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# Assessing Climate Risks to India's Power Sector: A District-Level and Asset-Level Methodology for Climate-Resilient Power Systems

Approach, Data Requirements, and Analytical Framework for Resilience Planning

Report Annexes

May, 2026



CLIMATE  
POLICY  
INITIATIVE

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# 1. PURPOSE AND DESIGN PRINCIPLES

This methodology provides a transparent, replicable, and engineering-grounded framework for quantifying physical climate risk for India's power-sector assets at the district scale. The framework is designed to support infrastructure planning, regulatory oversight, resilience prioritization, and climate-aligned financing decisions. It generates two complementary outputs:

- **Asset-Specific Climate Risk Factor (ACRF):** a dimensionless comparative index used for spatial risk mapping and screening across districts; and
- **Expected Annual Impact (EAI):** expressed in MWh per year, comprising:
  - **Expected Annual Loss (EAL):** for generation assets, representing energy not generated due to climate-induced outages or derating; and
  - **Energy Not Served (ENS):** for transmission and distribution assets, representing energy not supplied to end consumers.

The mathematical structure of this framework is consistent with the widely adopted hazard-exposure-vulnerability construct in climate risk assessment (IPCC, 2022). Under this formulation:

$$\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability}$$

where:

- **Hazard** represents the probabilistic occurrence and intensity of climate stressors acting on the power system;
- **Exposure** represents the installed capacity or served load subject to disruption; and
- **Vulnerability** represents the functional mapping from hazard intensity to performance degradation or physical failure.

Two core principles guide the design of this framework:

**Data-aligned hazard representation.** Climate hazards are represented in a manner consistent with the structure of available datasets. Daily climate time series enable an “event-day plus intensity” formulation, while hazards available only as discrete events or categorical severity classes are represented through event frequency and severity indicators. This approach avoids imposing daily-intensity constructs that the underlying data do not support (IPCC, 2022).

**Asset-physics consistency.** Vulnerability is represented through the dominant physical mechanisms by which climate hazards affect power-sector assets:

- **Chronic stresses** primarily operate through performance degradation — including derating, efficiency loss, and capacity constraints. Temperature-driven photovoltaic (PV) performance

losses and thermal constraints in electrical equipment are well-established mechanisms in the literature (Skoplaki & Palyvos, 2009; IEC, 2005).

- **Acute extremes** primarily operate through sudden failures and forced outages, characterized by failure likelihood and restoration duration. Fragility-curve approaches are standard tools for representing the intensity–damage relationship in infrastructure risk analysis (FEMA, 2020; IPCC, 2022).

Maintaining this separation between chronic and acute pathways clarifies how climate inputs propagate through asset behavior to operational outcomes, and ensures that the methodology remains physically interpretable at each stage.

## 2. OVERVIEW OF THE ANALYTICAL STAGES

The assessment follows six linked stages, which together constitute the full analytical stages from climate data inputs to financial impact outputs:

1. **Hazard representation** — defining the relevant climate hazards and classifying them by data type and dominant impact mechanism (chronic versus acute).
2. **District-level hazard characterization** — estimating district-level hazard frequency and intensity from historical climate records, normalizing these to a common scale, and constructing a composite hazard score for each hazard and district.
3. **Asset exposure** — mapping assets to districts, defining exposure metrics appropriate to each asset class (installed capacity for generation assets, distributed capacity for transmission lines, and average load served for distribution assets), and aggregating hazard characteristics along spatially extended assets.
4. **Vulnerability modeling** — quantifying asset vulnerability through: (i) chronic derating functions linking hazard intensity to performance degradation, and (ii) acute fragility and downtime relationships linking hazard intensity to failure probability and restoration duration.
5. **Risk integration (ACRF)** — combining hazard pressure and vulnerability into a dimensionless comparative risk surface for screening and prioritization.
6. **Impact quantification (EAL/ENS)** — translating expected annual downtime and chronic derating into expected annual energy impacts expressed in MWh per year.

This structure draws a deliberate distinction between **comparative risk signals** (ACRF) and **quantified operational impacts** (EAL and ENS). ACRF enables consistent hotspot identification across districts without requiring a complete loss of data. At the same time, EAL and ENS express climate risk in energy units directly relevant to system planning, reliability assessment, and financial analysis (IEA, 2021; CEER, 2020). The framework can be extended to a **cost-benefit analysis (CBA) of resilience measures**, enabling the economic appraisal of interventions that reduce asset vulnerability (Section 10).

## 3. CLIMATE HAZARDS AND DATA STRUCTURE

### HAZARD CLASSIFICATION

Hazards are classified as chronic or acute based on data availability and the dominant impact mechanism. This classification determines how each hazard is represented in the analytical pipeline and how its contribution to risk is computed.

#### CHRONIC HAZARDS: DAILY CONTINUOUS TIME SERIES

Chronic hazards are characterized by continuous observational records that permit consistent identification of exposure periods and derivation of intensity statistics from the same temporal distribution. They affect assets primarily through repeated or sustained exposure, producing gradual performance degradation or operational constraints over time. The chronic hazards considered in this framework are:

- **Temperature:** daily maximum and average temperatures (and minimum where available);
- **Rainfall:** daily precipitation totals;
- **Wind speed:** daily wind speed time series at 10 m and 100 m heights where available; and
- **Drought-induced water stress:** SPEI-3, a three-month screening indicator for drought conditions, while monthly river water discharge will be used to assess the potential operational impact of water stress on power-sector assets.

Unlike other chronic hazards, drought-induced water stress operates over longer hydrological timescales and affects asset performance through sustained reductions in usable water availability. It is accordingly represented using a monthly index (SPEI-3) and monthly river flow rather than a daily time series.

Well-established physical mechanisms include temperature-driven photovoltaic derating, transformer thermal stress, and water-availability constraints in cooling systems (Skoplaki & Palyvos, 2009; IEC, 2005).

#### ACUTE HAZARDS: EVENT-BASED OR CATEGORICAL INDICATORS

Acute hazards are represented as discrete events, each characterized by hazard-specific combinations of **frequency**, **spatial exposure**, and **intensity**. This reflects the distinct physical damage pathways through which different acute hazards impact power-sector assets. The acute hazards considered in this framework are:

- **Floods:** event frequency, inundation depth (m), and affected area where available;
- **Cyclones:** event frequency and wind speed or storm category;
- **Landslides:** susceptibility indices and/or event counts where available.

Because measurement variables and data structures differ across these hazards, each acute hazard is represented using **hazard-specific formulations** rather than a uniform structure imposed across all hazard types. For each hazard  $h$  and district  $d$ , three components are defined:

- annualized frequency,  $F_{h,d}$  (Eq. 1);
- spatial exposure,  $A_{h,d}$  (where applicable, Eqs. 31–33); and
- intensity,  $I_{h,d}$  (Eqs. 4–10).

These components are combined into a hazard score  $H_{h,d}$  (Eq. 14), while the intensity term  $I_{h,d}$  also enters directly into the fragility relationships used for vulnerability modeling (Eq. 27).

## 4. DISTRICT-LEVEL HAZARD CHARACTERIZATION

For each hazard 'h' and district 'd', a hazard score  $H_{h,d} \in [0,1]$  is constructed by combining information on both the frequency and the intensity of hazardous conditions. The derivation follows five sequential steps.

### STEP 1: DEFINING EVENT DAYS AND EVENT OCCURRENCES

The first step identifies the operationally relevant exposure periods within each hazard dataset.

For **chronic hazards**, exposure occurs only when a physical threshold relevant to equipment stress is exceeded. An exposure period is defined using a hazard-specific threshold applied to the relevant temporal unit:

- **Heat exposure days:** days on which the daily maximum temperature exceeds a defined threshold or percentile trigger;
- **Heavy rainfall days:** days on which daily precipitation exceeds a specified threshold;
- **High-wind days:** days on which wind speed exceeds a threshold relevant to asset stress; and
- **Drought exposure months:** months in which the monthly river water discharge falls below a defined operational threshold.

Engineering systems typically respond non-linearly beyond design thresholds rather than proportionally across all observed conditions. Exceedance-based event definitions, therefore, isolate operationally relevant exposure conditions and avoid diluting the signal with benign weather variability (IPCC, 2022; IEC, 2005; Skoplaki & Palyvos, 2009).

For **acute hazards**, an event corresponds directly to the recorded unit in the hazard dataset — for example, a flood occurrence or a cyclone landfall.

### STEP 2: ANNUALIZED EVENT FREQUENCY

Event frequency is annualized to ensure comparability across hazards with different observation windows and record lengths:

$$F_{h,d} = \frac{N_{h,d}}{Y_h} \quad (1)$$

where:

- $F_{h,d}$  — annualized frequency (events/year or days/year) of hazard \*h\* in district \*d\*;
- $N_{h,d}$  — count of event days (for daily chronic hazards), exposure months (for drought), or event occurrences (for acute hazards) in the dataset record; and
- $Y_h$  — number of years of available data for hazard \*h\*.

For drought,  $N_{h,d}$  counts the number of months in which river water discharge falls below the defined operational threshold. The resulting frequency, therefore, reflects the recurrence of hydrological stress periods rather than short-duration meteorological events.

Annualization is a standard normalization step in multi-hazard comparative assessment. It eliminates bias arising from unequal record lengths and differing temporal coverage across hazard datasets (IPCC, 2022). Note that  $N_{h,d}$  counts only days or months that exceed the defined threshold — consistent with the exposure-relevant definition in Step 1 — rather than the total length of the daily or monthly series. This ensures that frequency is explicitly tied to operationally relevant exposure conditions. Where acute datasets provide only event counts and coarse severity classes, frequency in Eq. (1) remains well-defined; intensity in such cases is handled through categorical scoring in Step 3 rather than requiring a continuous distribution.

### STEP 3: HAZARD INTENSITY

Frequency captures how often stress occurs; intensity captures how severe it is when it does. These two quantities represent complementary statistical properties of the hazard distribution and are not interchangeable.

#### CHRONIC HAZARD INTENSITY

For chronic hazards, intensity is estimated from the upper tail of the distribution of event-day values. Specifically, intensity is defined as a high quantile of the transformed hazard variable, conditional on the exposure period:

$$I_{h,d} = Q_{q_h} (Z_{h,d} | \text{exposure period}) \quad (2)$$

where:

- $I_{h,d}$  — intensity of chronic hazard \*h\* in district \*d\*;
- $Z_{h,d}$  — transformed hazard variable such that higher values indicate greater stress;
- $q_h$  — hazard-specific quantile level (e.g., 0.95); and
- *exposure period* — event days for daily hazards, or exposure months for drought.

For hazards where stress increases directly with the observed variable (temperature, rainfall, wind), the transformation is simply  $Z_{h,d} = X_{h,d}$ , where  $X_{h,d}$  is the raw hazard observation.

For drought, stress increases as river discharge declines. A **discharge-deficit transformation** is therefore applied to maintain a consistent direction of intensity:

$$Z_{\text{drought},d,m} = \max(0, W_d^{\text{thr}} - W_{d,m}) \quad (3)$$

where:

- $W_{d,m}$  — monthly river discharge in district \*d\* during month \*m\*;
- $W_d^{\text{thr}}$  — threshold discharge below which operational water stress occurs.

This transformation ensures that higher values of consistently correspond to greater stress, making drought intensity comparable in direction with other hazards. Under this formulation, drought intensity captures the **severity of the water deficit during low-discharge months** rather than absolute discharge levels.

Using high quantiles of the exceedance distribution provides a stable representation of typical extreme conditions while reducing sensitivity to isolated outliers in the observational record (IPCC, 2022).

## ACUTE HAZARD INTENSITY

Acute hazard intensity is derived from event-level or structural severity indicators that reflect the physical damage pathways relevant to each hazard type. Unlike chronic hazards, acute-intensity hazards are not estimated from a common daily distribution but from **hazard-specific parameters** at the event or district level.

A general representation is:

$$I_{h,d} = \text{Severity metric specific to hazard } h \quad (4)$$

where  $I_{h,d}$  denotes the representative intensity of hazard  $h$  in district  $d$ . The specific definition of  $I_{h,d}$  is as follows.

**Flood intensity** is represented by the representative inundation depth, which directly determines submergence extent and equipment damage thresholds:

$$I_{flood,d} = \text{Depth}_{flood,d} \quad (5)$$

**Landslide intensity** is represented by a susceptibility index, which reflects terrain instability and the likelihood of structural failure:

$$I_{ls,d} = SI_{ls,d} \quad (6)$$

**Snowfall intensity** may be represented by snow accumulation depth, which governs structural loading on towers and overhead lines (not used in our analysis):

$$I_{snow,d} = \text{Depth}_{snow,d} \quad (7)$$

**Cyclone intensity** is a multi-component representation, reflecting the multiple physical pathways through which tropical cyclones cause damage to power infrastructure:

$$I_{cyc,d}^{wind} = MSW_{cyc,d} \quad (8)$$

$$I_{cyc,d}^{surge} = PMSS_{cyc,d} \quad (9)$$

$$I_{cyc,d}^{rain} = PMP_{cyc,d} \quad (10)$$

where  $MSW_{cyc,d}$  is the maximum sustained wind speed,  $PMSS_{cyc,d}$  is the probable maximum storm surge, and  $PMP_{cyc,d}$  is the probable maximum precipitation associated with the cyclone event. For fragility modeling, these components are combined into a composite cyclone intensity:

$$I_{cyc,d} = I_{cyc,d}^{wind} + \gamma_1 I_{cyc,d}^{surge} + \gamma_2 I_{cyc,d}^{rain} \quad (11)$$

where  $\gamma_1$  and  $\gamma_2$  are scaling parameters reflecting the relative contribution of storm surge and precipitation to structural damage, to be calibrated using available engineering data or expert elicitation.

Event-based severity measures of this type align with the physical damage pathways of acute hazards and are consistent with multi-hazard risk practice, in which acute events are characterized by frequency and event-level severity rather than by continuous daily drivers (IPCC, 2022).

## STEP 4: NORMALIZATION TO A COMMON SCALE

To enable comparison of hazards on a common scale, frequency, and intensity are normalized using robust quantile scaling with winsorization. This procedure clips extreme district values at the 5th and 95th percentiles before normalizing, limiting the influence of outlier districts while preserving relative contrast across the majority of locations:

$$\widetilde{F}_{h,d} = clip\left(\frac{F_{h,d} - Q_{0.05}(F_h)}{Q_{0.95}(F_h) - Q_{0.05}(F_h)} \mid 0 \mid 1\right) \quad (12)$$

$$\widetilde{I}_{h,d} = clip\left(\frac{I_{h,d} - Q_{0.05}(I_h)}{Q_{0.95}(I_h) - Q_{0.05}(I_h)} \mid 0 \mid 1\right) \quad (13)$$

where:

- $\widetilde{F}_{h,d}$  — normalized frequency for hazard \*h\* in district \*d\*, constrained to [0, 1];
- $\widetilde{I}_{h,d}$  — normalized intensity for hazard \*h\* in district \*d\*, constrained to [0, 1];
- $F_h = \{F_{h,d}\}_d$  — cross-district set of annualized frequencies for hazard \*h\*;
- $I_h = \{I_{h,d}\}_d$  — cross-district set of intensities for hazard \*h\*;
- $Q_{0.05}(\cdot)$ ,  $Q_{0.95}(\cdot)$  — 5th and 95th percentiles across districts (winsorization bounds); and
- $clip(x, 0, 1)$  — truncation operator that bounds the output to [0, 1].

For drought, the normalized intensity is based on the discharge-deficit variable  $Z_{drought}$  (Eq. 3), ensuring consistency with the interpretation that higher normalized values represent more severe hydrological stress. Robust quantile scaling improves stability in comparative mapping by limiting the domination of a small number of extreme districts while preserving meaningful variation across the rest of the distribution (IPCC, 2022).

## STEP 5: HAZARD SCORE CONSTRUCTION

The district-level hazard score is constructed as a combination of normalized frequency and normalized intensity:

$$H_{h,d} = \widetilde{F}_{h,d} \cdot \tilde{I}_{h,d} \quad (14)$$

where:

- $H_{h,d}$  — normalized hazard score for hazard  $h$  in district  $d$ ;
- $\widetilde{F}_{h,d}$  — normalized frequency (Eq. 12); and
- $\tilde{I}_{h,d}$  — normalized intensity (Eq. 13).

The hazard score thus represents hazard pressure as a joint condition in which both frequent and severe exposure contribute to risk. For **drought**, the score combines the frequency of low-discharge months with the severity of discharge deficits during those months, thereby capturing both the recurrence and the magnitude of hydrological stress.

For **acute hazards**, the normalized intensity term  $\tilde{I}_{h,d}$  is derived from the hazard-specific severity indicators defined in Section 4.3.2. Where hazards exhibit additional spatial exposure characteristics — such as flood-affected areas or landslide-prone terrain — these are incorporated either into the frequency term (Eq. 1) or directly into the fragility relationship (Section 7.1), ensuring methodological consistency without introducing redundant aggregation terms.

## 5. ASSET EXPOSURE

### EXPOSURE REPRESENTATION AND ASSET-DISTRICT MAPPING

Within the hazard–exposure–vulnerability framework, exposure represents the magnitude of infrastructure or service at risk from climate hazards. In the power sector, exposure is inherently asset-specific and must reflect the physical and operational role of each asset class within the electricity system. Accordingly, exposure is defined differently for generation, transmission, and distribution assets, while maintaining consistency with the energy-based impact metrics (EAL and ENS) developed in Section 9.

#### GENERATION ASSETS

Generation assets are geographically fixed and are therefore mapped to a **single district**. All hazard, vulnerability, and impact calculations are performed using the district's hazard characteristics. For generation assets, exposure is defined as the rated installed capacity:

$$E_{gen,a,d} = InstalledCapacity_{a,d} \quad (15)$$

where:

- $E_{gen,a,d}$  — exposure of generation asset \*a\* in district \*d\* (MW); and
- $InstalledCapacity_{a,d}$  — rated generation capacity of asset \*a\*.

This definition directly aligns with the Expected Annual Loss formulation (Eqs. 37–38), in which installed capacity determines the scale of energy at risk from both acute outages and chronic derating.

#### TRANSMISSION ASSETS

Transmission assets differ fundamentally from generation assets in that they span multiple districts and are therefore exposed to spatially heterogeneous hazard conditions along their routing alignment. For a transmission line  $l$ , exposure is distributed proportionally across districts based on the fraction of line length within each district:

$$E_{trans,l,d} = Capacity_l \cdot \frac{Length_{l,d}}{Length_l} \quad (16)$$

where:

- $E_{trans,l,d}$  — exposure of transmission line \*l\* attributable to district \*d\* (MW or MVA-equivalent);

- $Capacity_l$  — rated transmission capacity of line  $l$ ;
- $Length_{l,d}$  — length of line  $l$  within district  $d$ ; and
- $Length_l$  — total length of line  $l$ .

Where precise routing data are unavailable, routing is approximated by a straight-line (beeline) connection between origin and destination districts; this is a screening-level approximation and may understate exposure in mountainous, coastal, or high-relief corridors. Where GIS-based route data are available — from utility shapefiles, official planning datasets, or validated open-source layers — actual transmission alignments should be used.

## SPATIAL AGGREGATION OF HAZARD FOR TRANSMISSION ASSETS

Because transmission assets span multiple districts, the hazard metrics applied to them must also be spatially aggregated. The effective hazard score experienced by transmission line  $l$  under hazard  $h$  is defined as a length-weighted average of district-level hazard scores:

$$H_{h,l}^{trans} = \sum_{d \in D_l} \left( \frac{Length_{l,d}}{Length_l} \right) H_{h,d} \quad (17)$$

where:

- $H_{h,l}^{trans}$  — effective hazard score for transmission line  $l$  under hazard  $h$ ;
- $H_{h,d}$  — district-level hazard score (Eq. 14); and
- $D_l$  — set of districts traversed by line  $l$ .

Similarly,

For acute hazards, a simple length-weighted average may understate localized risk because failure in a short, highly exposed segment can disrupt the operation of the entire transmission line. To account for this, the same length-weighted structure is retained, but district-level hazard scores are additionally weighted by their relative rank along the line corridor:

$$H_{h,l}^{trans} = \frac{\sum_{d \in D_l} Length_{l,d} \times rank(H_{h,d}) \times H_{h,d}}{\sum_{d \in D_l} Length_{l,d} \times rank(H_{h,d})} \quad (18)$$

where  $rank(H_{h,d})$  is assigned by ranking all districts traversed by the line  $l$  according to their district-level hazard score for hazard  $h$ . The district with the lowest hazard score receives the lowest rank, while the district with the highest hazard score receives the highest rank. Where a transmission line passes through districts, the rank values range from 1 to  $n$ .

This formulation preserves the role of line length in estimating exposure, while giving greater influence to high-hazard districts along the corridor. It is therefore more appropriate for acute hazards such as floods, cyclones, and landslides, where localized damage at one segment can affect the operation of the entire transmission line. At the same time, the formulation avoids

assigning the maximum district-level hazard score to the entire line, which may overstate exposure when the high-risk segment represents only a small share of the total line length.

Similarly, for acute hazard inputs used in fragility and downtime estimation, the same rank-weighted aggregation is applied to frequency and intensity separately:

$$F_{h,l}^{trans} = \frac{\sum_{d \in D_1} \text{Length}_{1,d} \times \text{rank}(H_{h,d}) \times F_{h,d}}{\sum_{d \in D_1} L_{1,d} \times \text{rank}(H_{h,d})} \quad (19)$$

$$I_{h,l}^{trans} = \frac{\sum_{d \in D_1} \text{Length}_{1,d} \times \text{rank}(H_{h,d}) \times I_{h,d}}{\sum_{d \in D_1} L_{1,d} \times \text{rank}(H_{h,d})} \quad (20)$$

These aggregated values —  $F_{h,l}^{trans}$  and  $I_{h,l}^{trans}$  — are subsequently used in fragility modeling (Eq. 25) and downtime estimation (Eq. 30), ensuring that failure probability and expected downtime reflect hazard exposure along the full transmission corridor rather than at a single representative point.

## DISTRIBUTION ASSETS

Distribution assets serve localized areas and are therefore mapped to a **single district**, analogously to generation assets. For distribution systems, exposure is defined in terms of the electrical demand served:

$$E_{dist,a,d} = \text{AvgLoadServed}_{a,d} \quad (21)$$

where:

- $E_{dist,a,d}$  — exposure of distribution asset \*a\* in district \*d\* (MW); and
- $\text{AvgLoadServed}_{a,d}$  — average load supplied by the asset under normal operating conditions.

This definition is consistent with reliability-based assessment frameworks, in which impacts on distribution systems are measured in terms of load interruption and energy not served to end consumers (IEEE, 2012; CEER, 2020). It also aligns directly with the ENS formulations in Section 9.2, where the average load served determines the magnitude of service disruption attributable to asset outages.

## 6. ASSET VULNERABILITY MODELING

Vulnerability is estimated separately for **generation, transmission, and distribution assets**, and separately for **chronic** and **acute** impact pathways. These two pathways correspond to the two distinct physical mechanisms through which climate hazards cause operational impacts: gradual performance degradation under sustained stress (chronic) and sudden physical failure under extreme events (acute).

Not all hazards are relevant to all asset classes. For each asset class *a*, a relevance set is defined that restricts the analysis to physically meaningful hazard–asset pairings:

- **Generation assets:** temperature, wind, rainfall, drought, cyclone, and flood;
- **Transmission assets:** wind/cyclone, flood, landslide, and temperature;
- **Distribution assets:** wind/cyclone, flood, rainfall, and temperature.

Restricting hazards to those with credible physical pathways avoids spurious risk attribution and improves the interpretability of composite risk indicators (IPCC, 2022). The vulnerability modeling procedures for chronic and acute hazards are described in Sections 7 and 8, respectively.

## 7. CHRONIC IMPACTS: PERFORMANCE DERATING AND CAPACITY CONSTRAINTS

Chronic hazards affect power infrastructure through repeated stress exposure rather than through sudden damage events. The impact pathway is:

**"Hazard exceedance → Performance reduction → Energy loss"**

The chronic impact assessment proceeds through four steps: defining the exposure fraction, applying an asset-specific derating function, computing the expected derating conditional on exposure, and normalizing the result into a vulnerability score.

### STEP 1: EXPOSURE FRACTION

The share of the year during which an asset is exposed to a given chronic hazard is computed as:

$$f_{h,d} = \frac{N_{h,d}^{exp}}{M_h} \quad (22)$$

where:

- $f_{h,d}$  — fraction of the year exposed to chronic hazard  $h$  in district  $d$ ;
- $N_{h,d}^{exp}$  — number of exposure periods (event days for daily hazards, or exposure months for drought); and
- $M_h$  — number of periods per year (365 for daily hazards; 12 for drought).

For drought,  $N_{h,d}^{exp}$  counts the number of months in which river discharge falls below the defined threshold (Section 4.1), representing the fraction of the year under hydrological stress.

This formulation explicitly represents “time-at-risk” and ensures that chronic derating is applied only during exposure-relevant periods rather than uniformly across the full year. This avoids systematic overestimation of annual impacts in climates with short extreme seasons and is consistent with threshold-based exposure accounting widely adopted in climate risk screening and extremes assessment (IPCC, 2022; Donat et al., 2013).

### STEP 2: DERATING FUNCTION

An asset-class-specific and hazard-specific derating function translates the realized hazard level on an exposure day into an instantaneous percentage reduction in output or capacity. The functional form is:

$$Derate_{a,h}(x) = \min \left( D_{a,h}^{\max}, s_{a,h} \cdot \max(0, x - T_{a,h}) \right) \quad (23)$$

where:

- $Derate_{a,h}(x)$  — instantaneous derating (%) for asset class  $a$  under hazard  $h$  at hazard level  $x$ ;
- $x$  — realized hazard level on a given day (a realization of  $Z_{h,d}$ );
- $T_{a,h}$  — asset-hazard derating threshold, which may differ from the general exposure threshold  $T_h$  where asset sensitivity diverges from generic equipment behavior;
- $s_{a,h}$  — derating slope/sensitivity beyond the threshold (percentage derating per unit of hazard exceedance);
- $D_{a,h}^{\max}$  — maximum derating cap consistent with engineering limits;
- $\max(\theta, \cdot)$  — ensures no derating is applied below the threshold; and
- $\min(\cdot)$  — caps derating at the engineering-consistent maximum.

The function has three physical properties: (i) no derating occurs below the threshold; (ii) derating increases monotonically beyond the threshold; and (iii) a physically meaningful maximum bounds derating. For drought, the input variable  $x$  corresponds to the discharge-deficit stress variable  $Z_{drought}$  (Eq. 3), ensuring that derating increases as water availability decreases, consistent with the operational behavior of water-dependent systems. Temperature-dependent PV output reduction and transformer thermal limits follow the same functional form, whereby performance deteriorates beyond reference design conditions but cannot exceed a total capacity-loss bound (Skoplaki & Palyvos, 2009; IEC, 2005).

### STEP 3: EXPECTED DERATING CONDITIONAL ON EXPOSURE

The expected derating on exposed days is computed empirically from the observed distribution of hazard values during the exposure period:

$$[Derate\%]_{a,h,d} = \mathbb{E}[Derate_{a,h}(Z_{h,d})|exposure\ period] \quad (24)$$

where:

- $\mathbb{E}[Derate\%]_{a,h,d}$  — expected derating (%) for asset class  $a$ , hazard  $h$ , district  $d$ , conditional on exposed days;
- $Z_{h,d}$  — hazard stress variable (raw observation for most hazards; discharge-deficit transformation for drought); and
- $Derate_{a,h}(\cdot)$  — derating function defined in Eq. (23).

The expectation is calculated empirically using the observed exceedance distribution in the historical climate record. For drought, the expectation is computed over the distribution of monthly discharge deficits during low-discharge months, translating hydrological stress directly

into expected operational derating. Empirical conditional expectation is commonly used in large-scale impact modeling where mechanistic simulation is infeasible (IPCC, 2022).

## STEP 4: CHRONIC VULNERABILITY SCORE

The chronic vulnerability score normalizes the expected derating by the maximum plausible derating for the relevant hazard-asset pairing, producing a bounded unitless index:

$$V_{a,h,d}^{chronic} = \min \left( 1 \mid \frac{\mathbb{E}[Derate\%]_{a,h,d}}{D_{a,h}^{\max}} \right) \quad (25)$$

where:

- $V_{a,h,d}^{chronic}$  — unitless chronic vulnerability score, ;
- $\mathbb{E}[Derate\%]_{a,h,d}$  — expected derating on exposed days (Eq. 24); and
- $D_{a,h}^{\max}$  — maximum derating cap (Eq. 23).

This normalization produces a vulnerability measure between 0 and 1 that represents the asset class's susceptibility to chronic stress and is suitable for aggregation with other hazards in the composite risk indicator (Section 8). For drought, the score represents the normalized performance loss under sustained water-stress conditions. Normalizing by the maximum plausible derating for the relevant hazard-asset pair ensures that the resulting index is dimensionally consistent and bounded, regardless of the physical units of the underlying hazard variable.

## 8. ACUTE IMPACTS: FAILURES, OUTAGES, AND RESTORATION

Acute hazards — floods, cyclones, landslides, and extreme winds — affect power systems through sudden physical damage. The impact pathway is:

**"Hazard intensity → Probability of failure → Restoration duration"**

Infrastructure risk assessment typically models this two-stage relationship using fragility curves combined with consequence functions (FEMA, 2020; IPCC, 2022). This methodology implements two modeling modes, selectable based on data availability:

- **Asset-level scalable mode:** applied where only limited technical data exist; treats the asset as a single equivalent unit.
- **Equipment-level detailed mode:** applied where component-level failure and restoration data are available; characterizes individual equipment items within an asset.

### FAILURE PROBABILITY; FRAGILITY RELATIONSHIP

For each asset class  $a$ , hazard  $h$ , and district  $d$ , the probability of failure per event is represented using a logistic fragility function:

$$P(F)_{a,h,d} = \frac{1}{1 + \exp[-(\beta_{0,a,h} + \beta_{1,a,h} I_{h,d})]} \quad (26)$$

where:

- $P(F)_{a,h,d}$  — probability that an asset of class  $a$  fails in district  $d$  when exposed to hazard  $h$  (per event);
- $I_{h,d}$  — hazard intensity (Eqs. 5-11, or the spatially aggregated equivalents Eqs. 19-20 for transmission assets);
- $\beta_{0,a,h}$  — intercept parameter controlling baseline failure propensity for the asset-hazard pair; and
- $\beta_{1,a,h}$  — slope parameter controlling the rate at which failure probability increases with intensity.

The logistic function is widely adopted in infrastructure fragility modeling because it is bounded within  $[0, 1]$ , increases monotonically with intensity, and is readily calibrated from limited anchor data (FEMA, 2020). Such functional forms are standard in engineering disaster-loss estimation frameworks.

For hazards with significant spatial exposure characteristics — such as flood-affected areas or landslide-prone zones — a spatial exposure multiplier  $A_{h,d} \in (0, 1]$  may be introduced to modify the effective failure probability:

$$P(F)_{a,h,d} = A_{h,d} \cdot \frac{I}{1 + \exp[\beta_{0,a,h} + \beta_{1,a,h} I_{h,d}]} \quad (27)$$

where  $A_{h,d}$  denotes the fraction of asset exposure in district  $d$  that is subject to hazard  $h$  (see Section 8.4 for the definitions of flood, landslide, and cyclone exposure terms). This formulation ensures that failure probability reflects both hazard severity and the spatial extent of exposure.

**Calibration of fragility parameters.** The parameters  $\beta_{0,a,h}$  and  $\beta_{1,a,h}$  are calibrated using two intensity-failure anchor points ( $I_1|F_1$ ) and ( $I_2|F_2$ ), representing engineering thresholds at which failure probabilities are known or can be assessed:

$$\beta_{1,a,h} = \frac{\log\left(\frac{F_2}{1-F_2}\right) - \log\left(\frac{F_1}{1-F_1}\right)}{I_2 - I_1} \quad (28)$$

$$\beta_{0,a,h} = \log\left(\frac{F_1}{1-F_1}\right) - \beta_{1,a,h} I_1 \quad (29)$$

where:

- $F_1, F_2$  — failure probabilities at intensity anchors  $I_1$  and  $I_2$ , respectively, both in (0, 1);
- $I_1, I_2$  — hazard intensity anchor levels, in the same units as  $I_{h,d}$ ; and
- $\log(\cdot)$  — natural logarithm.

Anchor-point calibration is standard practice where historical failure databases are unavailable, but engineering thresholds can be established from design standards, field experience, or expert elicitation (FEMA, 2020; IPCC, 2022).

## DOWNTIME MODELING

### STANDARD ASSET-LEVEL MODE

In the absence of intensity-specific restoration data, expected downtime per event is computed as the probability-weighted average of two outage regimes — failure requiring repair, and temporary interruption without structural damage:

$$EDT_{a,h,d} = P(F)_{a,h,d} \cdot D_{a,h}^{fail} + (1 - P(F)_{a,h,d}) \cdot D_{a,h}^{nonfail} \quad (30)$$

where:

- $EDT_{a,h,d}$  — expected downtime per hazard event (hours/event) for asset class  $a$ , hazard  $h$ , district  $d$ ;
- $P(F)_{a,h,d}$  — failure probability (Eq. 26);
- $D_{a,h}^{fail}$  — average restoration time conditional on physical failure (hours); and
- $D_{a,h}^{nonfail}$  — interruption duration for non-failure events such as protective shutdown or network isolation (hours).

Eq. (30) expresses the expected downtime per event as the conditional expectation of outage duration across the two operational regimes. Formally, letting denote downtime as a random variable and the failure event, the law of total expectation gives:

$$\mathbb{E}[D] = \mathbb{E}[D|F] P(F) + \mathbb{E}[D|\neg F] (1 - P(F))$$

which yields Eq. (30) when the conditional mean restoration durations are represented by  $D_{a,h}^{fail}$  and  $D_{a,h}^{nonfail}$ . This two-regime mixture formulation is standard in infrastructure risk modeling, providing a parsimonious representation of expected outage duration when detailed restoration-time distributions are unavailable but failure probabilities are known (FEMA, 2020; IPCC, 2022).

## HAZARD-SPECIFIC SPATIAL EXPOSURE TERMS

For selected acute hazards, spatial exposure is defined explicitly and incorporated into the failure probability formulation via the multiplier  $A_{h,d}$  in Eq. (27).

**Flood exposure** is represented as the return-period-weighted average of flood-affected area across return periods  $r$ :

$$A_{flood,d} = \sum_r \frac{1}{r} A_{flood,d}^{(r)} \quad (31)$$

where  $A_{flood,d}^{(r)}$  is the area affected in district  $d$  under return period  $r$  (years).

**Landslide exposure** is represented by the total area classified as landslide-susceptible within the district:

$$A_{ls,d} = Area_{ls,d} \quad (32)$$

**Cyclone exposure** is represented by the annualized landfall frequency for the district:

$$A_{cyc,d} = \frac{N_{cyc,d}^{landfall}}{Y} \quad (33)$$

where  $N_{cyc,d}^{landfall}$  is the number of cyclone landfalls recorded in district  $d$  over the data period of  $Y$  years.

## EXPECTED ANNUAL DOWNTIME

Expected annual downtime for asset class  $a$  in district  $d$  integrates event frequency with per-event expected downtime across all relevant acute hazards:

$$EAD_{a,d} = \sum_{h \in \text{acute}} F_{h,d} \cdot EDT_{a,h,d} \quad (34)$$

where:

- $EAD_{a,d}$  — expected annual downtime (hours/year) for asset class  $a$  in district  $d$  due to acute hazards;
- $F_{h,d}$  — annualized event frequency (Eq. 1); and
- $EDT_{a,h,d}$  — expected downtime per event (Eq. 30).

Eq. (34) estimates expected annual downtime by aggregating the direct outage contribution of each acute hazard and should therefore be interpreted as a first-order impact estimate. The core methodology does not explicitly model compound or cascading hazard interactions, such as cyclone-induced flooding, rainfall-triggered landslides, heat-drought co-occurrence, or sequential failures across interconnected grid assets. These effects are recognized as important risk amplifiers. However, they are excluded from the present assessment because they require event-level co-occurrence data, asset-level failure dependencies, and network topology information. Accordingly, the EAD, EAL, and ENS estimates represent direct asset-level impacts; compound and cascading effects may be incorporated in future iterations through scenario analysis or network-based reliability modeling (Section 9).

## ACUTE VULNERABILITY SCORE

Where a unitless vulnerability index is required for comparative risk scoring (Section 8), acute vulnerability is expressed as the fraction of the year that an asset is expected to be unavailable due to acute hazard events:

$$V_{a,d}^{\text{acute}} = \min \left( 1, \frac{EAD_{a,d}}{8760} \right) \quad (35)$$

where:

- $V_{a,d}^{\text{acute}}$  — unitless acute vulnerability,  $\in [0,1]$ ; and
- 8760 — total hours in a year.

This scaling converts expected annual outage hours into a bounded fraction of the year, making the metric compatible with the index structure used in the ACRF computation (Section 8).

## 9. ASSET-SPECIFIC CLIMATE RISK FACTOR (ACRF)

The ACRF integrates hazard pressure and asset vulnerability into a single dimensionless comparative risk indicator for each asset class  $a$  and district  $d$ :

$$ACRF_{a,d} = \frac{1}{|\mathcal{H}_a|} \sum_{h \in \mathcal{H}_a} H_{h,d} \cdot V_{a,h,d} \quad (36)$$

where:

- $ACRF_{a,d}$  — Asset-Specific Climate Risk Factor (unitless, comparative);
- $\mathcal{H}_a$  — relevance set of hazards for asset class  $a$  (Section 6);
- $|\mathcal{H}_a|$  — number of hazards included for asset class  $a$ ;
- $H_{h,d}$  — hazard score for hazard  $h$  in district  $d$  (Eq. 14); and
- $V_{a,h,d}$  — vulnerability of asset class  $a$  to hazard  $h$  in district  $d$ , defined as:
  - $V_{a,h,d}^{chronic}$  from Eq. (25) for chronic hazards; and
  - $V_{a,h,d}^{acute}$  from Eq. (35) for acute hazards, when a common unitless indexing scale is required.

The ACRF is a **screening metric** aligned with the hazard-exposure-vulnerability risk framing standard in climate risk assessment (IPCC, 2022). It is deliberately dimensionless so that districts and asset classes can be compared consistently even when detailed loss data are incomplete. It is interpreted as a comparative indicator for spatial risk mapping, hotspot identification, and investment prioritization — not as a direct measure of physical or financial loss. Where more precise impact quantification is required, the EAL and ENS metrics in Section 9 provide the appropriate outputs.

Where reliable outage, derating, or restoration data are available, the ACRF and EAL/ENS results can be validated against observed asset performance and the underlying vulnerability parameters recalibrated. In the absence of such data, results should be interpreted as indicative risk estimates for prioritization rather than validated predictions of actual outages.

## 10. EXPECTED ANNUAL IMPACT: EAL FOR GENERATION AND ENS FOR NETWORKS

The Expected Annual Impact (EAI) quantifies climate-induced operational disruption in energy terms (MWh/year). It is computed separately for generation assets (as Expected Annual Loss, EAL) and for transmission and distribution assets (as Energy Not Served, ENS), and separately for acute and chronic impact pathways.

### GENERATION ASSETS: EXPECTED ANNUAL LOSS (EAL)

For generation assets, climate impacts are measured as energy not generated due to outage-induced downtime (acute) or performance derating (chronic).

**Acute losses.** Annual energy losses attributable to acute hazard-induced outages are computed as:

$$EAL_{a,d}^{acute} = InstalledCapacity_{a,d} \cdot CF_{a,d} \cdot EAD_{a,d} \quad (37)$$

where:

- $EAL_{a,d}^{acute}$  — acute expected annual loss (MWh/year);
- $InstalledCapacity_{a,d}$  — installed capacity of asset class \*a\* in district \*d\* (MW);
- $CF_{a,d}$  — capacity factor representing expected annual utilization (fraction); and
- $EAD_{a,d}$  — expected annual downtime due to acute hazards (hours/year, Eq. 34).

**Chronic losses.** Annual energy losses attributable to chronic hazard-induced derating are computed as:

$$EAL_{a,d}^{chronic} = InstalledCapacity_{a,d} \cdot CF_{a,d} \cdot 8760 \cdot \sum_{h \in chronic} (f_{h,d} \cdot \mathbb{E}[Derate\%]_{a,h,d}) \quad (38)$$

where:

- $EAL_{a,d}^{chronic}$  — chronic expected annual loss (MWh/year);
- $f_{h,d}$  — annual exposure fraction for chronic hazard \*h\* (Eq. 22);
- $\mathbb{E}[Derate\%]_{a,h,d}$  — expected derating on exposed days (Eq. 24); and
- 8760 — hours per year.

For drought, represents the fraction of months with low discharge, and reflects the expected reduction in performance associated with water stress. Eq. (38) annualizes chronic losses by applying derating only during the exposed fraction of the year and using empirically derived

conditional expectations, directly implementing the data-aligned hazard representation described in Section 2 (IPCC, 2022; Skoplaki & Palyvos, 2009). Chronic EAL thus captures seasonal or prolonged output constraints — not short-duration outages.

**Total EAL.** The total expected annual loss combines both pathways:

$$EAL_{a,d}^{total} = EAL_{a,d}^{acute} + EAL_{a,d}^{chronic} \quad (39)$$

## TRANSMISSION AND DISTRIBUTION ASSETS: ENERGY NOT SERVED (ENS)

For network assets, climate impacts are measured as energy not supplied to consumers due to asset disruption.

**Acute ENS.** Annual unserved energy attributable to acute hazard-induced outages is computed as:

$$ENS_{a,d}^{acute} = AvgLoadServed_{a,d} \cdot EAD_{a,d} \cdot R_{a,d} \quad (40)$$

where:

- $ENS_{a,d}^{acute}$  — acute energy not served (MWh/year);
- $AvgLoadServed_{a,d}$  — average load supported by the asset under normal operation (MW);
- $EAD_{a,d}$  — expected annual downtime due to acute hazards (hours/year, Eq. 34); and
- $R_{a,d} \in (0, 1]$  — redundancy/load-transfer factor.

The redundancy factor  $R_{a,d}$  represents the proportion of asset downtime that translates into actual unserved energy after accounting for network topology and operational flexibility. It operationalizes the grid's ability to reroute power during contingencies. In radial or weakly meshed distribution systems,  $R_{a,d}$  approaches unity because outages directly interrupt supply with limited alternative routing. In meshed transmission networks or systems with parallel feeders, backup transformers, or switching capability,  $R_{a,d}$  takes lower values reflecting partial service continuity during the outage period. In implementation,  $R_{a,d}$  may be parameterized using available reliability indicators — such as feeder redundancy, N-1 compliance, or historical outage restoration patterns — or, where detailed topology data are unavailable, through documented engineering classification tiers (radial, looped, or meshed). This parameter captures network resilience rather than hazard exposure, thereby preventing systematic overestimation of ENS in well-interconnected systems (CEER, 2020).

**Chronic ENS.** Where chronic hazards constrain network capacity — for example, through thermal or ampacity limits on overhead lines — a derating-based ENS term is estimated as:

$$ENS_{a,d}^{chronic} = AvgLoadServed_{a,d} \cdot 8760 \cdot \sum_{h \in chronic} (f_{h,d} \cdot \mathbb{E}[Derate\%]_{a,h,d}) \cdot R_{a,d} \quad (41)$$

where terms follow the definitions established in Eqs. (22), (24), and (40).

**Total ENS.** The total expected energy not served combines both pathways:

$$ENS_{a,d}^{total} = ENS_{a,d}^{acute} + ENS_{a,d}^{chronic} \quad (42)$$

# 11. COST-BENEFIT ANALYSIS OF RESILIENCE MEASURES

## RATIONALE

While the preceding sections quantify physical climate risk and its operational impacts in energy terms, decision-makers ultimately require guidance on whether and where resilience investments are economically justified. Climate resilience measures — such as flood protection walls, elevated equipment platforms, improved drainage infrastructure, tower strengthening, or equipment hardening — entail upfront capital expenditure and ongoing maintenance costs. Their economic value lies in reducing asset vulnerability, lowering outage frequency or duration, and thereby avoiding energy losses and the associated economic consequences.

Infrastructure resilience cost-benefit analysis (CBA) is commonly framed as a comparison of incremental investment and operation and maintenance (O&M) costs against discounted avoided losses — comprising both avoided repair costs and avoided service disruption costs — over the asset's life (Hallegatte et al., 2019). This methodology extends the risk and impact framework to include a CBA of resilience measures, enabling systematic comparison between the expected cost of climate-induced impacts without intervention and the total cost of a resilience measure, along with the residual impact after implementation. The objective is to identify resilience interventions that are cost-effective, prioritizable, and aligned with system reliability and financial objectives.

## CONCEPTUAL FRAMEWORK

The CBA builds directly on the Expected Annual Impact metrics developed in Section 9. The central logic proceeds through four steps.

**Step 1: Baseline case (no resilience).** Climate hazards induce outages and derating, resulting in a baseline expected annual impact:

$$EAI_{a,d}^{base} \in \left\{ EAL_{a,d}^{base} \mid ENS_{a,d}^{base} \right\} \quad (43)$$

where  $EAL_{a,d}^{base}$  and  $ENS_{a,d}^{base}$  are the total expected annual loss and energy not served in the absence of any resilience intervention (Eqs. 39 and 42, respectively).

**Step 2: Resilience case.** A resilience measure modifies one or more elements of the vulnerability pathway — typically by increasing the hazard threshold at which damage occurs, reducing failure probability at a given hazard intensity, or reducing restoration time conditional on failure. This produces a reduced expected annual impact:

$$EAI_{a,d}^{res} \in \left\{ EAL_{a,d}^{res} \mid ENS_{a,d}^{res} \right\} \quad (44)$$

**Step 3: Avoided impact.** The primary benefit of the resilience measure is the difference in expected annual impact:

$$\Delta EAI_{a,d} = EAI_{a,d}^{base} - EAI_{a,d}^{res} \quad (45)$$

This is the core benefit channel: reduced expected losses attributable to reduced vulnerability, consistent with the logic of resilience appraisal (Hallegatte et al., 2019).

**Step 4: Economic valuation and cost comparison.** Avoided energy losses are monetized using appropriate valuation parameters (tariffs, value of lost load, or system cost proxies). Upfront and recurring costs of the resilience measure are then compared against the discounted stream of avoided losses over the asset's life.

## REPRESENTATION OF RESILIENCE MEASURES IN THE VULNERABILITY FRAMEWORK

Resilience measures are modeled as **parameter shifts** within the existing hazard-vulnerability-impact structure, rather than as separate ad hoc adjustments. This ensures full consistency with the risk assessment methodology and makes the counterfactual impact estimation tractable.

### CHRONIC HAZARD RESILIENCE

For chronic hazards, resilience measures typically modify derating behavior. Examples include improved cooling systems, better drainage infrastructure, or thermal insulation upgrades. Such measures are represented through one or more of the following parameter modifications in Eq. (23):

- an increase in the hazard threshold  $T_{a,h}$  — raising the level at which derating begins;
- a reduction in the derating slope  $s_{a,h}$  — lowering sensitivity to hazard exceedance; and/or
- a reduction in the maximum derating cap  $D_{a,h}^{\max}$  — limiting the worst-case performance impact.

These parameter changes reduce the expected derating (Eq. 24) and, therefore, reduce chronic EAL/ENS (Eqs. 38 and 41). Formally, the resilience intervention yields:

$$\mathbb{E}[\text{Derate}\%]_{a,h,d}^{res} < \mathbb{E}[\text{Derate}\%]_{a,h,d}^{base} \quad (46)$$

### ACUTE HAZARD RESILIENCE

For acute hazards, resilience measures primarily reduce the likelihood of failure and/or outage duration. Examples include flood-protection walls or raised plinths around substations, improved drainage and pumping systems, elevating equipment above anticipated flood levels, and reinforced tower foundations or structural strengthening. These interventions are represented by modifying one or more of the following parameters:

- the fragility curve intercept or slope, shifting the intensity level at which failure probability rises sharply (Eqs. 28–29);
- the failure probability at a given intensity, flattening the fragility response; and/or
- restoration times  $D_{a,h}^{fail}$  and/or  $D_{a,h}^{nonfail}$  (Eqs. 30).

These modifications reduce expected downtime per event (Eq. 30) and, hence, expected annual downtime (Eq. 34), which in turn reduces EAL and ENS (Eqs. 37–42). The logic — that physically strengthening assets reduces both repair costs and disruption durations — is central to the economics of infrastructure resilience (Hallegatte et al., 2019). Formally, the resilience case yields:

$$P(F)_{a,h,d}^{res}(I) < P(F)_{a,h,d}^{base}(I) \quad (47)$$

and/or

$$EDT_{a,h,d}^{res} < EDT_{a,h,d}^{base} \quad (48)$$

## CALCULATION OF AVOIDED ENERGY IMPACTS

Using the modified vulnerability parameters, the expected annual impact under the resilience case is recomputed using the same formulations as in Sections 7–9.

### GENERATION ASSETS — AVOIDED EAL

$$\Delta EAL_{a,d} = EAL_{a,d}^{base} - EAL_{a,d}^{res} \quad (49)$$

This represents the additional energy generated annually due to reduced outage time or lower derating under the resilience scenario.

### TRANSMISSION AND DISTRIBUTION ASSETS — AVOIDED ENS

$$\Delta ENS_{a,d} = ENS_{a,d}^{base} - ENS_{a,d}^{res} \quad (50)$$

This captures the reduction in unserved energy attributable to improved asset resilience.

## FINANCIAL IMPLICATION

The benefit stream in the CBA comprises two components: (i) avoided energy impacts valued in monetary terms, and (ii) avoided direct repair and replacement expenditure resulting from reduced physical damage. The first captures the economic value of improved service delivery; the second captures reductions in asset restoration costs not fully reflected in energy-based valuation alone (e.g., replacement of inundation-damaged switchgear). Both components are computed on an annualized expected basis to remain consistent with the expected-impact framework in Sections 7–9.

### GENERATION ASSETS

Avoided losses are valued using applicable tariffs, power purchase agreement (PPA) prices, or marginal system generation costs:

$$Benefit_{a,d}^{energy} = \Delta EAL_{a,d} \cdot Tariff_{a,d} \quad (51)$$

where  $Tariff_{a,d}$  (currency/MWh) represents the PPA tariff, market price proxy, or marginal generation cost applicable to the asset.

### TRANSMISSION AND DISTRIBUTION ASSETS

Avoided unserved energy is valued using the Value of Lost Load (VOLL), or consumer interruption cost estimates where available:

$$Benefit_{a,d}^{energy} = \Delta ENS_{a,d} \cdot VOLL_d \quad (52)$$

where  $VOLL_d$  (currency/MWh) is the value of lost load for district \*d\* or the representative region. VOLL is a standard reliability valuation metric used by regulators and system planners (CEER, 2020).

### AVOIDED REPAIR AND REPLACEMENT EXPENDITURE

In addition to avoiding energy impacts, resilience measures reduce expected physical damage to assets, thereby lowering repair, replacement, and restoration expenditures. This channel is modeled explicitly.

The expected repair cost per hazard event is:

$$ERC_{a,h,d} = P(F)_{a,h,d} \cdot C_{a,h}^{fail} + (1 - P(F)_{a,h,d}) \cdot C_{a,h}^{nonfail} \quad (53)$$

where  $C_{a,h}^{fail}$  is the average repair/replacement cost conditional on failure, and  $C_{a,h}^{nonfail}$  is the cost associated with a non-failure event (inspection, minor repairs, or reset following protective shutdown). Combining Eq. (53) with the annualized event frequency (Eq. 1), the annual expected repair cost is:

$$AERC_{a,d} = \sum_{h \in acute} F_{h,d} \cdot ERC_{a,h,d} \quad (54)$$

The avoided repair cost benefit from the resilience measure is therefore:

$$Benefit_{a,d}^{rep} = AERC_{a,d}^{base} - AERC_{a,d}^{res} \quad (55)$$

This term captures reductions in utility capital expenditure and extraordinary O&M arising from climate-induced asset damage and is treated as a core benefit component rather than an optional extension.

## TOTAL ANNUAL BENEFIT

The total annual benefit entering the CBA is the sum of monetized energy and repair-cost benefits:

$$AnnualBenefit_{a,d} = Benefit_{a,d}^{energy} + Benefit_{a,d}^{rep} \quad (56)$$

## COST COMPONENTS OF RESILIENCE MEASURES

The cost side of the analysis includes: (i) **capital expenditure (CAPEX)** — construction of flood walls, elevation works, structural reinforcement, drainage systems, or equipment upgrades; (ii) **operating and maintenance costs (O&M)** — periodic inspection, repairs, pumping costs, or maintenance of protective structures; and (iii) **replacement or retrofit timing** — where resilience is implemented mid-life, costs are adjusted to reflect the remaining asset life.

The present value of lifecycle costs over the analysis horizon  $L$  is:

$$PV \left( Cost \right)_{a,d} = CAPEX_{a,d} + \sum_{t=1}^L \frac{O\&M_{a,d,t}}{(1+r)^t} \quad (57)$$

where  $r$  is the discount rate and  $O\&M_{a,d,t}$  is the operating and maintenance cost in year  $t$ . Where a discrete mid-life retrofit cost  $CAPEX_{a,d,\tau}^{retro}$  occurs at year  $\tau$ , Eq. (57) is extended to include the term  $CAPEX_{a,d,\tau}^{retro} / (1+r)^\tau$ .

## COST-BENEFIT METRICS

The CBA reports three standard investment appraisal metrics.

### PRESENT VALUE OF BENEFITS:

$$PV\left(\text{Benefit}\right)_{a,d} = \sum_{t=1}^L \frac{\text{AnnualBenefit}_{a,d,t}}{(1+r)^t} \quad (58)$$

where  $\text{AnnualBenefit}_{a,d,t}$  may be constant in expectation under a stationary climate assumption, or time-varying if hazard trends, asset aging, or adaptation depreciation are explicitly modeled.

### NET PRESENT VALUE (NPV):

$$NPV_{a,d} = PV(\text{Benefit})_{a,d} - PV(\text{Cost})_{a,d} \quad (59)$$

### BENEFIT-COST RATIO (BCR):

$$BCR_{a,d} = \frac{PV(\text{Benefit})_{a,d}}{PV(\text{Cost})_{a,d}} \quad (60)$$

Resilience measures are considered economically attractive when  $NPV_{a,d} > 0$  and  $BCR_{a,d} > 1$  under the assumed valuation parameters and discount rate. For prioritization under constrained budgets, assets and districts can be ranked by BCR, by NPV, or by avoided ENS/EAL per unit of capital invested, depending on whether the objective emphasizes efficiency, absolute value, or reliability improvement.

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