Climate-Resilient Energy Infrastructure Valuation: A Scenario-Based Financial Assessment

Soh Young In[a*], Wonchan Lee[b], Youngjin Nam[a], Sieun Park[a]

[a]Korea Advanced Institute of Science and Technology, Daejeon, Republic of Korea

[b]Nvidia, Santa Clara, United States of America

[*]Corresponding author: Soh Young In; si2131@kaist.ac.kr

This research evaluates the climate resilience of energy infrastructure assets by analyzing their financial bankability under various climate scenarios. The study examines 73 utility-scale energy assets across the United States, including coal, natural gas, and solar PV installations, assessing their Debt Service Coverage Ratio (DSCR) projections under IPCC's Shared Socioeconomic Pathways through 2052. The findings reveal that while natural gas facilities show initial vulnerability but strong recovery potential, and coal plants demonstrate increasing vulnerability under severe climate scenarios, solar PV installations maintain the strongest financial resilience, particularly in high-irradiance regions like California and Texas, suggesting important implications for infrastructure investment in a changing climate.

1. Research Problem Statement

Climate change affects the global hydrological cycle, influencing the spatial and temporal distribution of precipitation and temperature (Allen and Ingram, 2002; Kumar et al., 2021). It has intensified the frequency and intensity of natural disasters such as floods, droughts, hurricanes, and heat waves(Field et al., 2012), posing considerable impacts on energy infrastructure systems. The Texas Coldwave of 2021 is an example of the vulnerabilities of energy systems to unexpected climate extremes. In addition to acute events, chronic events such as reduced precipitation, increasing sea-level rise, and rising temperature present substantial challenges to energy infrastructure operations. For example, a global temperature rise of 2°C could result in a decrease of 4.5% in power plant capacity (Carbon Brief, 2021). On hotter days, the air and water needed to cool power plants can become too warm, which can decrease the capacity of power plants by up to 10%(UNEP FI, 2024). This can lead to increased operating costs and reduced profitability, which in turn shows that existing infrastructure is designed for past climate conditions and is struggling to withstand increasingly frequent extreme events.

As critical infrastructure, energy systems are essential to the functioning of society. Therefore, the vulnerability of national infrastructures to extreme events plays a crucial role in determining society's resilience (Kumar et al., 2021). The potentially severe but highly uncertain impacts of climate change, combined with the high costs and budget constraints of infrastructure construction, make risk analysis essential for evaluating climate adaptation options (Shortridge & Camp, 2019). The escalating challenges posed by climate change are testing this resilience, highlighting the urgent need for financial decision-making in resilient infrastructure systems (Benevenuto, 2024) and a shift in how systemic risk is assessed. Quantitative climate risk analysis is essential to identifying vulnerabilities in existing and new infrastructure, improving risk allocation in decision-making, and ultimately reducing the vulnerabilities posed by climate change to energy systems.

However, the traditional methods for managing climate-related risks in infrastructure relied on historic climate data, which no longer represent the future due to the “end of stationarity” (Milly et al., 2008; Shortridge & Camp, 2019). Also, traditional engineering approaches such as safety factors or precautionary allowances can be used to improve infrastructure resilience to climatic extremes (Kundzewicz & Stakhiv, 2010), many infrastructure systems are subject to strict budgetary constraints that will not necessarily allow for these approaches. This is particularly pressing as traditional asset valuation for infrastructure have not sufficiently accounted for climate-related risks (In et al., 2022), leading to a significant underestimation of the challenges involved. There is a need to assessing climate risk that aligns future climate data and enables the climate resilience of energy assets to be evaluated in terms of financial decision-making.

For bridging the gap, this research evaluates the climate resilience of U.S. energy infrastructure assets from a financial perspective through a scenario-based cash flow analysis. It draws upon concepts from systems integration and organizational strategy to frame climate resilience as an intrinsic value driver for infrastructure projects. This approach is informed by seminal works in the field (Artto et al., 2009; Lycett et al.,2004; Pellegrinelli, 2011) and responds to calls for research that situates program management within a broader strategic and organizational context (Denicol et al., 2021; George et al., 2023).

2. Brief Research Methodology and Approach

To assess the financial resilience of infrastructure assets to climate risks, we integrate climate impacts—both positive and negative—into cash flow projections and evaluate asset resilience under various climate conditions. Our analysis consists of three main components: (1) cash flow projection and financial analysis, (2) climate risk impact assessment, and (3) scenario-based asset valuation.

We analyze the valuation of diverse energy infrastructure assets across different climate scenarios, examining how their financial resilience varies by asset type and geographic location. Our dataset comprises 73 utility-scale energy infrastructure assets in the United States, including 37 coal power plants, 7 natural gas facilities, and 29 solar PV installations. We source our data from the National Renewable Energy Laboratory (NREL) Annual Technology Baseline (ATB) and the Global Energy Observatory.

2.1. Cash Flow Projection and Financial Analysis

We analyze four key cash flow components over an asset's life cycle: revenues, capital expenditures (CAPEX), operational costs (OPEX), and financing costs.

The revenue considers both power sales revenue and capacity payments for fossil fuel-based assets, and only reflects power sales revenue for solar assets. OPEX are common across asset types and include fixed and variable operating costs, insurance, property taxes, and, for fossil fuel assets, fuel costs. Financing costs were debt service, principal, and interest. It derived from CAPEX by considering the debt ratio, loan tenor, and interest rate.

$$Cash\ Flow\ Available\ for\ Debt\ Service_t = Revenue_t - OPEX_t - CAPEX_t$$

To assess asset bankability and resilience, we calculate two key financial metrics: Debt Service Coverage Ratio (DSCR) measures an asset's ability to service its debt using operating income and Internal Rate of Return (IRR) measures the profitability and economic viability of investments. This approach provides insights into the financial risks of climate change and supports climate-resilient infrastructure decisions.

$$DSCR = \frac{Cash\ Flow\ Available\ for\ Debt\ Service}{Debt\ Service}$$

$$NPV = \sum_{t}^{T} \frac{Cash\ Flow_t}{(1 + IRR)^t} = 0$$

2.2. Climate Risk Impact Assessment

We examine how specific climate factors affect an asset's lifetime cash flow. Different infrastructure systems require specific design considerations for the climate hazards they are exposed to, alongside considerations of multi-hazard interactions(Verschuur et al., 2024). Each climate hazard is addressed as a distinct climate risk factor. Based on prior research, each climate risk factor is defined in terms of its relationship with the operation of energy infrastructure. These relationships are referred to impact mechanisms. In this study, five climate risk factors, air temperature, precipitation, discharge, river water temperature, and extreme events, were considered.

For air temperature, we consider increases in natural gas turbine heat rate and fuel usage caused by increased air temperatures. According to Ibrahim and Rahman (2013), we estimate a 0.15% increase in OPEX with a 0.1°C ambient temperature increase due to increased fuel usage. As a results, air temperature(tas_t) affects fuel usage, leading to an increase in OPEX. It contributes to a decline in the DSCR. Increased air temperature has the opposite effect on coal power plants, depending on the type of cooling system employed. According to Henry and Pratson (2016), in a closed-loop cooling system, a 1°C rise in ambient air temperature results in a 0.45% increase in net efficiency. For Solar PV, Dubey et al. (2013) reviewed the temperature-dependent electrical efficiency of PV modules, with the linear expression obtained from Evans (1981), where 25°C is the optimal temperature (T_{ref}) for solar PV. The material properties determine the temperature coefficient (β_{ref}), and for crystalline silicon modules, it is about 0.004K-1 (Notton et al., 2005).

$$\eta_c = \eta_{T_{ref}} (1 - \beta_{ref} (T - T_{ref}))$$

For extreme weather, Tesselaar et al. (2020) assessed the impacts of climate change on the EU flood insurance market using a dynamic integrated flood insurance model (DIFI) and projected future insurance premiums by different climate scenarios. While acknowledging the difference in regions and types of physical risk between their analysis and our simulation, we use their projections as benchmarks for insurance cost increases. Therefore, we consider the annual escalation rate of insurance cost as 2%, 4%, and 5% for SSP126, SSP370, and SSP585, respectively

2.3. Scenario-based Asset Valuation

We project asset values under various climate scenarios using the Intergovernmental Panel on Climate Change (IPCC) Shared Socioeconomic Pathways (SSPs). In its recent publication, the IPCC scenarios have been developed to incorporate the socioeconomic impact on the pathways, namely Shared Socioeconomic Pathways (SSPs). For the simulation, input climate forcings and output data from ISIMIP Phase 3a and 3b are utilized, covering the period from 2023 to 2052 with monthly data. For the climate scenarios, three future climate scenarios (SSP126, SSP370, SSP585) and one historical scenario (historical) are selected, which are also forced to the ISIMIP CIMs. SSP126 assumes a significant focus on sustainability, with the expected temperature rise by 2100 compared to the pre-industrial level being 1.8°C. SSP585 posits fossil fuel development, leading to a high-temperature rise of up to 4.4°C by 2100. SSP370 stands between these scenarios, with assumptions involving regional rivalry between countries.

Our scenario considers four variables, which are selected in 2.2.: air temperature (tas), precipitation (pr), discharge (dis), and river water temperature (triver). For air temperature and precipitation, we use both observation-based reanalysis climate datasets (GSWP3-W5E5) and their counterfactuals, which were made available through selected climate models by ISIMIP. Here, five climate models (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, UKESM1-0-LL) are used. It is also important to note that these climate forcings are bias-corrected using ISIMIP3BASD v2.5.0 and W5E5 v2.0. Discharge and river water temperature data are from historical and future outputs of the global hydrological model (GHM), WaterGAP2-2e. The historical and future simulation periods for input forcings, climate models, and CIMs cover 1901 to 2019 and 2015 to 2100, respectively, provided into monthly, 0.5° X 0.5° (˜50km at the equator) resolution. The historical reference value for each variable is calculated as the mean value from 1991 to 2019. Unlike conventional frameworks that rely solely on historical climate data to address future projections, this approach integrates both historical and future climate data for a more comprehensive simulation. However, an important caveat is that future climate projections from climate models can have inherent uncertainties. Hence, we utilize the ensemble mean of the climate model outputs to mitigate these uncertainties.

3. Key Findings

Our analysis reveals distinct patterns in how climate change affects the financial resilience of different energy infrastructure assets. Natural gas plants show initial vulnerability but strong recovery potential, while coal plants demonstrate increasing vulnerability under severe climate scenarios after 2040, particularly in SSP585. Solar PV installations maintain the strongest overall financial resilience despite significant regional variations, with notably higher performance in high-irradiance regions like California and Texas (DSCR ranging from 1.5 to 2.3). These findings suggest that infrastructure investors and policymakers should carefully consider both asset type and geographical location in their decision-making, with particular attention to the growing financial advantages of renewable energy infrastructure in climate-resilient portfolios.

3.1. DSCR Projection by Asset Type

In the natural gas case, we observe instances where initial DSCR starts from below 1 under SSP 126, SSP 370, and SSP 585 scenarios. More severe climate scenarios render natural gas power plants more susceptible, suggesting that climate change weakens debt repayment capabilities relative to the baseline scenario (without adopting any climate condition). However, after initial defaults, DSCR rapidly recovers, exhibiting an overall increasing trend, albeit with some fluctuations due to external climate conditions.

Coal power plants exhibit different results than the other two asset types. While other assets show regional variability, coal power plants do not exhibit any regional variation. It might be because the sample size for coal was limited (seven in total), and the major risk factor in the coal cases–increasing insurance premiums–does not incorporate regional variability. In terms of projections under different scenarios, the DSCR projection under SSP126 exhibits an increasing trend, whereas the slope significantly decreases for SSP370. For the SSP585 scenario, DSCR peaks around 2040, followed by a downturn until the end year of the tenor. It appears that the debt repayment capability of coal power plants is more vulnerable to severe climate change scenarios in the long run. However, despite the downward trend after its peak, DSCR values for coal power plants do not reach the default during the simulation period.

For solar PV, notable regional variability is observed, primarily attributed to the different power generation yields influenced by the solar irradiance levels of regions. The mean DSCRs, with their widespread, show distinct differences across climate change scenarios, mainly due to the scenario-specific escalation rates of insurance premiums and minor fluctuations from air temperature and precipitation impacts. Like coal, solar PV's DSCR projection under the SSP126 scenario shows an upward trend, while one under the SSP370 scenario shows a slower increasing trend with a peak. SSP585 shows a peak DSCR around 2040 and decreases until the end year of the tenor. Given the high initial DSCR values, solar PV plants do not reach the default during the simulation timeframe.

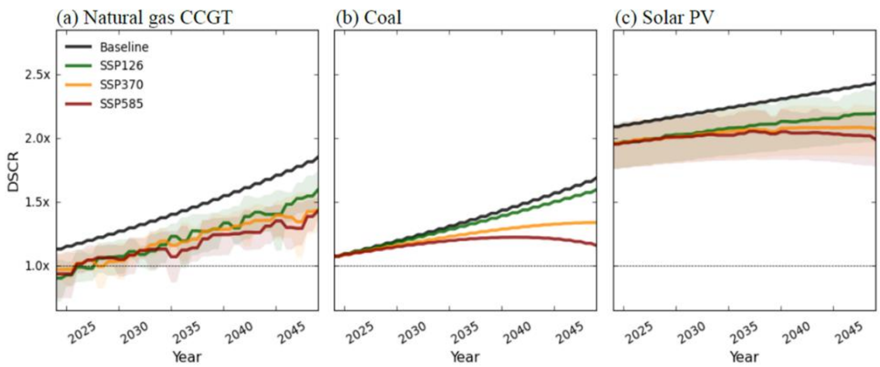

Fig 1. DSCR Projection by Asset Type

3.2. Average DSCR Projection by Asset Type and Geographical Location

These results show how assets with identical specifications can experience different financial impacts from climate change based on their geographic region. Solar PV plants exhibit the more pronounced regional differences, with average DSCR values ranging from 1.5 to 2.3.

Higher values above 2.0 are observed in California and Texas, areas known for high solar irradiance. In contrast, other regions show lower average DSCR values between 1.5 and 1.8. This suggests that regions with higher solar irradiance levels are more conducive to solar power generation, as reflected in higher average DSCR values. For natural gas CCGT assets, average DSCR values range from 1.0 to 1.4, with lower values noted in Texas and Louisiana. The average DSCR values are observed to be higher for assets located at higher latitudes, possibly explained by regional variation in river discharge, although its precise relevance should be further investigated.

Fig 2. Average DSCR Projection by Asset Type and Geographical Location

4. Implications

This research aims to make a significant impact on climate change mitigation and adaptation within the infrastructure sector, contributing to a sustainable and resilient global infrastructure landscape. By delivering advanced analytics to assess and manage climate-related financial risks, it supports informed decision-making aligned with global climate goals. The successful application of climate risk analysis could revolutionize infrastructure financing by bridging the existing disconnect between engineering sustainability and financial viability. By enabling a profound understanding of climate risks and their financial implications, this research promises to be instrumental in fostering resilient infrastructure development, offering a robust defense against potential environmental adversities. Also, it will provide a much-needed compass for navigating the economic challenges posed by climate change.

For more accurate cash flow estimates, future analyses should consider additional policy variables such as carbon prices, production-based incentives, and investment tax credits. In addition, the sample size of coal-fired power plants in the analysis is relatively small (7), and the imbalance in sample size between asset types reduces the generalizability of the results for this asset type and should be addressed in the future.

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