



Discussion Paper

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

May, 2026



CLIMATE
POLICY
INITIATIVE

ACKNOWLEDGMENTS

We acknowledge the paper's lead authors and contributors, and extend our special thanks to Vivek Sen, Saarthak Khurana, Tariq Habib, and Neha Khanna for their invaluable guidance and contributions. We are also grateful to Gireesh Shrimali and Dharendra Kumar for their inputs to refine the approach and methodology.

In addition, we'd like to thank our CPI colleagues Saumya Tiwari, Kirsty Taylor, Tanuj Joshi, and Elana Fortin for editing, design, and reviews.

AUTHORS

Arnab Sarkar

arnab.sarkar@cpiglobal.org

Krishna Kumar

krishna.kumar@cpiglobal.org

Malavika Thampi

malavika.thampi@cpiglobal.org

Zeya Farhan

zeya.farhan@cpiglobal.org

CONTACT

Tariq Habib

tariq.habib@cpiglobal.org

Saumya Tiwari

saumya.tiwari@cpiglobal.org

ABOUT CLIMATE POLICY INITIATIVE

CPI is an analysis and advisory organization with deep expertise in finance and policy. Our mission is to help governments, businesses, and financial institutions drive economic growth while addressing climate change. CPI has offices in Brazil, India, Indonesia, South Africa, the United Kingdom, and the United States.

REGION

India

SECTOR

Power Sector

KEYWORDS

Power sector, Climate Stress, Resilience

MEDIA CONTACT

Rob Kahn,

Director, Global Communications

rob.kahn@cpiglobal.org

Saumya Tiwari,

Communications Manager

saumya.tiwari@cpiglobal.org

RECOMMENDED CITATION

CPI. (2026). *Assessing Climate Risks to India's Power Sector: A District-Level and Asset-Level Methodology for Climate-Resilient Power Systems*. Climate Policy Initiative.



LIST OF ABBREVIATIONS

ACRF	Asset-Specific Climate Risk Factor
ADB	Asian Development Bank
Bn	Billion
CBA	Cost-Benefit Analysis
CEA	Central Electricity Authority
CERC	Central Electricity Regulatory Commission
CF	Capacity Factor
Cr	Crore
CPSU	Central Public Sector Undertaking
CRAF	Climate Risk Assessment Framework
DTR	Distribution Transformer
EAD	Expected Annual Downtime
EAI	Expected Annual Impact
EAL	Expected Annual Loss
EDT	Expected Downtime per Event
EM-DAT	Emergency Events Database
ENS	Energy Not Served
EPC	Engineering, Procurement and Construction
FEMA	Federal Emergency Management Agency
GW	Gigawatt
GVA	Gigavolt-Ampere
Hz	Hertz
HV	High Voltage
IEC	International Electrotechnical Commission
IMD	India Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
IPP	Independent Power Producer
INR	Indian Rupee
ISSB	International Sustainability Standards Board

J&K	Jammu & Kashmir
JICA	Japan International Cooperation Agency
km/h	Kilometers per hour
kV	Kilovolt
LT	Low Tension
MDB	Multilateral Development Bank
Mn	Million
MNRE	Ministry of New and Renewable Energy
MVA	Megavolt-Ampere
MW	Megawatt
MWh	Megawatt-hour
NOAA	National Oceanic and Atmospheric Administration
NPV	Net Present Value
OEM	Original Equipment Manufacturer
O&M	Operation and Maintenance
PMSS	Probable Maximum Storm Surge
PMP	Probable Maximum Precipitation
PV	Photovoltaic
RE	Renewable Energy
RCP	Representative Concentration Pathway
SPEI	Standardized Precipitation Evapotranspiration Index
SPEI-3	Standardized Precipitation Evapotranspiration Index (3-Month)
TCFD	Task Force on Climate-related Financial Disclosures
USD	United States Dollar
VOLL	Value of Lost Load

TABLE OF CONTENTS

List of Abbreviations	iii
1. Introduction	1
Changing climatic patterns over the past 30 years in India	1
Physical Risks and the Power System	3
The Need for a Structured Climate Risk Assessment Framework for the Power Sector	5
The National Adaptation Plan and the Imperative for Sector-Specific Climate Risk Frameworks	8
2. Approach and Methodology	13
Conceptual Foundations	13
Scope of Assessment	15
Stage 1: Hazard Classification and Data Structure	17
Stage 2: District-Level Hazard Characterization	19
Stage 3: Asset Exposure	22
Stage 4: Vulnerability Modeling	24
Stage 5: Asset-specific Climate Risk Factor (ACRF)	29
Stage 6: Expected Annual Impact: EAL and ENS	30
Stage 7: Cost-Benefit Analysis of Resilience Measures	32
Summary of Key Outputs	33
3. Conclusion	35
Way Forward	36
4. References	37

LIST OF FIGURES

Figure 1: India's changing climate trajectory over the past three decades	2
Figure 2: Impacts of climate-induced extreme weather events on power assets in India over the past decade	4
Figure 3: Model Flow	10
Figure 4: Analytical stages of methodology	16

LIST OF TABLES

Table 1: Examples of the Climatic Impacts on Power Infrastructure	5
Table 2: Multilateral and Indian Context	7
Table 3: Literature Gaps	7
Table 4: Framework Outputs	14
Table 5: Scope and Boundaries	15
Table 6: Chronic Climate Hazards	17
Table 7: Acute Climate Hazards	17
Table 8: Climate Hazards Relevant to Power Assets	18
Table 9: Summary of key framework outputs	34

1. INTRODUCTION

Over the past three decades, India endured more than 400 extreme events, including floods, heatwaves, and cyclones. This underscores how multi-hazard exposure now characterizes the Indian climate system rather than periodic climate hazards. India's climate risk profile is characterized by rising temperatures, frequent heatwaves, erratic precipitation, and increasing acute hazard exposure. According to the Climate Risk Index published by Germanwatch, India ranked 6th among the nations hit hardest by extreme weather over the past 30 years (Germanwatch, 2025). The Intergovernmental Panel on Climate Change (IPCC) has established that each additional 0.1°C of warming drives discernible, non-linear increases in the intensity and frequency of temperature and precipitation extremes, as well as droughts. This indicates early signs of approaching the long-term limit (United Nations, 2023), which could materially affect long-lived infrastructure, including power and other industries.

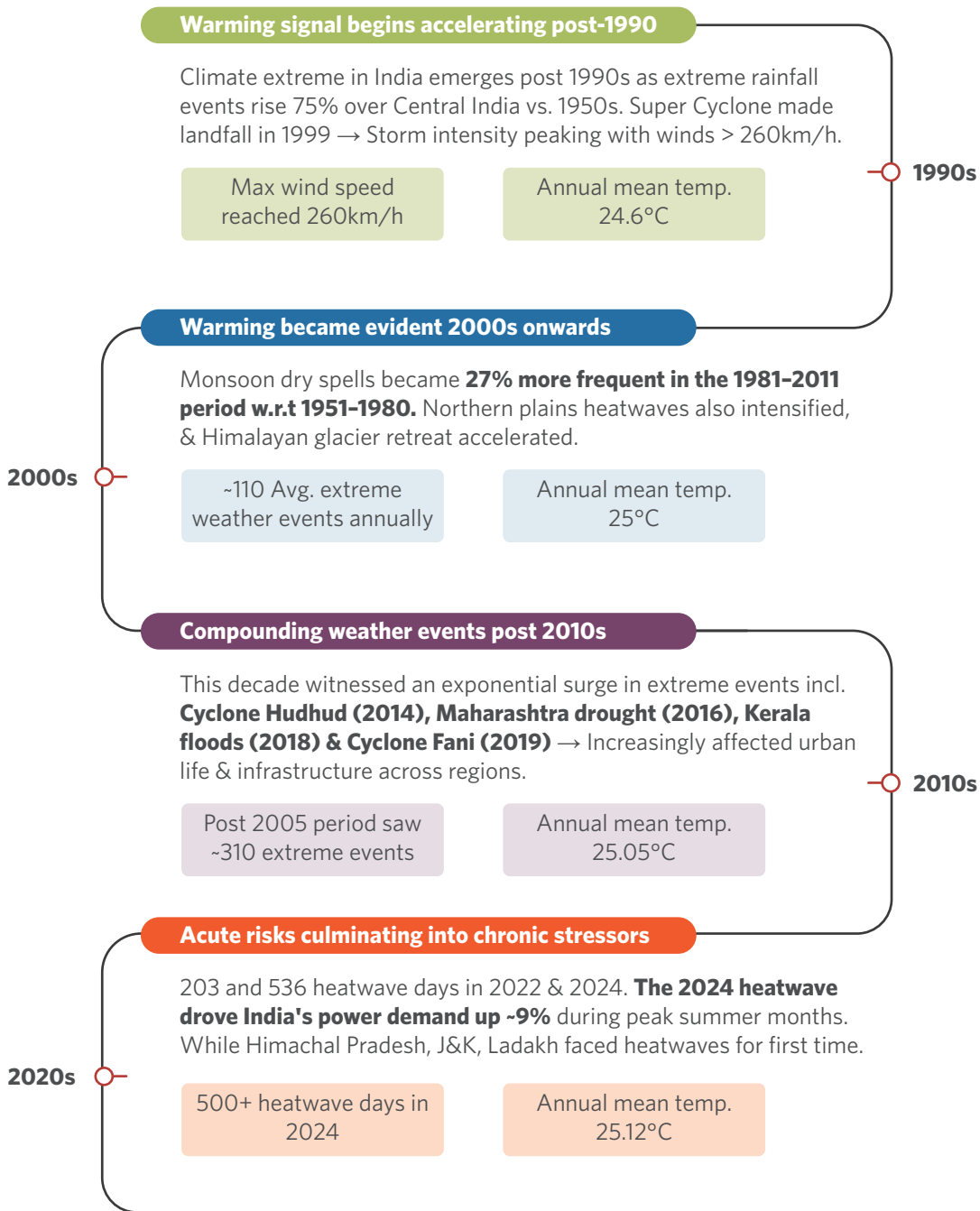
The following section highlights the trend of a changing climate across India over the past three decades and underscores its implications for the power sector.

CHANGING CLIMATIC PATTERNS OVER THE PAST 30 YEARS IN INDIA

India's mean surface temperature has risen by approximately 0.9°C between 1901 and 2024, with modest increases in the early 20th century accelerating sharply from the 1990s onward (NOAA, 2025). Over the past 50 years, approximately 11,158 extreme weather events have occurred in India. World Bank's Emergency Events Database (EM-DAT) data shows a rise from around 4 events in the 1950s to approximately 20 in 2018 alone, while India Meteorological Department (IMD) data indicates an increase from around 50 events in the 1970s to approximately 400 in 2019 alone (Tolani et al., 2024). These figures, however, understate the character of the change. What India is experiencing is not uniform warming but a non-linear shift in the climate system across two key dimensions: temperatures and precipitation, which can lead to various climate-induced extreme weather events.

Heatwaves have increased in frequency, intensity, and geographic reach, as northern and central states have accumulated over 500 cumulative heatwave days over the past decade (Das, 2025a). Warming signals have also extended into the Himalayan region, including Himachal Pradesh, Jammu & Kashmir, and Ladakh. Figure 1 depicts a decadal growth in extreme weather events and their interrelation with evolving warming patterns.

Figure 1: India's changing climate trajectory over the past three decades



Source: CPI analysis compiled using existing literature (World Bank Group, n.d.), (CEEW, 2020) (Mahapatra et al., 2018)

Total annual rainfall has remained broadly stable over 120 years, but this masks a significant structural shift in pattern, timing, and intensity. Dry spells during the monsoon became 27% more frequent in 1981–2011 relative to 1951–1980, while extreme daily rainfall events (>150mm/day) over Central India increased by around 75% between 1950 and 2025 (Press Information Bureau, 2025). More frequent dry spells interspersed with short, intense wet bursts are simultaneously driving drought and flood events, sometimes within the same season and

geography. Districts like Patna in Bihar, Alappuzha in Kerala, and Golaghat in Assam have faced dual risks (Department Of Science & Technology, 2024).

These shifts are not occurring in isolation. Rising temperatures and changing rainfall patterns are interdependent, and together they amplify both chronic and acute stressors. This interaction affects the baseline resilience of ecosystems and infrastructure, which defines the emerging risk environment for India's long-lived physical infrastructure.

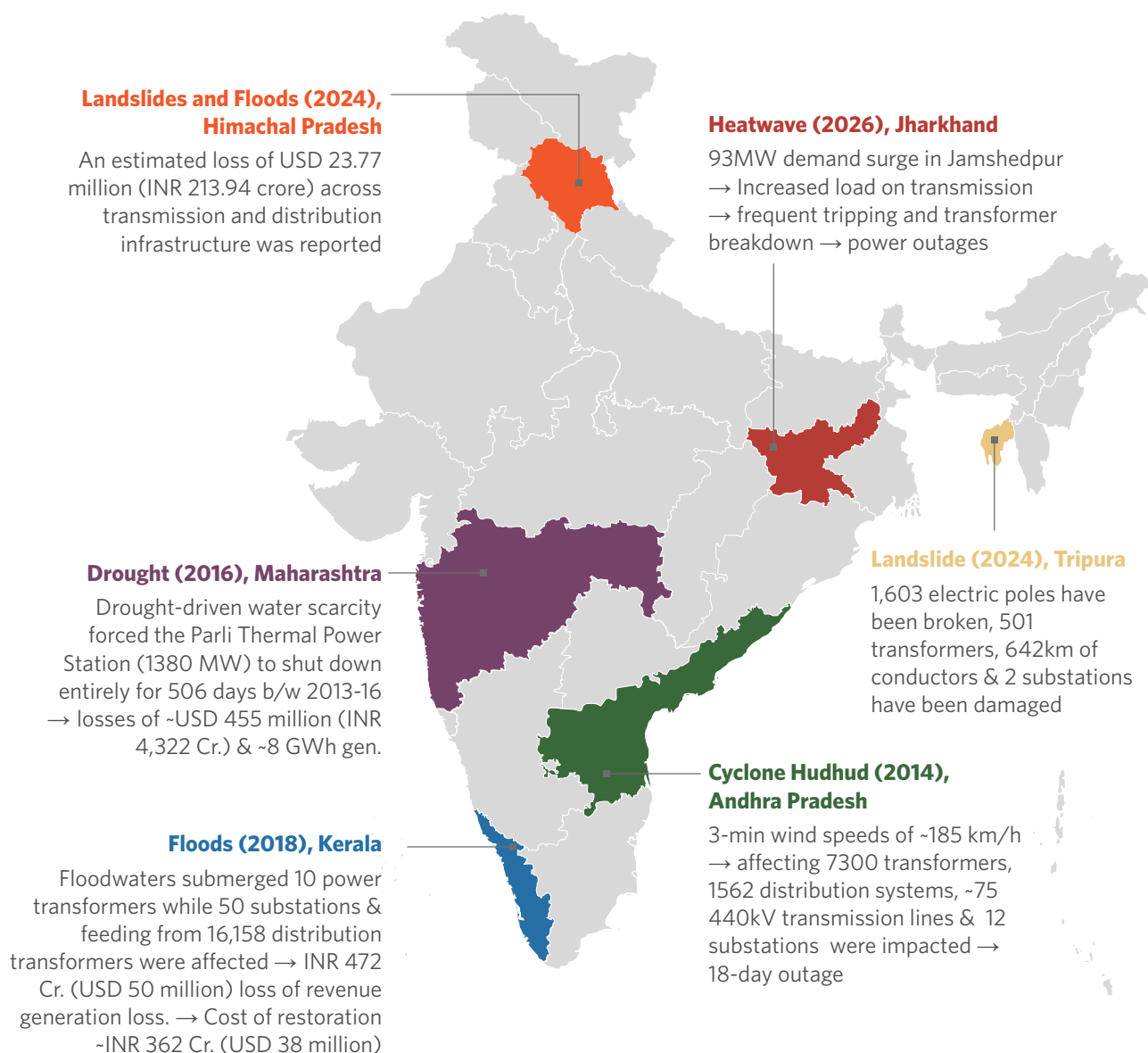
PHYSICAL RISKS AND THE POWER SYSTEM

Heat stress, extreme rainfall, tropical cyclones, and flooding are increasingly affecting power assets. Asia's biggest power utilities are already losing USD 6.3Bn (INR 59,850 Cr.)¹ annually to climate-related extreme events (Das, 2025b). India's power sector is at a critical juncture where India's climate-induced extreme event exposure converges with economic and infrastructure risk. Power sector assets, designed against historical climate parameters and built to operate for 2-4 decades, are now entering a different, evolving operating environment. The sector's value chain, from fossil fuel extraction, generation, transmission, and last-mile distribution, is structurally exposed across every layer. The sector's capital intensity, multi-decade asset lifetimes, and systemic interdependence mean that climate risk vulnerability could compound over the long term.

India's power sector is undergoing rapid expansion, driven by industrialization and economic growth. Global and national climate commitments and reduced technology costs have further accelerated this expansion. In India, as of 2026, the total installed capacity has reached around 520 GW, comprising 248.5 GW (47.7%) of fossil fuel sources and 271.9 GW (52.3%) of non-fossil fuel sources, making it the third-largest renewable energy capacity in the world (Ministry of Power, 2026). It has also set a target for 60% of cumulative installed power capacity to come from non-fossil fuel sources by 2035 (Cabinet, 2026). For integrating the growing renewable energy capacity, physical infrastructure, such as power plants, transmission, distribution, and storage systems, needs to be well planned to address climate-linked physical vulnerability.

¹ 1 USD = INR 95 as of May 2026 ([Federal Reserve](#))

Figure 2: Impacts of climate-induced extreme weather events on power assets in India over the past decade



Source: CPI analysis compiled using existing literature; (Soonee et al., 2015), (Sphere India, 2024), (Viswanathan, 2018), (Kerala State Electricity Board Limited, 2019), (Rohit Mullick, 2026), and (Luo, 2017)

Acute climate risks arising from extreme weather events, such as floods, cyclones, and landslides, can cause sudden, visible disruptions to power assets, including forced outages, physical damage to infrastructure, and direct revenue losses. Figure 2 highlights key incidents in which acute climate risks have impacted power systems in India. In contrast, chronic climate risk stems from gradual shifts in baseline climate conditions, including rising temperatures, erratic rainfall, and changes in wind patterns, that impose a gradual degradation in asset performance over a prolonged period, leading to efficiency losses, capacity derating, higher maintenance requirements, and reduced asset lifetimes. Both dimensions of climate risk can lead to financial losses for generating assets. Impacts of climate stressors on the power infrastructure have been highlighted in Table 1

Table 1: Examples of the Climatic Impacts on Power Infrastructure

Component	Event	Factors	Impact
Thermal power plants ClimateChange Post, 2013) (Petrakopoulou et al., 2020)	High temperatures	Operating efficiency decline: A rise in ambient air temperature of about 1 °C would reduce the thermal efficiency of a plant by 0.1-0.5 % in the absence of a cooling system. Equipping the plant with recirculating systems results in a derating range of 0.5% to 0.7% with a 10°C increase, while equipping it with a once-through system results in a derating range of 0.3% to 0.4% with a 10 °C increase.	Reduced generation
	Water stresses	Cooling water shortages during drought.	Plant derating
Solar PV modules	High temperatures (Waaree, 2025)	Approx. 0.4-0.5% efficiency loss per °C above 25°C - reaching up to -30% at 85°C.	Reduced generation
	High winds (International Electrotechnical Commission, 2014)	Design tolerance typically has a maximum threshold of 40 m/s, although it depends on the mounting design and the angle from the ground.	Structural damage risk
Wind turbines	High winds (vlab. amrita.edu, 2015)	Cut-out speed of approximately 25 m/s.	Turbine shutdown
	High temperatures (International Electrotechnical Commission, 2019) (Al-Khayat et al., 2021)	Wind turbines are designed to operate at rated capacity over an ambient temperature range of -10°C to 40°C. >40°C operations are OEM-specific with derating generally initiating above 40°C and forced shutdown at approximately 45°C to 50°C. The derating curve between these thresholds is manufacturer-specific.	Reduced generation/shutdown
Transmission lines	High temperatures (Jackson, 2024)	Conductor sag with an increase in ambient temperature.	Reduced line capacity
Substations	Floods	Water ingress into transformers and control systems.	Outage and equipment damage

Translating these physical exposures into energy and revenue lost metrics requires a quantitative, asset-level framework.

THE NEED FOR A STRUCTURED CLIMATE RISK ASSESSMENT FRAMEWORK FOR THE POWER SECTOR

Earlier sections have established certain narratives that, taken together, define the analytical challenge the methodology tries to solve. India's changing climate is reshaping the operating conditions for power-sector infrastructure through both chronic stressors and acute events. As the country rapidly expands power infrastructure, with assets expected to operate for decades under conditions different from those assumed at design, a structured framework is needed to translate climate exposure into asset-level operational and financial impacts and to inform resilient planning, regulation, and investment decisions.

Globally, climate change is increasingly recognized as the primary risk to physical infrastructure, with 97% of infrastructure investors identifying physical climate risk as significant and 76% expecting material impacts on investments (EDHEC, 2024). For India, this concern is particularly

material because the power sector is expanding even as baseline climate conditions are shifting, with rising temperatures, erratic precipitation, and more frequent acute hazards altering the operating environment for long-lived infrastructure. The need for developing a structured Climate Risk Assessment Framework (CRAF) is compounded by several developments specific to India's power sector. For example, the pace of capital deployment in transmission infrastructure, over 191,000 circuit-kilometers of transmission lines and 1,274 GVA of transformation capacity, is planned under the National Electricity Plan between 2022-23 and 2031-32 (Ministry of Finance, 2024). The window for integrating resilience considerations at the design stage is narrow. Infrastructure designed with climate-proofing in mind could help avoid stranded asset risks and unplanned retrofitting costs, as it adapts to physical hazards that may intensify over its operational life.

Box 1: Power Sector Investments in India

India's clean energy investments reached approximately USD 68 billion (INR 5.61 Lakh Cr.) in 2023, with a supplementary share of capital expected to originate from international climate finance sources such as MDBs, green bonds, and blended finance instruments (IEA, 2024). These sources are progressively integrating physical climate risk assessment frameworks, aligned with emerging standards such as the Task Force on Climate-Related Financial Disclosures (TCFD) and the International Sustainability Standards Board (ISSB), into investment decisions.

LITERATURE REVIEW

A range of frameworks, datasets, and analytical tools on climate risk and energy infrastructure have been produced over the last decade. As highlighted in Table 2, several international agencies and research organizations have contributed valuable approaches to climate risk screening.

Table 2: Multilateral and Indian Context

MDB Frameworks	Indian Frameworks
<p>ADB's Guidelines for Climate-Proofing Investment in the energy sector set out a step-by-step approach for incorporating adaptation measures into energy investment projects, including screening at the concept stage, climate risk and adaptation assessment during project preparation, and identification of adaptation options during design. The World Bank's Climate and Disaster Risk Screening Tools characterize hazard exposure for projects and national plans. JICA's Climate Finance Impact Tool (Climate-FIT) provides internal guidance for formulating climate-related projects under official development assistance, with separate adaptation and mitigation modules covering broad sectoral categories. Each of these frameworks has played an important role in mainstreaming climate risk into development finance, and their adoption across MDB lending portfolios has shaped how climate considerations are incorporated into project appraisal globally.</p>	<p>Within India, the Council on Energy, Environment, and Water's Climate Vulnerability Index offers the most granular assessment of climate exposure across the country's districts, mapping flood, drought, and cyclone risk using a composite scoring framework. The Centre for Study of Science, Technology and Policy's (CSTEP) Karnataka resilience study estimates reductions of 0.4–0.7% in thermal efficiency and 0.3–0.5% in solar efficiency under RCP 8.5 temperature projections. It categorizes plant risk using a composite of indicators for temperature and rainfall changes. Both contributions have advanced the conversation on subnational climate exposure and the impacts on asset-level performance in India.</p>

Source: (World Bank, n.d.); (JICA, 2023); (ADB, 2013); (CEEW, 2020); (CSTEP, 2021)

While the MDB tools fulfill their intended function of flagging whether climate risk is relevant at the project concept stage, the existing frameworks could be augmented to meet the decision support needs of Indian power-sector planners, regulators, and financiers. Four structural gaps are therefore seen across international and Indian literature, as shown in Table 3.

Table 3: Literature Gaps

Quantification Gap	Engineering Gap
<p>Peer frameworks work with risk ratings and qualitative narratives rather than energy-denominated impact estimates. For planners setting resilience standards and financiers looking at investments, the question is not whether a project faces "moderate" or "high" climate risk, but how many MWh of generation are expected to be lost in the absence of resilience measures.</p>	<p>Translating climate risk into energy losses requires knowing how a specific asset responds to a hazard, such as output loss from a solar panel on a hot day or the failure probability of a transmission tower in a cyclone of a certain intensity. Current screening tools identify hazard exposure and assess vulnerability qualitatively. Indian literature has begun engaging with asset-level performance impacts, paving way to apply this logic consistently across asset classes and hazards at the national scale.</p>
Resolution Gap	Economic Considerations
<p>India's power system is geographically distributed across regions with distinct hazard profiles, yet most current tools are project-level and designed for single-investment decisions. The CEEW Climate Vulnerability Index operates at the district level, applying the same generalized score to thermal plants, solar parks, substations, and transmission corridors alike. The CSTEP study is asset-specific as it addresses some of the above concerns covering a single asset class in a single state. A district-wide, asset-wise framework is needed to identify hotspots, target reinforcement, and allocate finance across India's diverse infrastructure base.</p>	<p>Identifying that an asset is at risk is one step; deciding whether to invest in resilience is the next step, and existing frameworks do not extend into cost-benefit territory. For approving cost recovery for resilience expenditure, the absence of a defensible, parameter-consistent CBA framework means climate-adaptive investments are appraised using ad hoc methods rather than established ones.</p>

The subsequent sections first lay out the India specific institutional and policy context for the proposed assessment, describe the theory of change, and then follow up with the approach and methodology (A&M) which aims to complement the ongoing adaptation work in India and address the gaps identified in the literature.

THE NATIONAL ADAPTATION PLAN AND THE IMPERATIVE FOR SECTOR-SPECIFIC CLIMATE RISK FRAMEWORKS

India's National Adaptation Plan (NAP), expected to be released in 2026, will represent a defining moment in the country's climate policy architecture. The NAP is designed to function as the government's authoritative macro-level roadmap for climate adaptation, establishing standardized climate scenarios, national baselines for temperature rise, sea-level change, and precipitation shifts, as well as localized hazard maps derived from the best available scientific evidence. It will rank sectors by vulnerability, set out policy and regulatory intentions for future building codes, zoning laws, and adaptation mandates, and signal the direction of public investment in resilience infrastructure. For the first time, India's diverse ecosystem of planners, regulators, financiers, and project developers will have a single, nationally endorsed reference point for climate data inputs and policy direction.

However, the NAP is, by design, a directive framework and not an operational toolkit. It will define the boundaries of the climate risk landscape and identify which sectors face the highest exposure, but it will not prescribe sector-specific risk-scoring methodologies, asset-level vulnerability calculators, or investment-grade loss estimation models. This is not a gap in the NAP's design; it is an intentional feature. Climate risk assessment at the operational level requires methodologies that are calibrated to the engineering characteristics, financial structures, and regulatory environments of individual sectors. A risk framework for the power sector, where the relevant variables include thermal derating coefficients, conductor sag thresholds, and cooling water availability, is fundamentally different from one designed for agriculture, urban infrastructure, or coastal fisheries. The NAP provides climate science; each sector must build the engineering and financial translation layer.

WHY SECTOR-SPECIFIC RISK FRAMEWORKS ARE ESSENTIAL

Three structural factors explain why the NAP cannot, and should not, provide ready-made risk calculators for individual sectors. First, risk appetite varies fundamentally across stakeholders. A public policy framework defines risk in terms of societal harm and systemic stability; a commercial lender or independent power producer (IPP) views risk through the lens of capital preservation, loan default probability, and return on equity. The same climate hazard that a regulator might classify as "moderate" at the national level could be financially material for a specific project with thin debt service coverage margins. Second, methodological dynamism demands flexibility. Climate risk assessment science is evolving rapidly, with new datasets, improved downscaling techniques, and refined damage functions emerging regularly. Regulators are increasingly aligning with global disclosure frameworks such as the International Sustainability Standards Board (ISSB) and the Task Force on Climate-related Financial Disclosures (TCFD), but they prefer to issue principles-based guidelines rather than freezing a single mathematical formula into policy. Embedding a rigid calculation methodology in the NAP would risk obsolescence within years. Third, the heterogeneity within sectors is too great

for centralized standardization. Within the power sector alone, the risk profile of a solar farm in an arid zone, where heat degradation on photovoltaic panels and water scarcity for cleaning are the dominant stressors, differs fundamentally from that of a hydroelectric plant in a glacial catchment exposed to changing rainfall patterns and glacial lake outburst floods, or a coastal thermal plant vulnerable to cyclone-driven storm surge and saltwater intrusion.

THE POWER SECTOR: WHY IT WARRANTS IMMEDIATE ATTENTION

Among all sectors that the NAP will address, the power sector stands out as requiring the most urgent development of a dedicated climate risk assessment framework, for several reinforcing reasons. The power sector is the backbone of economic activity; every other sector's ability to adapt to climate change depends on a reliable electricity supply. A climate-induced failure in the power system does not merely affect the utility or generator; it cascades across hospitals, water treatment plants, communication networks, cold chains, and industrial production. The systemic interdependence of the power sector means that its climate vulnerability is, in effect, a multiplier of vulnerability across the entire economy.

Furthermore, the power sector is uniquely capital-intensive and characterized by multi-decade asset lifetimes. A thermal power plant commissioned today will operate until the 2050s or 2060s; a transmission corridor built this year will carry power for 30 to 40 years. These assets are being designed and financed against historical climate parameters that are already diverging from the conditions they will face over their operational lives. The window for integrating climate resilience at the design stage, where orders of magnitude are cheaper than retrofitting, is narrow and closing. India's power sector is simultaneously undergoing the largest capacity expansion in its history, with over 520 GW of installed capacity as of 2026, a target of 60% non-fossil capacity by 2035, and over 191,000 circuit-kilometers of new transmission lines planned under the National Electricity Plan. Every gigawatt of new capacity and every kilometer of new line commissioned without a structured climate risk assessment represents a potential stranded asset or an unplanned retrofitting liability.

The financial ecosystem around power sector investments is also evolving in ways that demand quantitative climate risk tools. India's clean energy investments reached approximately USD 68 billion in 2023, with a growing share of capital originating from international climate finance sources, multilateral development banks, green bonds, and blended finance instruments, all of which are progressively integrating physical climate risk assessment into their investment criteria. Globally, 97% of infrastructure investors now identify physical climate risk as significant, and 76% expect material impacts on their portfolios. Without a sector-specific framework that can translate national climate data into asset-level risk scores and bankable loss estimates, Indian power sector participants risk being unable to access, or being priced out of, the capital they need to build a resilient grid.

It is against this backdrop that CPI has developed the Climate Risk Assessment Framework (CRAF) presented in this paper. The framework is designed to function as the sector-specific analytical layer that sits between the NAP's macro-level climate data and the granular, decision-relevant outputs that power sector stakeholders require. It takes the national climate scenarios, hazard maps, and policy signals that the NAP will provide and translates them, through a rigorous seven-stage methodology, into district-level hazard indices, asset-specific vulnerability scores, quantified energy loss estimates, and cost-benefit analyses of resilience investments.

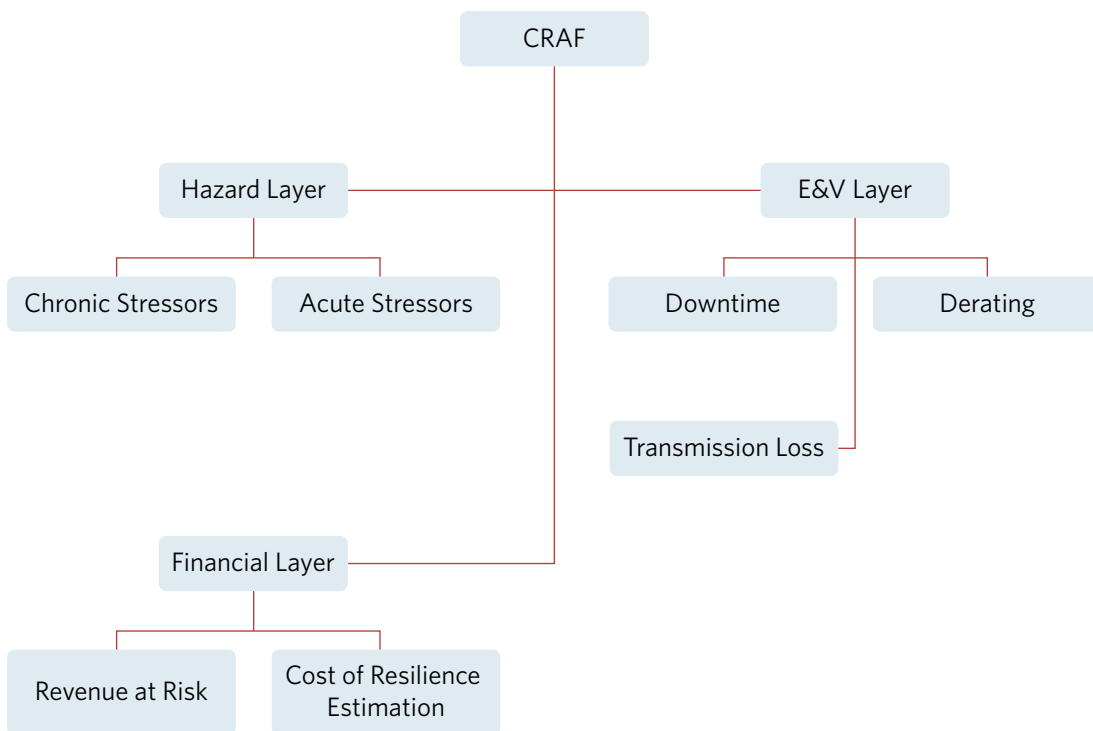
The following sections describe the institutional relevance of this framework and the detailed methodology that underpins it.

INSTITUTIONAL RELEVANCE

India is making substantial advances in renewable energy integration. The proposed CRAF as shown in Figure 3 is intended to supplement existing power sector planning, regulatory oversight and resilience prioritization by adding a quantitative climate risk layer to decision-making. Its unique contribution could lie in translating climate hazard data into asset-level energy-loss metrics.

The framework could generate **Expected Annual Loss (EAL)** and **Energy Not Served (ENS)** estimates calibrated to conditions in the Indian power sector. These outputs may help move climate risk assessment from broad exposure mapping to decision-relevant estimates of operational and financial impact.

Figure 3: Model Flow



WHAT THIS MEANS FOR POWER SECTOR ACTORS

With the NAP's release anticipated in early June 2026, power sector stakeholders should prepare to treat it as the single source of truth for climate data inputs and policy direction. However, the analytical heavy lifting, translating those inputs into project-level risk assessments, investment decisions, and resilience strategies, will remain squarely the responsibility of individual organizations. The framework presented in this paper is designed to support precisely this effort, but the organizational implications extend across the entire value chain.

FOR PROMOTERS AND PROJECT DEVELOPERS

Project developers, whether independent power producers (IPPs), renewable energy developers, or central public sector undertakings (CPSUs), will need to embed the localised climate projections provided in the NAP directly into their engineering design, site-selection, and project-structuring processes. This is not a compliance exercise; it is a commercial imperative. If the NAP highlights an accelerating drought trend in a specific region, promoters must scientifically demonstrate how their plant will maintain cooling capacity or handle thermal stress under projected conditions, and prove that design resilience to their lenders, equity investors, and insurers before financial close. For solar developers, this means accounting for the cumulative impact of rising ambient temperatures on photovoltaic panel efficiency over the project's 25-year life, not merely at the point of commissioning. For wind developers, it means evaluating whether changing wind patterns and increasing frequency of extreme gusts will alter capacity factors and structural loading beyond the design envelope assumed in the power purchase agreement. For thermal generators, it means stress-testing cooling system adequacy against projected drought frequency and severity, not against historical averages that no longer represent future operating conditions.

Promoters who integrate the CRAF's outputs into their project preparation, using district-level hazard indices to inform site selection, asset-specific vulnerability scores to guide engineering specifications, and Expected Annual Loss estimates to quantify the value of resilience investments, will be better positioned to secure financing at competitive terms, satisfy lender due diligence requirements, and reduce the probability of climate-induced underperformance over the asset life.

FOR FINANCIERS AND INVESTORS

Domestic and international financiers, including commercial banks, development finance institutions, multilateral development banks, and institutional investors, will need to establish internal Climate Risk Scoring Frameworks as a core component of their credit appraisal and investment decision processes. The NAP's hazard maps and climate scenarios will serve as the foundational baseline data, but each institution's risk team must design the proprietary assessment matrices that translate a physical hazard into a financial metric. For example, a district classified as "High Risk for Extreme Heat Days" in the NAP must be translated into a projected percentage decline in annual energy production, which in turn must be modelled through to its impact on the Debt Service Coverage Ratio (DSCR), the loan-to-value ratio, and the probability of default over the tenor of the financing. This translation requires exactly the kind of engineering-grounded, asset-specific vulnerability modelling that the CRAF provides.

Financiers who rely solely on qualitative climate risk screening, classifying projects as "low," "medium," or "high" risk without quantifying the expected financial impact, will find themselves at a growing disadvantage. International capital providers are increasingly requiring quantified physical climate risk assessments aligned with TCFD and ISSB standards as a condition of participation in syndicated lending, green bond issuances, and blended finance structures. The CRAF's Expected Annual Loss (EAL) and Energy Not Served (ENS) outputs, expressed in MWh and monetised at applicable tariffs or the Value of Lost Load, provide the quantitative foundation that financiers need to satisfy these disclosure requirements, differentiate between projects with materially different risk profiles, and price climate risk into lending terms rather than absorbing it as an unquantified contingency.

FOR INSURERS AND RISK TRANSFER MARKETS

The insurance and reinsurance industry has a critical role in the climate resilience ecosystem for the power sector. The CRAF's asset-level fragility models, expected downtime estimates, and annualized loss calculations provide an India-specific actuarial basis for developing parametric insurance products, business interruption cover, and catastrophe bonds tailored to power sector assets. Insurers can use the framework's output to move beyond historical loss experience, which is increasingly unreliable as a predictor of future claims in a non-stationary climate, towards forward-looking, engineering-grounded risk pricing. For parametric products in particular, the framework's district-level hazard indices and event frequency estimates can serve as the trigger basis, enabling faster claims settlement and reducing basis risk.

FOR EPC CONTRACTORS AND TECHNICAL CONSULTANTS

Engineering, procurement, and construction (EPC) firms and technical consultants will find that climate-resilient design is transitioning from a value-added differentiator to baseline expectation. As promoters and financiers adopt quantitative climate risk frameworks, the technical specifications embedded in EPC contracts will increasingly reference specific resilience parameters: flood elevation requirements derived from return-period inundation modelling, wind-loading standards calibrated to projected cyclone intensities, thermal management systems sized to future ambient temperature projections rather than historical averages, and drainage infrastructure designed for extreme rainfall events that are becoming more frequent. The CRAF provides the analytical bridge between climate science and engineering specification, enabling EPC contractors to quantify the cost and benefit of specific hardening measures and to demonstrate, in the language of avoided energy losses and avoided repair expenditure, why resilience investments are commercially justified.

THE BOTTOMLINE

The forthcoming National Adaptation Plan should be understood as the foundational operating system for India's climate adaptation architecture. It will provide the core data, the policy boundaries, and the rules of the environment within which all actors must operate. But each organization, whether a project developer structuring a bid, a bank appraising a loan, an insurer pricing policy, or an EPC firm designing a plant, will still need to write its own software to navigate that environment. The Climate Risk Assessment Framework presented in this paper is designed to serve as that software for the power sector: a structured, transparent, and replicable methodology that converts the NAP's macro-level inputs into the micro-level, asset-specific, financially quantified outputs that decision-makers need. Those who build this analytical capability ahead of the NAP's release will be best positioned to act on its data from day one; those who wait will face a steeper, costlier, and more time-pressured learning curve as regulators, investors, and markets begin to demand quantified climate risk assessments as standard practice.

2. APPROACH AND METHODOLOGY

This section presents the proposed methodological framework for assessing the physical climate risks to India's power sector assets and for conducting a cost-benefit analysis (CBA) of resilience measures. The framework's seven analytical stages transform raw climate data into quantified risk and impact estimates for power assets, which are then used to assess the cost-effectiveness of resilience measures. It is built to be transparent, replicable, and engineering-grounded, ensuring its output can be used consistently across utilities, regulators, planners, and insurers. This framework is intended as a practical tool that can be scaled up using ground-level data to generate results usable for planning, investment decisions, and regulatory oversight.

Climate risk is not a uniform threat but the product of three interacting factors: 1) the probability and intensity of a climate stressor at a given location; 2) the magnitude of infrastructure exposed to that stressor; and 3) the degree to which that infrastructure is susceptible to damage or performance loss when exposed. The sections below describe, in sequence, the conceptual foundations of the framework, the scope of the assessment, and the seven analytical stages. The main text highlights the key steps, concepts, and outputs of the methodology to keep the discussion accessible and focused, while the full technical methodology, including detailed equations, parameter definitions, intermediate calculations, and asset-class-specific formulations, is provided as the annexure.

CONCEPTUAL FOUNDATIONS

The risk framework is anchored in the hazard–exposure–vulnerability (H×E×V) construct, the international standard for quantitative climate risk assessment (Christopher B. Field, 2014). Under this construct, risk is understood as the product of three conceptually separable components, each requiring its own data and analytical methods.

Risk = Hazard × Exposure × Vulnerability

Hazard describes the probability and intensity of a climate stressor at a given location, how often it occurs, and how severe it is when it does. In this framework, hazard is characterized separately for each of eight climate stressors at the district level.

Exposure describes the extent to which power assets are exposed to climate stressors. It is quantified in the given analysis using the installed generation capacity, transmission capacity, or load served that lies within the exposed district. Exposure is the scale parameter: the more capacity at risk, the greater the potential impact.

Vulnerability describes how susceptible a power asset is to damage, performance degradation, or failure when exposed to a climate stressor. Vulnerability is determined by the equipment's engineering characteristics and the severity of the conditions it faces.

TWO IMPACT PATHWAYS

The framework design distinguishes climate impacts into two independent and parallel pathways, each driven by different physical mechanisms. These pathways are assessed separately and used to derive vulnerability scores.

IMPACT PATHWAY FOR CHRONIC STRESS: PERFORMANCE DERATING

Chronic stress would reduce asset performance through sustained exposure rather than causing immediate physical damage. This is typically reflected as performance derating, where the output or efficiency of an asset can decline.

For instance, a solar panel produces less electricity at 45°C than at 25°C: the relationship between temperature and output loss is a continuous engineering function (Skoplaki & Palyvos, 2009). A thermal power plant drawing water from a river, for instance, running below its full capacity, must reduce load or risk damaging its condenser and cooling towers. A wind turbine experiencing sustained winds above its rated speed has its control system limit the power output to protect its equipment. In each case, the mechanism is a reduction in rated output in proportion to the extent to which conditions exceed the relevant engineering threshold. The effect is gradual, but it accumulates across many threshold-exceeding days in a year, and across many assets in a district, to produce substantial annual energy losses.

IMPACT PATHWAY FOR ACUTE STRESS: SUDDEN FAILURE AND OUTAGE

Acute stress affects the power sector through sudden physical damage, typically in the form of an outage or a failure. For instance, a cyclone speed exceeding a transmission tower's design limits may cause it to collapse, leading to an outage of the transmission lines. When floodwater inundates a substation, transformers, switchgear, and cable terminations can be damaged or short-circuited, leading to prolonged outages that can take several weeks to months to restore. Similarly, a landslide can damage a transmission corridor or block access to a generation facility. For acute risks, two conditions are considered: 1) the restoration time in the event of a failure and 2) the interruption duration in the event of a non-failure. These impacts are assessed through a fragility analysis to estimate failure and outage probabilities.

FRAMEWORK OUTPUTS

The framework produces three distinct types of output, each designed for a specific decision purpose as highlighted in Table 4.

Table 4: Framework Outputs

Output	Description
Asset-Specific Climate Risk Factor (ACRF)	A dimensionless comparative index, used for spatial risk mapping and screening across districts.
Expected Annual Impact (EAI)	Converts risk into operational and financial consequences expressed in MWh per year. For generation assets, it is measured as the Expected Annual Loss (EAL) , representing energy not generated due to climate-induced outages or derating. For transmission and distribution assets, it takes the form of Energy Not Served (ENS) , representing energy not supplied to end consumers.
Cost-Benefit Analysis (CBA) of Resilience Measures	Identifies specific resilience interventions and models their effect on climate-induced impacts, including performance derating, outages, and asset damage. It compares expected annual impact under baseline and resilience scenarios, monetizes the avoided losses, and assesses whether these benefits justify the upfront and recurring costs of the intervention over the asset life.

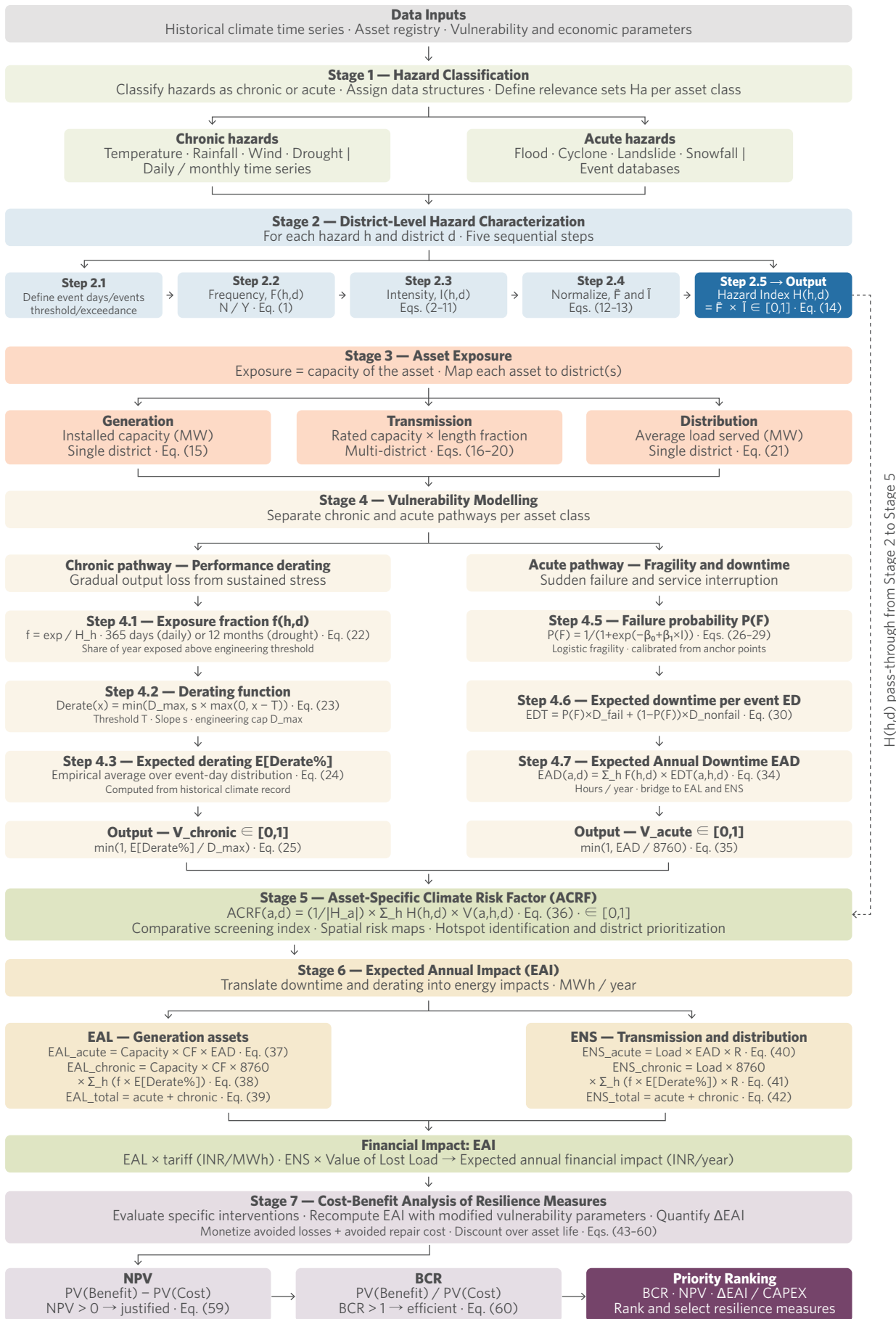
SCOPE OF ASSESSMENT

Table below defines the scope of this assessment across four dimensions: time period, risk coverage, data boundary, asset coverage, and hazards. This given methodology considers only greenfield projects.

Table 5: Scope and Boundaries

Dimension	Boundary	Rationale
Time period	Historical climate data covering more than 30 years from around 1990 to 2024	Long enough to capture the multi-year climate variability and return period of rare extreme events.
Risk coverage	Physical climate risks only; transition risks are excluded	Physical risks directly affecting asset performance are tractable using engineering-based methods, Transition risks (policy evolution, stranded assets, carbon pricing mechanisms) operate through economic channels and require distinct analytical frameworks.
Spatial Coverage	District level; consistent methodological assumptions across all regions	The district is the finest administrative unit for which consistent climate data is available nationwide. Applying common assumptions preserves comparability as a risk score across districts. Spatial variability of climate impacts has been considered uniformly within a district due to limited data availability. Parallely, associated resilience costs differ across and within districts, therefore these costs have been considered to be uniform.
Asset coverage	Generation Assets: Thermal, solar PV, and wind Transmission Assets: HV lines, towers, substations Distribution Assets: LT lines, distribution transformers, and substations	For Generation Assets: Nuclear and hydro assets are not considered due to their strategic importance and limited data availability. For transmission lines, the straight-line (beeline) routing approximation method is considered, as asset-level data precision is constrained by data availability. For Distribution, assets are considered at the district level, as they serve localized demand and are spatially linked to a defined service area. Exposure is measured through average load served, which captures the scale of demand at risk from climate-induced outages.

Figure 4: Analytical stages of methodology



ANALYTICAL STAGES

The methodology proceeds through seven stages, as shown in Figure 4. This logic follows the framework's conceptual structure: characterize the hazard; define what is exposed; model the vulnerability of the exposed assets; combine hazard and vulnerability into a comparative risk index; translate the risk into quantified energy impacts; and then evaluate which resilience investments are justified and should be prioritized. The subsequent section explains the mechanics of the calculations and the reasoning behind each stage.

STAGE 1: HAZARD CLASSIFICATION AND DATA STRUCTURE

Stage 1 involves identifying hazards as either chronic or acute. This also defines the data structure used to represent the hazard, the statistical method used to derive frequency and intensity, and the vulnerability model applied in Stage 4.

CHRONIC HAZARDS: CONTINUOUS TIME SERIES

The framework identifies four chronic hazards as illustrated in Table 6:

Table 6: Chronic Climate Hazards

Chronic Hazards	Climate variables
Extreme temperature	Daily maximum and mean temperatures capture the stress on equipment from ambient heat.
Extreme rainfall	Daily precipitation totals are relevant to equipment submergence risk and to operations in areas prone to extreme rain events.
Extreme wind	Daily wind speed at 10 m and 100 m height, relevant for both chronic wind-loading stress and turbine cut-out thresholds.
Drought-induced water stress	The Standard Precipitation Evapotranspiration Index with a 3-month accumulation period (SPEI-3) is used as the primary screening indicator, and monthly river discharge is considered to reflect the availability of cooling water for thermal generation.

Most chronic hazards datasets are in the form of daily time series. Drought is an exception. The monthly drought index, i.e., the SPEI-3, captures short to medium-term moisture deficits. Water availability stress operates over hydrological timescales that are mostly monthly in character: a river does not typically fall below its operational minimum for a single day.

ACUTE HAZARDS: EVENT-BASED RECORDS

The framework identifies three acute hazards as shown in Table 7:

Table 7: Acute Climate Hazards

Acute Climate Hazard	Climate Variables
Floods	Characterized by event frequency, inundation depth, and affected area, the primary impact mechanism is the submergence of electrical equipment below floodwater.
Cyclones	Characterized by maximum sustained wind speed, storm surge, and probable maximum precipitation, cyclones can damage assets through multiple pathways simultaneously.
Landslides	Characterized by terrain susceptibility and event frequency, the primary impact mechanisms are the displacement of transmission towers and the blockage of access routes.

Each of these hazards differs fundamentally in its physical character; they are represented using hazard-specific formulations rather than a single uniform structure. It includes the frequency with which events occur (events per year), a severity indicator specific to that hazard's damage pathway, and, for hazards with significant spatial variability, spatial exposure.

HAZARD RELEVANCE BY ASSET CLASS

Not every hazard poses a credible risk to every asset class. Restricting the analysis to hazard-asset pairs with genuine physical pathways prevents spurious risk attribution and maintains the ACRF's interpretability. For each asset class, a relevant set of hazards (\mathcal{H}_a) is defined and applied consistently throughout Stages 4–6.

Table 8: Climate Hazards Relevant to Power Assets

Hazard	Generation	Transmission	Distribution
Extreme temperature	✓	✓	✓
Extreme rainfall	✓	—	✓
Extreme wind	✓	✓	✓
Drought (water stress)	✓	—	—
Flood	✓	✓	✓
Cyclone	✓	✓	✓
Landslide	—	✓	✓

STAGE 2: DISTRICT-LEVEL HAZARD CHARACTERIZATION

For each of the eight hazards and each of India's districts, Stage 2 constructs a Hazard Index that captures two complementary dimensions of climate risk: how often a stressor exceeds operationally relevant thresholds, and how severe it is when it does. For instance, a district exposed to very frequent mild floods faces a different risk profile from one exposed to rare but catastrophic inundations. The Hazard Index is designed to reflect this joint condition.

IDENTIFYING OPERATIONALLY RELEVANT EXPOSURE PERIODS

The first step is to identify, within the historical climate record, events or time periods relevant to infrastructure performance. Instead of considering all climatic conditions, the analysis focuses only on those that exceed the threshold at which the asset performance begins to decline or fail.

For chronic hazards, an exposure period is defined as a day (or month, for drought) during which conditions exceed a hazard-specific engineering threshold, e.g., $T_{\max} >$ the heat exposure derating threshold.

For acute hazards, the definition is simpler: each recorded occurrence in the event database, each flood occurrence, each cyclone landfall, or each landslide event, constitutes one exposure event.

This exceedance-based definition is critical. Engineering systems are not uniformly sensitive across all conditions; for instance, a transformer designed for an optimal operating limit of 40°C begins to derate only when that threshold is exceeded, and the physics are non-linear. For acute hazards, each recorded event occurrence in the relevant database constitutes one exposure event.

STEP 2.2: ANNUALIZED EVENT FREQUENCY

Event frequency is calculated by dividing the count of exposure-relevant events over the observation period by the number of years of data available:

$$F_{h,d} = \frac{N_{h,d}}{Y_h} \quad (\text{Eq. 1 of annexure})$$

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).

Annualization places all hazards on a common temporal basis, enabling fair comparison across stressors with different record lengths and different data frequencies. Frequency can be explicitly tied to operationally relevant exposure conditions. For instance, a flood database covering 20 years and a temperature record covering 30 years can be compared if both are expressed as rates per year.

STEP 2.3: HAZARD INTENSITY

Frequency measures how often a stressor occurs; intensity measures how severe it is when it does. These two complement each other for better hazard characterization.

CHRONIC HAZARD INTENSITY

For chronic hazards, intensity is defined as the high quantile of the distribution of stressor values during the exposure period, typically the 95th percentile, or as the threshold-exceeding days or months in the historical record. This upper-tail quantile captures the typical severity of extreme conditions, providing a stable representation that is not dominated by a single anomalous year.

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

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 temperature, rainfall, and wind, Z equals the raw observed value, since higher values indicate greater stress. For drought, stress increases as the river discharge falls, so the framework applies a discharge-deficit transformation to maintain directional consistency across all hazards:

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

where:

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

This ensures that drought-induced water stress captures the magnitude of the water deficit during low-river discharge periods, rather than the absolute discharge level.

ACUTE HAZARD INTENSITY

For acute hazards, intensity is derived from event-level severity indicators that reflect the specific physical mechanism through which each hazard causes damage. The framework uses hazard-specific indicators, rather than applying a common intensity measure across all acute hazards:

- **Flood intensity** is represented by inundation depth (m), the primary determinant of whether electrical equipment is submerged and damaged.
- **Landslide intensity** is represented by a terrain susceptibility index, reflecting the probability that terrain conditions produce slope failure.

- **Cyclone intensity** is a composite measure combining maximum sustained wind speed (MSW), probable maximum storm surge (PMSS), and probable maximum precipitation (PMP):

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

where:

- γ_1 and γ_2 are scaling parameters calibrated to reflect the relative contribution of surge and precipitation to infrastructure damage, relative to wind loading.

This framework uses a composite cyclone intensity measure, as only wind speed would understate total cyclone risk in districts where storm surge or rainfall-induced flooding is the dominant damage mechanism. Tropical cyclones can cause damage through multiple simultaneous pathways: wind damage to towers and conductors, storm surge flooding of coastal substations, and extreme rainfall flooding of inland infrastructure.

STEP 2.4: NORMALIZATION TO A COMMON SCALE

Frequency and intensity are expressed in different units across different hazards and must be placed on a common scale before they can be combined. The framework uses quantile scaling with winsorization, clipping values at the 5th and 95th percentiles of the cross-district distribution for each hazard:

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

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

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
- $\text{clip}(x, 0, 1)$ — truncation operator that bounds the output to [0, 1].

Winsorizing at the 5th and 95th percentiles prevents a single extreme outlier district from dominating the scale and making all other districts appear nearly risk-free by comparison, a critical property for a national-scale comparative assessment. Districts at or below the 5th percentile receive a normalized score of 0; those at or above the 95th percentile receive 1. All others are scaled proportionally within this range.

STEP 2.5: CONSTRUCTING THE HAZARD INDEX

The Hazard Index for each hazard and district is constructed as a combination of normalized frequency and normalized intensity:

$$H_{h,d} = \widetilde{F}_{h,d} * \widetilde{I}_{h,d} \quad (\text{Eq. 14 of annexure})$$

where:

- $H_{h,d}$ — normalized hazard score for hazard (h) in district (d), $\in [0,1]$;
- $\widetilde{F}_{h,d}$ — normalized frequency (Eq. 12); and
- $\widetilde{I}_{h,d}$ — normalized intensity (Eq. 13).

The resulting Hazard Index ($H_{h,d}$) is produced separately for each of the eight hazards across all districts and flows into both the ACRF (Stage 5) and the Expected Annual Impact calculations (Stage 6).

STAGE 3: ASSET EXPOSURE

Exposure defines the scale of infrastructure or service that is subject to each climate hazard. It is the scale parameter that determines the magnitude of the potential energy impact. In the power sector, the appropriate exposure metric differs by asset class because different assets contribute to risk in different ways and at different spatial scales.

GENERATION ASSETS

For generation assets, exposure is the plant's rated installed capacity (MW). Generation assets such as thermal plants, solar farms, and wind installations are fixed at a single geographic location. All hazard, vulnerability, and impact calculations use the district's climate characteristics.

$$E_{gen,a,d} = InstalledCapacity_{a,d} \quad (\text{Eq. 15 of annexure})$$

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

TRANSMISSION ASSETS

Transmission assets span multiple districts. A long-distance high-voltage line may pass through dozens of districts, each with its own hazard profile. The capacity of the line exposed to any given district is determined by the fraction of the line's total length that falls within that district:

$$E_{trans,l,d} = Capacity_l \cdot \frac{Length_{l,d}}{Length_l} \quad (\text{Eq. 16 of annexure})$$

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)

This formulation ensures that districts through which a larger share of the line passes contribute more to the line's overall exposure. District fractions are approximated using a straight-line, or beeline, route between the origin and destination districts.

Following the same concept, hazard scores are aggregated along the full corridor. For chronic hazards, the effective hazard score is calculated as a length-weighted average of district-level hazard scores:

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

where:

- $rank(H_{h,d})$ is assigned by ranking all districts traversed by line l according to their district-level hazard score for hazard h .
- $H_{h,l}^{trans}$ is the effective hazard score for transmission line l under hazard h
- $H_{h,d}$ is district-level hazard score (Eq.14)

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

$$F_{h,l}^{trans} = \frac{\sum_{d \in D_l} Length_{l,d} \times rank(H_{h,d}) \times F_{h,d}}{\sum_{d \in D_l} Length_{l,d} \times rank(H_{h,d})} \quad (\text{Eq. 19 of annexure})$$

$$I_{h,l}^{trans} = \frac{\sum_{d \in D_l} Length_{l,d} \times rank(H_{h,d}) \times I_{h,d}}{\sum_{d \in D_l} Length_{l,d} \times rank(H_{h,d})} \quad (\text{Eq. 20 of annexure})$$

These aggregated values $F_{h,l}^{trans}$ and $I_{h,l}^{trans}$ are subsequently used in fragility modeling and downtime estimation, ensuring that transmission asset risk reflects hazard exposure along the full corridor rather than at a single representative point.

DISTRIBUTION ASSETS

For distribution assets, exposure is the average load served in MW. Distribution assets serve localized areas and are mapped to a single district. The load served is the appropriate capacity

metric because consumers experience climate impact on distribution infrastructure as unserved energy: the greater the load an asset serves, the more energy consumers lose if the asset fails or is derated.

$$E_{dist,a,d} = AvgLoadServed_{a,d} \quad (\text{Eq. 21 of annexure})$$

where:

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

STAGE 4: VULNERABILITY MODELING

Vulnerability describes how climatic conditions translate into impacts on the performance and operation of power assets. Stage 4 is an analytically intensive stage where the impact pathways for chronic and acute climate stresses are assessed.

THE IMPACT PATHWAY FOR CHRONIC STRESS: PERFORMANCE DERATING

Chronic hazards reduce asset output through sustained or repeatedly recurring stress that degrades performance without necessarily causing physical failure. The impact pathway can be summarized as:

Hazard exceedance → Performance reduction → Energy loss

The chronic vulnerability model proceeds through four sequential steps: characterizing the fraction of the year during which the asset is exposed to above-threshold conditions; defining the performance loss on each exposure day; computing the expected performance loss averaged over the exposure period; and normalizing that expected loss to a dimensionless vulnerability score.

STEP 4.1A: EXPOSURE FRACTION

The exposure fraction ($f_{h,d}$) is the share of the year during which the hazard exceeds its relevant threshold in district d:

$$f_{h,d} = \frac{N_{h,d}^{exp}}{M_h} \quad (\text{Eq. 22 of annexure})$$

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).

The exposure fraction is crucial because it determines how much of the year's potential generation is at risk from chronic derating. Derating is applied only during the exposed fraction, not across all 8,760 hours (365 days * 24 hours), preventing the systematic overestimation of annual losses in regions with short extreme seasons.

STEP 4.1B: DERATING FUNCTION

The derating function maps the realized stressor value on any given exposure day to an instantaneous percentage reduction in asset output:

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

(Eq. 23 of annexure)

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;
- $\max(0, \cdot)$ — ensures no derating is applied below the threshold; and
- $\min(\cdot)$ — caps derating at the engineering-consistent maximum.

The function has three physical properties that hold across a wide range of equipment types. First, no derating occurs below the threshold as equipment operating within design limits delivers its rated output. Second, derating begins once the threshold is exceeded, consistent with empirical temperature coefficients for PV modules (Skoplaki & Palyvos, 2009) and transformer thermal loading guides (International Electrotechnical Commission, 2011). Third, derating is bounded at $D_{a,h}^{\max}$ — the engineering cap on performance loss for that asset-hazard pair. For drought, the stressor variable (x) is the discharge-deficit transformation $Z_{drought}$, ensuring that derating increases as water availability falls.

STEP 4.1C: EXPECTED DERATING AND CHRONIC VULNERABILITY SCORE

The expected derating on the exposure period is computed empirically as the average of the derating function applied to each observed threshold-exceeding value in the 30-year record:

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

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).

This conditional expectation captures the full distribution of stressor severity during exposure periods and not just the median or the extreme. It is then normalized by the engineering maximum to produce a dimensionless chronic vulnerability score bounded between 0 and 1:

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

where:

- $V_{a,h,d}^{chronic}$ — unitless chronic vulnerability score, $\in [0,1]$;
- $\mathbb{E}[Derate\%]_{a,h,d}$ — expected derating on exposed days (Eq. 24); and
- $D_{a,h}^{max}$ — maximum derating cap (Eq. 23).

A score of 0 means the asset experiences no meaningful chronic derating from that hazard in that district. A score of 1 indicates that the expected derating reaches the engineering maximum during exposure periods. Normalization ensures dimensional consistency across all hazards and asset classes, enabling aggregation within the ACRF.

THE IMPACT PATHWAY FOR ACUTE RISKS: FRAGILITY AND DOWNTIME

Acute hazards operate through a completely different mechanism from chronic hazards, and the vulnerability model reflects this. Rather than characterizing a gradual reduction in performance, the acute model characterizes the probability that an extreme event and the duration of the resulting service interruption physically damage an asset. The impact pathway is:

Hazard intensity → Failure probability → Restoration duration → Annual downtime

The acute vulnerability model proceeds through three steps: estimating the probability of failure under a given event intensity using a logistic fragility function; estimating the expected downtime per event; and combining per-event downtime with event frequency to obtain expected annual downtime.

STEP 4.2A: FAILURE PROBABILITY; THE LOGISTIC FRAGILITY FUNCTION

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

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

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. 4-11, 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 the standard tool for fragility modeling of infrastructure (FEMA, n.d.). It is bounded between 0 and 1, rises with increasing hazard intensity, and can be calibrated from two intensity-failure anchor points derived from engineering design standards, observed damage records, or expert elicitation. Parameters $\beta_{0,a,h}$ and $\beta_{1,a,h}$ are calibrated as:

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

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

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.

For hazards with spatial extent where the fraction of the district reached by an event matters as well as its intensity, a spatial exposure multiplier $A_{h,d}$ scales the failure probability by the proportion of asset exposure affected: return-period-weighted inundation area for floods, annualized landfall frequency for cyclones, and fraction of susceptible terrain for landslides.

STEP 4.2B: DOWNTIME MODELING

The expected downtime per event captures what happens after a failure probability is established. The framework models two outage regimes: when an asset is physically damaged (a tower collapses, a transformer is inundated), it must be repaired or replaced before service

can be restored; and, secondly, the asset undergoes a preventive shutdown to avoid asset failure. The conditional restoration time includes the time required for emergency response, parts procurement, and physical repair.

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

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).

The two-regime formulation is standard in infrastructure risk modeling (FEMA, n.d.). It distinguishes between events that cause physical damage, requiring the repair or replacement of components and potentially taking days or weeks, and events that trigger protective shutdowns or network isolation without causing damage, which require only a reset and clearance once conditions improve. Combining the two regimes via the law of total expectation is likely to yield the correct expected outage duration per event, weighted by each outcome's probability.

Where detailed component-level data are available, the framework can operate in equipment-level mode: individual components receive their own fragility and downtime parameters, and the asset-level failure probability is computed as the complement of the probability that all critical components survive. This series-system approximation reflects the real failure logic of electrical assets.

STEP 4.2C: EXPECTED ANNUAL DOWNTIME AND ACUTE VULNERABILITY SCORE

Expected Annual Downtime (EAD) integrates per-event downtime with annualized event frequency across all relevant acute hazards in the asset class's relevance set:

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

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).

EAD is the bridge between hazard occurrence and annual operational impact. It tells us the total expected annual outage hours from all relevant acute hazards combined. A district exposed to floods twice a year, with 18 expected outage hours per flood, contributes 36 flood-outage hours annually, before adding contributions from cyclones, landslides, or other hazards.

For use in the dimensionless $ACRF_{a,d}$ is converted to an acute vulnerability score by expressing it as a fraction of the annual hours:

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

where:

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

STAGE 5: ASSET-SPECIFIC CLIMATE RISK FACTOR (ACRF)

The ACRF brings together the Hazard Index from Stage 2 and the vulnerability scores from Stage 4 into a single, dimensionless risk indicator for each combination of asset class and district. It is the primary output for comparative risk analysis: a standardized, nationally consistent signal that allows planners to rank districts and asset classes by overall climate risk pressure.

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

where:

- $ACRF_{a,d}$ — Asset-Specific Climate Risk Factor (unitless, comparative);
- \mathcal{H}_a — relevance set of hazards for asset class (a);
- $|\mathcal{H}_a|$ — 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
 - $V_{a,d}^{acute}$ from (Eq. 35) for acute hazards, when a common unitless indexing scale is required.

The ACRF is a combination of hazard pressure and vulnerability. A district facing severe floods (high) but with well-protected, flood-hardened infrastructure (low $V_{a,d}^{acute}$) contributes less flood risk to the ACRF than one facing moderate floods with unprotected equipment. This correctly reflects the physical reality: risk is jointly determined by hazard and vulnerability, not by either alone. Averaging over ensures that asset classes with larger relevance sets are not mechanically assigned higher ACRF values regardless of actual risk severity.

The ACRF is a comparative screening metric. Hypothetically, a district with ACRF = 0.75 for solar generation is among the most exposed in India by the joint measure of hazard pressure and vulnerability; it does not necessarily lose 75% of its output to climate hazards. ACRF maps are produced separately for each asset class, allowing planners to identify, for instance, that the districts most exposed to transmission infrastructure are not always the same as those most exposed to distribution networks. This granularity reflects the different hazard relevance sets and vulnerability profiles that apply to each asset class.

STAGE 6: EXPECTED ANNUAL IMPACT: EAL AND ENS

Stage 6 converts the risk framework into operational and financial consequences. Where the ACRF identifies the greatest risk, the Expected Annual Impact (EAI) quantifies what that risk means in energy and monetary terms, making it directly relevant to generation planning, reliability regulation, tariff determination, and financial appraisal.

6.1 EXPECTED ANNUAL LOSS: GENERATION ASSETS

For generation assets, climate impact is measured as energy not generated: the gap between what an asset would have produced under normal conditions and what it actually produces in the presence of climate hazards. Total EAL combines contributions from the acute and chronic pathways.

ACUTE EAL

Acute EAL captures energy that would be lost during outages caused by extreme events. It is the product of the asset's normal output rate and the expected annual hours it is offline:

$$EAL_{a,d}^{acute} = InstalledCapacity_{a,d} \cdot CF_{a,d} \cdot EAD_{a,d}$$

(Eq. 37 of annexure)

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 EAL

Chronic EAL captures the cumulative generation loss due to derating throughout the year. Derating is applied only during the exposed fraction of the year, preventing overestimation:

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

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.

$$EAL_{a,d}^{total} = EAL_{a,d}^{acute} + EAL_{a,d}^{chronic} \quad (\text{Eq. 39 of annexure})$$

6.2 ENERGY NOT SERVED: NETWORK ASSETS

For transmission and distribution assets, climate impact is measured as energy not delivered to consumers. The formulas parallel those for EAL, but use load served as the exposure variable and introduce a network redundancy factor .

The redundancy factor $R_{a,d} \in (0,1]$ represents the proportion of outage time that actually results in unserved energy, after accounting for the network's ability to reroute power around the failed element. In radial feeders with no backup supply path, $R_{a,d}$ approaches 1.0; every hour of feeder outage means an hour of unserved energy for all connected consumers. In strongly meshed transmission networks with full N-1 capability, $R_{a,d}$ may be as low as 0.1-0.3; the system can typically reroute around a single failed element, limiting the consumer impact to brief switching periods. $R_{a,d}$ is parameterized by feeder redundancy tier (radial, looped, or meshed) or, where detailed topology data are available, by N-1 compliance assessments.

$$ENS_{a,d}^{acute} = AvgLoadServed_{a,d} \cdot EAD_{a,d} \cdot R_{a,d} \quad (\text{Eq. 40 of annexure})$$

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.

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

$$ENS_{a,d}^{total} = ENS_{a,d}^{acute} + ENS_{a,d}^{chronic} \quad (\text{Eq. 42 of annexure})$$

FINANCIAL IMPACT

EAL and ENS are converted to monetary terms using valuation parameters appropriate to each asset class. For generation assets, EAL is multiplied by the applicable tariff or power purchase agreement price to yield expected annual revenue loss. For network assets, ENS is multiplied by the Value of Lost Load (VOLL), the economic cost that consumers and the economy assign to unserved electricity, to yield the expected annual economic impact of unreliability. VOLL is the standard metric for reliability valuation in electricity systems worldwide (World Bank Group, 2020).

STAGE 7: COST-BENEFIT ANALYSIS OF RESILIENCE MEASURES

Stage 7 completes the analytical pipeline. Having established the scale of climate-induced losses through the EAI estimates in Stage 6, the CBA stage evaluates which resilience investments are economically justified and how they should be prioritized. Investment guidance could benefit from risk quantification, providing a clearer picture of the problem for decision-makers. Stage 7 closes that gap, translating the energy and financial loss estimates from preceding stages into a ranked program resilience intervention, each assessed against a consistent economic benchmark.

REPRESENTING RESILIENCE MEASURES IN THE VULNERABILITY MODEL

The framework considers resilience measures as changes in parameter within the existing vulnerability model rather than treating them as external adjustments applied after the fact. This approach preserves full methodological consistency: the same equations that produced the baseline EAI estimate are used to produce the resilience-case EAI estimate, with specified parameters modified to reflect the engineering effect of the intervention.

Chronic resilience measures, including improved cooling systems, thermal insulation upgrades, drainage improvements, modify the derating function parameters: they raise the threshold T (so that derating begins at a higher stressor level), reduce the slope s (so that derating increases less steeply beyond the threshold), or lower the cap ($D_{a,h}^{\max}$) (so that the worst-case performance loss is reduced). Any of these changes reduces the expected derating ($\mathbb{E}[Derate\%]_{a,h,d}$) during exposure periods and therefore reduces chronic EAL or ENS directly through Eqs. (38) and (41).

Acute resilience measures such as flood walls, raised plinths, tower strengthening, improved drainage, and modifications to the fragility curve or the restoration time can reduce fragility and shorten restoration time. A flood barrier around a substation effectively could shift the fragility curve to the right: the asset will not fail until water reaches a higher depth, so the failure probability $P(F)_{a,h,d}$ is lower at any given inundation depth. Faster emergency response and pre-positioned replacement equipment reduce $D_{a,h}^{fail}$. Both changes reduce expected downtime per event EDT and therefore reduce EAD (Eq. 34) and the resulting EAL and ENS.

COMPUTING THE ECONOMIC RETURN

The benefit of a resilience measure is the annual reduction in expected impact: the difference between the baseline EAI (without the measure) and the resilience-case EAI (with the measure). This avoided impact, i.e., expressed in MWh per year, is then monetized:

$$\Delta EAI_{a,d} = EAI_{a,d}^{base} - EAI_{a,d}^{res} \quad (\text{Eq. 45 of annexure})$$

Total annual benefits include two channels: the value of avoided energy losses (additional generation delivered or additional load served, valued at tariff or VOLL) and the reduction in expected physical repair and replacement expenditure (assets that do not fail do not need to be repaired, and the associated material, labor, and emergency response costs are avoided). Both channels will be computed on an annualized expected-value basis, consistent with the EAI framework. Annual benefits are then discounted over the asset's remaining life to produce a Present Value of Benefits.

This will be compared against the Present Value of Costs, upfront capital expenditure plus discounted operation and maintenance obligations, to yield two standard investment appraisal metrics:

- **Net Present Value (NPV)** = PV(Benefits) – PV(Costs). A positive NPV will confirm that the measure will generate more economic value than it costs over the appraisal horizon and quantifies the net gain. NPV is the appropriate criterion for judging whether a measure is economically justified.
- **Benefit-Cost Ratio (BCR)** = PV(Benefits) / PV(Costs). A BCR greater than 1.0 will confirm the economic viability. Where multiple competing resilience measures are under consideration, and budgets are constrained, BCR is the appropriate ranking criterion as it measures return per rupee of investment. A higher-BCR measure delivers more economic value per unit of capital committed than a lower-BCR measure.

For ranked portfolio analysis, measures can alternatively be ranked by ΔEAI per rupee of capex or by avoided megawatt-hours per rupee invested, which is a direct measure of reliability improvement efficiency. The choice of ranking criterion depends on whether the objective is to maximize economic return, maximize net value, or maximize reliability improvement per unit of investment.

SUMMARY OF KEY OUTPUTS

Table 9 provides a tentative summary of the framework, their units, the equations that produce them, and their primary decision-relevant uses. The outputs form a coherent progression: the Hazard Index characterizes the climate threat; the vulnerability scores characterize the engineering response to that threat; the ACRF combines them into a comparative risk signal; the EAI converts risk into operational consequences; and the CBA metrics convert consequences into investment guidance.

Table 9: Summary of key framework outputs

Output	Unit	Key equation ²	Primary use
Hazard Index ($H_{h,d}$)	[0, 1]	Eq. (14)	District-level climate risk characterization. Input to ACRF and EAL across all asset classes. Enables comparison of hazard pressure across 640+ districts and 8 hazards.
Chronic vulnerability ($V_{a,h,d}^{chronic}$)	[0, 1]	Eq. (25)	Normalized performance susceptibility of asset class a to hazard h in district d. Captures the expected derating relative to the engineering maximum.
Acute Vulnerability ($V_{a,d}^{acute}$)	[0, 1]	Eq. (35)	Expected fraction of the year that assets are unavailable due to acute hazard events. Bridges downtime modeling and the comparative risk index.
Expected Annual Downtime ($EAD_{a,d}$)	hours/year	Eq. (34)	Total outage hours from all relevant acute hazards. Direct input to EAL (Eq. 39) and ENS (Eq. 42). Key operational reliability indicator.
Asset-Specific Climate Risk Factor ($ACRF_{a,d}$)	[0, 1]	Eq. (36)	Comparative risk index for spatial mapping, hotspot identification, and investment prioritization. Screening signal and not a loss metric.
Expected Annual Loss ($EAL_{a,d}^{total}$)	MWh / year	Eq. (39)	Total climate-induced generation loss (acute + chronic). Monetized at the applicable tariff or opportunity cost for financial appraisal and regulatory reporting.
Energy Not Served ($ENS_{a,d}^{total}$)	MWh / year	Eq. (42)	Total energy not delivered to consumers due to network outages and derating. Monetized at VOLL for reliability investment analysis and regulatory benchmarking.
Net Present Value ($NPV_{a,d}$)	INR	Eq. (59)	Economic return on a resilience measure over its appraisal horizon. NPV > 0 confirms economic justification of the intervention.
Benefit-Cost Ratio ($BCR_{a,d}$)	Unitless	Eq. (60)	Investment efficiency metric for ranking competing resilience measures. A BCR > 1 confirms viability; a higher BCR signals a greater return per rupee invested.

² Corresponding equations are detailed in the Annexure.

3. CONCLUSION

India's power sector is at an inflection point where the pace of capacity expansion must be reconciled with a rapidly changing climate. Over the past three decades, the country has experienced a measurable increase in the frequency and severity of both chronic climate stressors and acute extreme weather events. These trends are not transient; they represent a structural shift in the operating environment for power infrastructure designed to function for two to four decades. The convergence of rising temperatures, erratic precipitation, intensifying cyclones, and drought-induced water stress with an expanding and diversifying asset base creates a compounding risk that existing planning frameworks have not been designed to address.

The Climate Risk Assessment Framework (CRAF) presented in this paper offers a structured, engineering-grounded, and replicable methodology to bridge this gap. By anchoring the analysis in the internationally recognized hazard-exposure-vulnerability construct and extending it through seven analytical stages, the framework moves climate risk assessment from qualitative screening to quantified, decision-relevant outputs. The district-level Hazard Index captures both the frequency and severity of eight climate stressors across India's diverse geography. The asset-level vulnerability models distinguish between the gradual performance derating caused by chronic stress and the sudden failures triggered by acute events, using engineering-based parameters calibrated to the physical characteristics of each asset class. The Asset-Specific Climate Risk Factor (ACRF) synthesizes these into a nationally comparable risk signal, while the Expected Annual Loss (EAL) and Energy Not Served (ENS) metrics translate risk into the operational and financial language that planners, regulators, financiers, and insurers require.

Crucially, the framework does not stop at risk identification. The cost-benefit analysis module in Stage 7 evaluates whether specific resilience interventions are economically justified, enabling a shift from reactive disaster response to proactive, evidence-based resilience investment. By representing resilience measures as parameter changes within the same vulnerability model that produced the baseline loss estimates, the framework ensures full methodological consistency between the problem diagnosis and the investment appraisal.

With India's National Adaptation Plan expected in the coming weeks, the timing of this framework is particularly relevant. The NAP will provide the macro-level direction, standardized climate scenarios, and sectoral policy signals. However, translating that direction into asset-level risk scores, investment-grade loss estimates, and bankable resilience business cases will remain the responsibility of power sector stakeholders. The CRAF is designed to serve precisely this function: converting national climate data and policy boundaries into the granular, quantified outputs that project developers, financiers, regulators, and grid operators need to make informed decisions. As higher-resolution datasets, improved asset inventories, and more detailed equipment-level parameters become available, the modular structure of the framework allows each analytical stage to be refined without altering the overall architecture, ensuring that the methodology remains current and scalable as India's climate risk landscape and power sector continue to evolve.

WAY FORWARD

This discussion paper aims to establish the methodological foundation for applying climate risk assessment to India's power sector assets. The framework is intentionally modular and can be tailored to meet the context-specific requirements of stakeholders. As higher-resolution climate datasets, updated event records, improved asset inventories, and more detailed equipment-level information become available, the hazard, exposure, and vulnerability inputs can be refined without changing the overall modeling structure.

The next stage of work will apply the methodology at the district scale across India's power sector asset base, using the hazard datasets, sample asset models, and vulnerability parameters described in the preceding sections. The results will be published in a subsequent technical brief, demonstrating how **CRAF** could supplement existing planning and financing strategies by identifying where climate risks may turn out to be most material, which assets could be most exposed, and where resilience investments are likely to be economically justified.

4. REFERENCES

- ADB. (2013). *Guidelines for Climate Proofing Investment in the Energy Sector*. https://www.adb.org/sites/default/files/institutional-document/33896/guidelines-climate-proofing-investment-energy-sector_0.pdf
- Al-Khayat, M., Al-Rasheedi, M., Gueymard, C. A., Haupt, S. E., Kosović, B., Al-Qattan, A., & Lee, J. A. (2021). Performance analysis of a 10-MW wind farm in a hot and dusty desert environment. Part 2: Combined dust and high-temperature effects on the operation of wind turbines. *Sustainable Energy Technologies and Assessments*, 47, 101461. <https://doi.org/10.1016/j.seta.2021.101461>
- Cabinet. (2026). *Cabinet approves India's Nationally Determined Contribution (2031-2035) to be communicated to the United Nations Framework Convention on Climate Change*. <https://www.pib.gov.in/www.pib.gov.in/Pressreleaseshare.aspx?PRID=2245209>
- CEEW. (2020). *Preparing India for Extreme Climate Events: Mapping Hotspots and Response Mechanisms*. <https://ruralindiaonline.org/en/library/resource/preparing-india-for-extreme-climate-events-mapping-hotspots-and-response-mechanisms/>
- Christopher B. Field. (2014). (PDF) Climate change 2014: Impacts, adaptation, and vulnerability - IPCC WGII AR5 summary for policymakers. In ResearchGate. https://www.researchgate.net/publication/272150376_Climate_change_2014_impacts_adaptation_and_vulnerability_-_IPCC_WGII_AR5_summary_for_policymakers
- ClimateChangePost. (2013). *Climate change impacts on thermal power plants*. <https://www.climatechangepost.com/news/climate-change-impacts-on-thermal-power-plants/>
- CSTEP. (2021). *Climate Risk Profile for Power Sector in Karnataka*. https://cstep.in/wp-content/uploads/2025/06/Climate-Risk-Profile-for-Power-Sector-in-Karnataka_Final.pdf
- Das, P. (2025a, November 20). *Heatwaves drive 9% of India's electricity demand surge in 2024: Study warns of deepening heat-power trap*. Down To Earth. <https://www.downtoearth.org.in/energy/heatwaves-drive-9-of-indias-electricity-demand-surge-in-2024-study-warns-of-deepening-heatpower-trap>
- Das, P. (2025b, December 10). *Asia's power giants already losing \$6.3 billion a year to climate hazards, report warns*. Down To Earth. <https://www.downtoearth.org.in/energy/asias-power-giants-already-losing-63-billion-a-year-to-climate-hazards-report-warns>
- Department Of Science & Technology. (2024). *District-level Climate Risk Assessment for India: Mapping Flood and Drought Risks released | Department Of Science & Technology*. <https://dst.gov.in/district-level-climate-risk-assessment-india-mapping-flood-and-drought-risks-released>
- EDHEC. (2024). *Climate change: Why are infrastructure investors aware of the risk while failing to measure it? |*. <https://www.edhec.edu/en/research-and-faculty/edhec-vox/climate-change-infrastructure-investors-aware-risk-while-failing-to-measure-it>
- FEMA. (n.d.). *Hazus | FEMA.gov*. <https://www.fema.gov/flood-maps/products-tools/hazus>
- Germanwatch. (2025, February 12). *Climate Risk Index 2025 | Germanwatch e.V*. <https://www.germanwatch.org/en/93013>

- IEA. (2024). *India – World Energy Investment 2024 – Analysis*. IEA
- International Electrotechnical Commission. (2011). *IEC 60076-1:2011*. <https://webstore.iec.ch/en/publication/588>
- International Electrotechnical Commission. (2014). *Photovoltaic Systems—Design Qualification*. <https://cdn.standards.iteh.ai/samples/20144/9e84f3fd5835497f9198f3e661107e41/IEC-62817-2014.pdf>
- International Electrotechnical Commission. (2019). *IEC 61400-1:2019*. <https://webstore.iec.ch/en/publication/26423>
- Jackson. (2024). (PDF) *REDUCTION OF SAG EFFECTS ON TRANSMISSION LINE DUE TO TEMPERATURE CHANGE*. ResearchGate. https://www.researchgate.net/publication/385173977_REDUCTION_OF_SAG_EFFECTS_ON_TRANSMISSION_LINE_DUE_TO_TEMPERATURE_CHANGE
- JICA. (2023). *JICA Climate-FIT (Adaptation)*. https://www.jica.go.jp/Resource/english/our_work/thematic_issues/climate/fh2q4d000000phbl-att/adaptation_all.pdf
- Kerala State Electricity Board Limited. (2019). *Annual Administration Report*.
- Luo, T. (2017). *Droughts and Blackouts: How Water Shortages Cost India Enough Energy to Power Sri Lanka*. <https://www.wri.org/insights/droughts-and-blackouts-how-water-shortages-cost-india-enough-energy-power-sri-lanka>
- Mahapatra, B., Walia, M., & Saggurti, N. (2018). Extreme weather events induced deaths in India 2001–2014: Trends and differentials by region, sex and age group. *Weather and Climate Extremes*, 21, 110–116. <https://doi.org/10.1016/j.wace.2018.08.001>
- Ministry of Finance. (2024). *National Electricity Plan (Transmission) launched by Cabinet Minister for Power and Housing & Urban Affairs*. <https://www.pib.gov.in/www.pib.gov.in/Pressreleaseshare.aspx?PRID=2064751>
- Ministry of Power. (2026). *Power Generation Capacity from Various Sources*. <https://www.pib.gov.in/Pressreleaseshare.aspx?PRID=2238921®=3&lang=2>
- NOAA. (2025, May 29). *Climate change: Global temperature | NOAA Climate.gov*. <https://www.climate.gov/news-features/understanding-climate/climate-change-global-temperature>
- Petrakopoulou, F., Robinson, A., & Olmeda-Delgado, M. (2020). Impact of climate change on fossil fuel power-plant efficiency and water use. *Journal of Cleaner Production*, 273, 122816. <https://doi.org/10.1016/j.jclepro.2020.122816>
- Press Information Bureau. (2025). *The Indian Monsoon*. <http://www.pib.gov.in/PressNoteDetails.aspx?Notelid=154892>
- Rohit Mullick. (2026, January 29). Snow, rain disrupt over 800 roads across Himachal; 121 water supply schemes affected, power outages recorded. *The Times of India*. <https://timesofindia.indiatimes.com/city/chandigarh/snow-rain-disrupt-over-800-roads-across-himachal-121-water-supply-schemes-affected-power-outages-recorded/articleshow/127726790.cms>
- Skoplaki, E., & Palyvos, J. A. (2009). On the temperature dependence of photovoltaic module electrical performance: A review of efficiency/power correlations. *Solar Energy*, 83(5), 614–624. <https://doi.org/10.1016/j.solener.2008.10.008>

Soonee, S., Narasimhan, S., Nallarasan, N., Rathour, H., Yadav, G., Bhan, S., & Mali, R. R. (2015). *Impact of very severe cyclone 'Hudhud' on power system operation*. 1-5. <https://doi.org/10.1109/INDICON.2015.7443840>

Sphere India. (2024). *Floods & Landslides in Tripura*.

Tolani, H., Neogi, S. B., Gupta, S. D., Mishra, S. S., & Samtani, R. (2024). Analyzing dynamics of extreme weather events (EWE) in India: Unfolding trends through statistical assessment of 50 years data (1970–2019). *BMC Environmental Science*, 1(1), 12. <https://doi.org/10.1186/s44329-024-00012-4>

United Nations. (2023). *1.5°C: what it means and why it matters*. United Nations. United Nations. <https://www.un.org/en/climatechange/science/climate-issues/degrees-matter>

Viswanathan, M. (2018, September 4). *Kerala State Electricity Board rues its loss: Rs 850 crore and counting*. The New Indian Express. <https://www.newindianexpress.com/states/kerala/2018/Sep/04/kerala-state-electricity-board-rues-its-loss-rs-850-crore-and-counting-1867145.html>

vlab.amrita.edu. (2015). *Wind Turbine -Power production in Wind Turbine (Theory): Wind energy Labs: Mechanical Engineering: Amrita Vishwa Vidyapeetham Virtual Lab*. <https://vlab.amrita.edu/index.php?sub=77&brch=297&sim=1743&cnt=1>

Waaree. (2025). *Solar Panel Performance: Irradiance & Temperature's Impact*. Waaree. <http://www.waaree.com/blog/irradiance-temperature-in-solar-panel-performance/>

World Bank. (n.d.). *World Bank Climate and Disaster Risk Screening | The World Bank Climate and Disaster Risk Screening Tools*. <https://climatescreeningtools.worldbank.org/>

World Bank Group. (2020). *How Valuable is the Reliability of Residential Electricity Supply in Low-Income Countries*. <https://documents1.worldbank.org/curated/en/619261593538219342/pdf/How-Valuable-is-the-Reliability-of-Residential-Electricity-Supply-in-Low-Income-Countries-Evidence-from-Nepal.pdf>

climatepolicyinitiative.org