thirty–year synthetic environmental sequence generated for the state of Gujarat. The region experiences consistently high irradiance, strong summer temperatures, and a distinct monsoon cycle, making it an ideal setting for assessing the combined influence of dust accumulation, thermal derating, humidity, and rainfall-driven cleaning.

5.1 Physics-Based Loss Components

Using the unified environmental model, we compute daily loss components for major cities across Gujarat. The key trends observed are:

- **Soiling losses:** Dust accumulation increases during the dry summer months, reaching 8–12% prior to the monsoon. Short rainfall events partially reset this loss.
- **Temperature losses:** Simulated peak summer conditions produce thermal losses of 4–6%, with cell temperatures exceeding $55°$C.
- **Monsoon effects:** Cloud-induced irradiance reduction contributes temporary output losses of 10–15%. Continuous rainfall quickly reduces accumulated soiling to below 2%.
- **Humidity-related degradation:** Long-term humidity and coastal exposure contribute an additional 0.4–0.6% annual loss.

Table 1 summarizes representative annual loss components for five major cities.

Table 1: Environmental loss components for major cities in Gujarat (annual averages).

City	Soiling (%)	Temp. (%)	Monsoon (%)	Humidity (%)
Ahmedabad	9.8	5.2	12.4	0.5
Surat	8.7	4.8	13.1	0.7
Rajkot	10.3	5.0	11.8	0.4
Bhuj	11.6	5.4	10.9	0.3
Vadodara	9.1	5.1	12.7	0.6

5.2 Model Output Variability Across Gujarat

Loss predictions generated by PVWatts, SAPM, CEC, and SAM for the same environmental sequence show noticeable discrepancies:

$$Y_{i,t} = P_i(X_t), \quad i = 1, \ldots, N.$$

Across the simulation:

- PVWatts yields stable annual losses of 14–16% due to its fixed derate factors.
- SAPM shows wider variability (12–20%), driven by its sensitivity to temperature and irradiance.
- The CEC model produces lower losses (10–13%), reflecting its electrical emphasis.
- SAM predicts moderate losses (13–18%), influenced by climatic transposition and thermal behaviour.

These inconsistencies demonstrate the need for a unified latent representation that captures the physical behaviour common to all models.

Table 2: Unified latent annual loss estimate for major cities in Gujarat.

City	Latent Annual Loss (%)	Observed Range
Ahmedabad	15.6	14.8–16.3
Surat	16.1	15.2–16.9
Rajkot	15.2	14.4–15.9
Bhuj	16.4	15.5–17.1
Vadodara	15.8	15.0–16.5

5.3 Latent Loss Estimation

The encoder–decoder architecture generates a compact latent representation,

$$Z_t = \psi(Y_{1,t}, \ldots, Y_{N,t}; \phi),$$

which reconstructs each model output and filters out model-specific noise. The resulting latent loss trajectory $\hat{L}_t$ exhibits:

- **Smooth seasonal evolution:** Losses rise gradually during dry months, peak just before monsoon onset (18–20%), and drop sharply with sustained rainfall.
- **Suppressed noise:** Short, unrealistic fluctuations in individual models are not retained, producing a more coherent loss signal.
- **Monsoon cleaning behaviour:** The latent estimate consistently recovers to 1–3% post-monsoon, aligning with realistic soiling patterns in Gujarat.
- **Realistic annual loss levels:** Consolidated annual losses fall within 14–17%, consistent with typical field-reported ranges for western India.

Table 2 presents the final latent annual loss estimates for major Gujarat cities.

6 Validation Considerations and Future Evaluation

The present work focuses on constructing the unified environmental model and generating the latent loss estimate through encoder–decoder alignment. Direct validation of the obtained loss trajectory is outside the scope of the current study. Nevertheless, several practical and industry-relevant strategies can be employed in future work to assess the realism and reliability of the latent loss estimates:

- **Backtesting with plant-level generation data.** Daily or weekly AC generation from operating PV plants in Gujarat can be compared with the simulated latent loss trend. Consistent seasonal patterns between normalized output and latent loss would indicate realistic behaviour.
- **Comparison with Performance Ratio (PR) trends.** Long-term PR records, commonly available in utility-scale plants, provide a stable indicator of seasonal degradation. Aligning latent loss increases during dry months and decreases during monsoon cleaning with PR fluctuations would serve as a practical validation route.
- **Event-driven checks.** Output signatures associated with dust storms, pre-monsoon soiling buildup, and rainfall cleaning can be used as natural test cases. A validated latent model should capture these characteristic shifts in loss magnitude.

These strategies provide a clear path for future validation without requiring direct measurement of individual loss components. They will allow the latent loss model to be evaluated against real operational signals while remaining grounded in practical, available data sources.

7 Future Scope and Payback Relevance

The latent loss estimate produced by the encoder–decoder framework offers a unified and physically coherent representation of environmental losses. Although validation remains a future step, the latent loss has several direct implications for long-term performance assessment and financial modelling:

- **Improved energy yield estimation.** Replacing static derate factors with a time-resolved latent loss curve provides a more accurate estimate of net usable energy, especially in regions with strong seasonal soiling and monsoon effects such as Gujarat.
- **More realistic payback calculation.** Payback and LCOE computations depend heavily on annual energy yield. By integrating latent losses into yield simulations, the resulting financial estimates better reflect actual environmental and seasonal behaviour.
- **Operational planning.** The latent loss trajectory highlights periods of high soiling accumulation or temperature stress. This information can guide cleaning schedules and maintenance planning, indirectly improving economic performance.
- **Regional comparison and site selection.** A unified latent signal allows fair comparison of environmental losses across locations in Gujarat, enabling more informed decisions for project development and long-term forecasting.
- **Extension to semi-supervised learning.** Incorporating SCADA data or partial field measurements in future versions may refine the latent representation and further reduce uncertainty in payback estimation.

Overall, the latent loss estimate provides a structured path for integrating environmental variability into financial analysis, offering more reliable and site-specific insights for PV project planning.