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HIGH-PERFORMANCE COMPUTING FRAMEWORKS FOR CLIMATE AND ENERGY INFRASTRUCTURE RISK ASSESSMENT

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Abstract

This study addresses a persistent problem in climate and energy infrastructure risk assessment: despite growing adoption of cloud and enterprise high performance computing (HPC) environments, decision makers still lack clear quantitative evidence on which HPC framework capabilities most improve the quality and usefulness of risk assessment outputs. The purpose of the study was to test, in a quantitative cross sectional, case-based design, how key HPC capability dimensions predict Risk Assessment Effectiveness (RAE) in operational settings. Data were collected using a 5-point Likert scale survey from a case sample of cloud and enterprise HPC users involved in climate exposed energy infrastructure risk work (N = 168), including 41.7% operations and reliability, 27.4% risk and resilience planning or asset management, 18.5% data and analytics, and 12.5% IT or HPC administration. The key independent variables were Scalability or Throughput (SCAL), Computational Efficiency (EFF), Data Integration Readiness (DATA), Simulation or Model Execution Capability (SIM), and Reliability or Availability (REL), with RAE as the dependent variable. The analysis plan included internal consistency testing, descriptive statistics, Pearson correlations, and multiple regression with multicollinearity diagnostics. The measures demonstrated strong reliability (Cronbach's alpha ranged from 0.81 to 0.90; overall alpha = 0.93). Descriptive results indicated above neutral capability levels (SCAL M = 3.74, SD = 0.71; EFF M = 3.61, SD = 0.76; DATA M = 3.92, SD = 0.69; SIM M = 3.79, SD = 0.73; REL M = 3.58, SD = 0.78) and moderately high effectiveness (RAE M = 3.83, SD = 0.68). RAE correlated positively with all capability dimensions, with the strongest associations observed for DATA (r = 0.69) and SIM (r = 0.61). The regression model was statistically significant and explained 58% of the variance in RAE ($F(5,162) = 44.72$, $p < .001$; $R^2 = 0.58$; Adj. $R^2 = 0.56$), with acceptable multicollinearity (VIF 1.42 to 2.18). Headline findings show that DATA ($\beta = 0.31$, $p < .001$), SIM ($\beta = 0.24$, $p = 0.002$), and REL ($\beta = 0.19$, $p = 0.008$) were significant predictors, while SCAL was marginal ($\beta = 0.11$, $p = 0.087$) and EFF was not significant ($\beta = 0.07$, $p = 0.210$). These results imply that organizations seeking stronger climate and energy risk assessments should prioritize data integration pipelines, reliable platform availability, and scenario execution capacity, and treat raw scaling and efficiency as secondary unless they directly enable those capabilities.

Keywords

High Performance Computing; Climate and Energy Infrastructure Risk; Data Integration Readiness; Simulation and Scenario Modeling; Reliability and Availability.

INTRODUCTION

High-performance computing (HPC) frameworks refer to integrated hardware–software environments—such as parallel clusters, distributed systems, and accelerated architectures—designed to execute large-scale computations by splitting workloads across many processors and memory spaces. In climate and energy research, HPC capacity is not treated as a general productivity tool; it is treated as enabling infrastructure that supports numerically intensive simulation, probabilistic analysis, and high-volume data processing required for climate hazard characterization and infrastructure risk assessment (Collins et al., 2006). Climate-related risk assessment can be described as the structured estimation of the likelihood and consequences of climate-driven hazards acting on exposed systems, using quantitative evidence and models to represent uncertainty and variability. Energy infrastructure, in this context, includes generation assets, transmission and distribution networks, and their operational dependencies that collectively deliver electricity as an essential service, with reliability and restoration representing measurable performance outcomes (Ward, 2013).

Figure 1: HPC-Enabled Framework for Climate and Energy Infrastructure Risk Assessment

The international significance of this topic follows from the fact that large outages are associated with cascading social and economic disruption across regions and sectors, and historical event records show persistent patterns of large-scale interruptions rather than a stable decline in major failures (Hines et al., 2009). Extreme weather hazards that interact with energy systems are shaped by meteorological variability and long-run climate change signals, with evidence linking hazard intensity characteristics to measurable changes in cyclone behavior (Emanuel, 2005). At the same time, climate model development has expanded the computational demands of producing physically consistent scenario outputs at scales relevant to decision contexts, motivating the use of coupled climate system models and ensemble-based probabilistic reasoning (Collins et al., 2006). Within this combined domain, "frameworks" denote the reproducible pipelines that connect climate modeling, hazard translation, infrastructure exposure representation, and statistical or simulation-based consequence estimation, often requiring HPC resources to manage ensemble size, spatial resolution, and uncertainty propagation (Dawson, 2018). Quantitative risk assessment in this setting therefore emerges as a computationally mediated practice that links climate science and infrastructure reliability through defensible modeling steps and traceable evidence.

Risk to electricity infrastructure is frequently operationalized through measurable outage outcomes, because outage counts, spatial distributions, and restoration durations provide observable indicators of both component vulnerability and system-level performance. Statistical modeling studies have demonstrated that outage behavior varies systematically with hazard intensity metrics and system attributes, supporting the view that risk can be estimated as a function of physical, infrastructural, and contextual predictors rather than treated as a purely random shock. Spatially explicit modeling has been used to predict hurricane- and ice-storm–related outages at granular geographic units using generalized linear mixed modeling with spatial correlation, highlighting how storm characteristics and protective device density can structure outage likelihood (Liu et al., 2008; Mohiul, 2020). Related work extended outage estimation by modeling the spatial distribution of outages during Gulf Coast hurricanes using physically measurable storm variables rather than storm-identifier indicators, improving transferability across events and strengthening the interpretability of drivers (Han et al., 2009; Jinnat & Kamrul, 2021). Predictive accuracy has been further advanced through flexible non-linear methods, including generalized additive models for hurricane outage forecasts that capture non-linear relationships among predictors and outcomes (Hawchar & et al., 2020; Rabiul & Samia, 2021). Pre-storm decision contexts have motivated prestorm estimation approaches that support resource staging and restoration planning by forecasting likely damage to distribution assets before landfall, aligning risk estimation with operational needs (Guikema et al., 2010; Mohiul & Rahman, 2021). These modeling choices matter internationally because cyclone impacts are not localized technical failures; they represent service interruptions across dense populations and supply chains, and empirical evidence indicates that blackouts and major interruptions remain a persistent reliability concern with identifiable temporal patterns (Han, Guikema, & Quiring, 2009; Rahman & Abdul, 2021). Risk assessment therefore benefits from a quantitative orientation that treats outages as measurable consequences tied to explainable hazard and infrastructure features, and from computational capacity that supports event libraries, spatial grids, and repeated model evaluation across scenarios.

Risk assessment for climate-exposed energy infrastructure also involves representing uncertainty, because climate hazards, infrastructure conditions, and restoration processes exhibit variability at multiple scales. Probabilistic framing becomes central when decision-makers need distributions of outcomes rather than single-point estimates, particularly for high-impact, low-frequency extremes. Climate projection science has developed probabilistic approaches that use multi-model ensembles to express uncertainty in future climate states, creating a foundation for risk pipelines that need scenario distributions rather than deterministic projections (Rougier, 2007; Haider & Shahrin, 2021). This approach aligns with infrastructure risk modeling, where uncertainty in hazard intensity, exposure, and fragility can be propagated into outage distributions using simulation or probabilistic statistical models (McRoberts et al., 2018; Zulqarnain & Subrato, 2021). Extreme-event studies also shape the hazard side of risk assessment by clarifying how cyclone intensity characteristics relate to historical warming-era behavior, offering empirical signals that are relevant to stress testing and scenario selection (Rahman, 2022; Schaeffer & et al., 2012). The reliability literature complements this by emphasizing that major failures can emerge from interacting operational conditions and environmental stressors, with outage histories providing evidence that reliability outcomes cluster in time and season rather than distribute uniformly (Habibullah & Mohiul, 2023; Rocchetta et al., 2015). At the systems level, resilience analysis introduces structured ways to quantify how engineered systems absorb disruption and recover, connecting the "risk" concept to performance trajectories and recovery outcomes rather than only failure occurrence (Hasan & Waladur, 2023; Nateghi et al., 2014). "Wicked problem" framing has also been applied to climate risk management, emphasizing that climate risks often involve interconnected constraints, multiple stakeholders, and contested priorities, which affects how evidence and uncertainty are interpreted within governance and planning processes (Panteli & Mancarella, 2015). Within a quantitative research setting, these bodies of work motivate modeling choices that capture uncertainty in both hazards and outcomes, and they justify computational frameworks capable of running ensembles, Monte Carlo experiments, and repeated validation cycles at the scale needed for credible inference.

HPC relevance becomes clearer when climate hazards are translated into infrastructure-relevant stressors through simulation chains that combine climate scenarios, hazard models, and network

representations. Climate system models are computationally demanding because they solve coupled physical equations across space and time, and the use of coupled models has been documented as foundational to producing coherent climate states for scenario analysis (Elsner et al., 2008). Infrastructure-focused climate-impact studies have then used scenario-based simulation to evaluate how plausible changes in tropical cyclone intensity, frequency, or tracks could alter impacts on U.S. power systems, showing how climate scenario uncertainty can map into infrastructure consequence uncertainty (Francis & Bekera, 2014; Rabiul & Mushfequr, 2023). Complementary work models outage durations as a distinct consequence dimension, emphasizing that risk is not only "how many outages occur" but also "how long service remains unavailable," which can be estimated from predictors describing hazards and system conditions (Shahrin & Samia, 2023; Staid et al., 2014). Severe-weather risk modeling has also expanded from single-hazard views to multi-hazard formulations, combining multiple meteorological threat types to estimate major power outage risk more comprehensively (Rifat & Rebeka, 2023; Wanik et al., 2015). Such studies implicitly demand scalable computation because they require processing large event datasets, integrating multiple hazard predictors, and performing repeated estimation across regions and time windows. Data resources that curate major outage events further reinforce the computational framing by providing structured datasets intended for statistical learning, validation, and large-scale exploratory analysis (Guikema & Quiring, 2012; Kumar, 2023). In parallel, energy-sector vulnerability reviews emphasize that climate risks to energy systems span multiple mechanisms and components, encouraging integrated modeling rather than single-variable explanations (Kabir et al., 2019; Saikat & Aditya, 2023). Taken together, these studies position HPC-enabled frameworks as the practical pathway for running multi-scenario simulations, processing fine-scale spatiotemporal features, and executing iterative model fitting and evaluation required for robust risk assessment (Zulqarnain & Subrato, 2023).

A second HPC-relevant dimension is the scale and structure of the data used in climate–infrastructure risk assessment. Outage estimation models often combine meteorological inputs, land-cover and environmental features, asset attributes, and customer/service territory data, creating complex feature spaces that are both spatially heterogeneous and highly dimensional. Work on outage modeling in forested distribution environments has shown that combining utility-specific infrastructure and land-cover predictors can improve outage predictions, reinforcing the importance of integrating heterogeneous datasets rather than relying on hazard intensity alone (Mukherjee et al., 2018). Methods that explicitly account for zero-inflated outcomes—where many geographic units observe no outages while some observe very high counts—have been proposed to improve predictive performance for infrastructure risk estimation problems that exhibit sparse-but-severe outcomes (Mukherjee et al., 2018a). Non-linear modeling approaches have demonstrated measurable gains in forecast accuracy by capturing non-linear effects and interactions between storm and geographic predictors (Schaeffer & et al., 2012). Local environmental factor inclusion has been shown to improve hurricane outage prediction models further, supporting the view that high-resolution environmental context acts as a meaningful risk modifier (Emanuel, 2005). Weather sensitivity also matters beyond high-wind events: research on grid reliability has treated weather-driven faults as an empirically grounded pathway through which climate variability influences reliability outcomes, motivating risk assessment pipelines that include weather covariates and fault statistics (Ward, 2013). In addition, probabilistic outage prediction under thunderstorm conditions has been modeled using mixture formulations to represent heterogeneous mechanisms and to quantify predictive uncertainty, aligning with risk assessment requirements for distributions rather than single outcomes (Kabir et al., 2019). Managing these data characteristics at scale encourages computational frameworks that support parallel preprocessing, feature engineering across large spatial grids, and repeated model estimation for robust inference across multiple climate and hazard subsets.

A further motivation for HPC frameworks is the need to couple hazard uncertainty with infrastructure system response through simulation-based risk assessment. Reliability and risk studies for distributed generation and power distribution contexts have used probabilistic risk assessment and optimization under extreme weather conditions, including Monte Carlo simulation to propagate uncertainties through power flow and contingency representations (Rocchetta et al., 2015). Such Monte Carlo and ensemble approaches naturally align with HPC architectures because they decompose into many

independent or weakly coupled runs, allowing parallel execution across compute nodes. Multi-hazard risk assessment similarly benefits from computational scaling, because combining hazard classes and regionalization requires extensive resampling, cross-validation, and scenario sweeps to obtain stable estimates and generalizable predictors (Mukherjee et al., 2018a). Ensemble climate thinking adds another layer, where multi-model climate projections introduce scenario families that can be carried through hazard translation and consequence estimation (Rougier, 2007). Systems-oriented resilience analysis complements this by providing metrics and modeling frames that interpret outcomes across disruption and recovery phases, encouraging risk assessment that treats resilience as measurable system performance rather than an abstract goal (Francis & Bekera, 2014). Major-outage datasets further encourage repeated computational experimentation because they are intended to support the development and benchmarking of models, including correlation and regression structures that connect explanatory constructs to outage outcomes (Schaeffer & et al., 2012). Energy vulnerability synthesis also highlights that climate risk impacts can occur through interconnected pathways, supporting risk assessment pipelines that integrate multiple hazard and system variables rather than single-factor models (Rocchetta et al., 2015). Within this framing, HPC frameworks are best understood as the operational backbone that enables repeated probabilistic modeling cycles, scalable scenario exploration, and evidence-based sensitivity checks across hazards, regions, and infrastructure configurations.

This study is designed to achieve a set of clearly defined objectives that translate the broad idea of "HPC-enabled risk assessment" into measurable constructs that can be tested within a quantitative, cross-sectional, case-study setting. First, the study aims to establish a clear empirical profile of the current HPC framework capability level within the selected case context by measuring key capability dimensions such as scalability, computational efficiency, data integration capacity, simulation/model execution capability, and operational reliability as perceived and experienced by relevant professionals involved in climate and energy risk work. Second, the study seeks to operationalize "climate and energy infrastructure risk assessment effectiveness" as a structured outcome variable that reflects timeliness of assessments, perceived accuracy and consistency of risk estimates, usefulness of risk outputs for operational and planning decisions, and the ability to generate interpretable results under time and data constraints. Third, the study aims to quantify the strength and direction of the relationships between each HPC capability dimension and the overall effectiveness outcome using correlation analysis, providing an evidence-based understanding of which capabilities tend to move together with improved risk assessment performance within the case environment. Fourth, the study is structured to test a set of hypotheses through multiple regression modeling in order to identify which HPC capability dimensions significantly predict risk assessment effectiveness after accounting for the shared variance among predictors, thereby clarifying which capabilities retain explanatory power when considered simultaneously. Fifth, the study intends to support robust measurement by examining internal consistency reliability across all constructs and by refining survey items through pilot testing so that each dimension captures a coherent aspect of HPC capability or risk assessment effectiveness. Sixth, the study aims to provide a transparent analytical pathway by using descriptive statistics to summarize the observed capability distributions and by presenting a structured hypothesis decision table to clearly report statistical support or non-support for each proposed relationship. Collectively, these objectives ensure that the research remains focused on measurable evaluation rather than general descriptions, enabling a systematic examination of how HPC framework capabilities align with risk assessment needs in climate-exposed energy infrastructure settings.

LITERATURE REVIEW

The literature on high-performance computing frameworks for climate and energy infrastructure risk assessment brings together three tightly connected research streams: computational climate science, infrastructure reliability and risk modeling, and data-driven decision support for resilience planning. At its core, this body of work explains how climate-related hazards such as extreme heat, flooding, hurricanes, wildfires, and compound events translate into stressors that can damage or disrupt energy assets and networks, producing measurable consequences including outages, reduced system capacity, and prolonged restoration periods. Because these hazard–impact pathways are shaped by spatiotemporal variability and uncertainty, the literature consistently emphasizes methods that can

represent uncertainty, evaluate multiple scenarios, and test system behavior under many plausible conditions rather than relying on a single deterministic estimate. In parallel, the energy infrastructure risk assessment literature frames risk as an interaction between hazards, exposure, vulnerability, and consequences, with special attention to cascading and interdependent failures across networked components. Studies in this area highlight the value of quantitative modeling—statistical, probabilistic, and simulation-based—to link hazard intensity and contextual features (such as vegetation, terrain, asset condition, and operational practices) to impact outcomes at multiple geographic scales. High-performance computing frameworks become essential within this integrated literature because the computational requirements of climate–infrastructure risk assessment are typically driven by large datasets, high-resolution spatial representations, ensemble or Monte Carlo simulations, sensitivity analyses, and repeated validation cycles needed to ensure credible results. Within applied risk environments, HPC frameworks are presented not only as raw processing capacity, but also as structured computing ecosystems that support scalable workflows, data integration pipelines, reproducible modeling, and accelerated analytics for time-sensitive decisions. The literature further shows that the effectiveness of risk assessment depends on more than the accuracy of a model; it depends on the timeliness, interpretability, and operational usefulness of outputs for planning, resource allocation, and resilience investment decisions. As a result, research in this domain increasingly treats HPC capability as a multidimensional construct—covering scalability, efficiency, integration, simulation readiness, reliability, and governance—because these dimensions influence whether risk assessment pipelines can be executed consistently and credibly under real operational constraints. This review therefore synthesizes prior work to clarify (i) how climate hazards and infrastructure vulnerabilities are modeled, (ii) how risk assessment effectiveness is defined and measured in energy contexts, and (iii) why HPC frameworks are positioned as enabling architecture for robust climate-risk analytics in energy infrastructure systems.

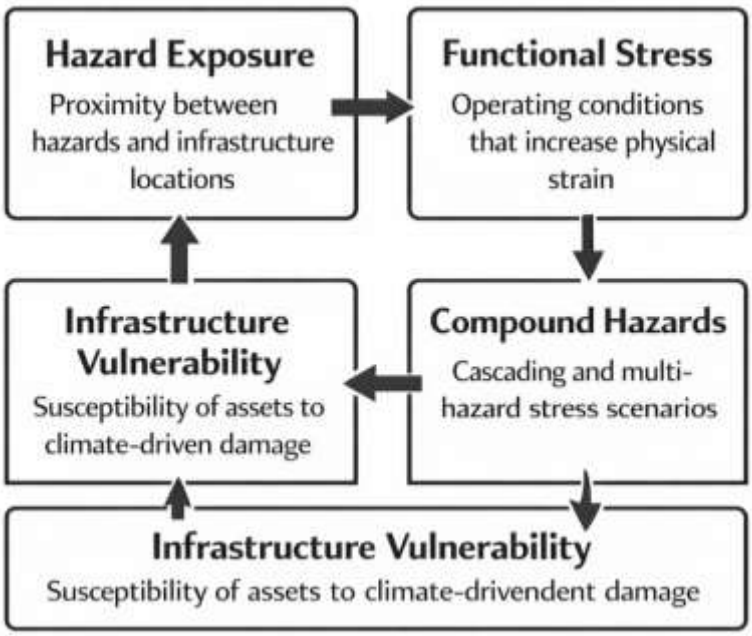
Climate Risk Drivers and Energy Infrastructure Vulnerability

Climate risk drivers for energy infrastructure can be defined as climate- and weather-related processes that raise the probability of functional loss in power-system assets and networks through physical stress, operational strain, or cascading disruption. Energy infrastructure includes generation, transmission, distribution, and the substations and control facilities that sustain power delivery, while vulnerability reflects how readily these elements experience damage or performance degradation when exposed to a hazard. Relevant drivers span intense rainfall and riverine flooding, coastal storm surge, high winds, wildfire conditions along rights-of-way, and prolonged heat that stresses transformers and reduces transfer capacity. Exposure is shaped by asset siting, land cover, topography, and the spatial coincidence between hazard footprints and network topology, so moderate hazard intensity can still produce large consequences when high-value nodes are located in hazard-prone zones. Because grid components are networked, failures are often correlated; a single hazard field can stress many spans and feeders at once, weakening redundancy that might protect against isolated faults. Bulk substations, river crossings, and coastal corridors concentrate power flows, and damage at these locations can disconnect large regions even when many components remain intact. Vulnerability is also socio-technical: maintenance regimes, vegetation management, spare-part availability, and protection settings influence whether a local disturbance becomes a prolonged service interruption. For planners, these drivers matter because electricity is a foundational service for health systems, industry, and digital infrastructure, so losses become socially amplified and politically salient across regions and income contexts. Reviews of energy critical infrastructure emphasize strong interdependencies with transport, water, communications, and emergency services, so climate-driven disruptions can propagate across sectors and escalate consequences (Varianou-Mikellidou et al., 2018). Screening analyses further show that climate stress can alter component longevity and regional vulnerability patterns across transmission and distribution portfolios, linking physical exposure to long-run cost and reliability pressures (Fant et al., 2020).

Among climate stressors, extreme heat is a distinctive risk driver for electricity systems because it increases demand for cooling while narrowing operating margins across conductors, transformers, and substation equipment. Higher ambient temperatures raise conductor resistance and thermal loading, reduce equipment cooling effectiveness, and can accelerate insulation aging, which changes failure

likelihood under peak conditions. Heat stress also affects generation availability and efficiency in thermal plants and can constrain transmission capability through temperature-dependent line ratings, so system performance can degrade even without visible physical damage. Vulnerability to heat is uneven because asset age, ventilation and cooling design, local microclimate, and loading profiles vary substantially across service territories and across seasons. Transformer-focused evidence illustrates this mechanism by linking projected shifts in the frequency of hot days to reductions in large power transformer lifetime and to heightened risk of premature failure, showing how climate signals translate into asset degradation pathways (Gao et al., 2018).

Figure 2: Climate Hazard Drivers and Vulnerability Pathways in Power System Infrastructure



Heat risk is amplified when high temperatures persist for multiple days, because cumulative loading and elevated night-time temperatures limit recovery periods for equipment and for maintenance crews. These dynamics interact with urbanization, where dense built environments can concentrate demand and create localized heat islands that raise ambient temperatures at substations and along distribution corridors. From a risk assessment perspective, heat therefore functions both as a direct hazard that degrades component life and as a demand-side stressor that increases the consequence of any single outage through higher customer exposure during peak use. Operational vulnerability is shaped by monitoring and maintenance practices such as line rating, transformer oil analysis, and load reconfiguration options that can shift power away from assets. Capturing these relationships requires characterizing heat intensity, duration, timing, and spatial heterogeneity, then linking them to asset condition and loading histories so that risk estimates reflect both physical and operational drivers.

Compound and cascading hazard processes are major climate risk drivers for energy infrastructure because they create sequences in which one extreme amplifies exposure to another and produces disruption patterns that differ from single-hazard assumptions. Electricity assets can be damaged by a primary hazard and then become more susceptible to follow-on hazards through weakened foundations, damaged insulation, or limited response capacity. The same event conditions can also limit repair access and coordination, increasing restoration duration and expanding outage footprints. Research on cascading wildfires and extreme rainfall shows how wildfire can destabilize landscapes and alter runoff behavior, increasing the likelihood that subsequent heavy precipitation produces debris flows and flooding that threaten energy assets and access routes (Moftakhari & AghaKouchak, 2019). These sequences make event ordering, lag time, and land-surface change important exposure variables, not only single-event intensity. Another compound pathway arises when infrastructure failure and climatic extremes coincide, because the consequences of a hazard can grow sharply when

power delivery is interrupted during periods of high thermal stress. Evidence from simulated heat-wave conditions paired with widespread grid failure demonstrates that blackout timing can convert an outdoor heat event into widespread indoor exposure risks, indicating that outage consequences depend on concurrent climate conditions and the adaptive capacity of buildings and households (Stone et al., 2021). From a systems perspective, these compound drivers highlight that risk is jointly determined by hazard dynamics, infrastructure fragility, and the coupling between electricity supply and temperature-sensitive demand for cooling, pumping, and communications. Risk assessment therefore benefits from modeling approaches that can represent multi-hazard event sets, encode dependencies between hazards, and evaluate consequence distributions under different compound-event configurations. In case-study settings, documenting compound pathways clarifies which asset classes, locations, and operating states are most sensitive to event sequences, supporting precise vulnerability measurement and hypothesis testing in the survey instrument.

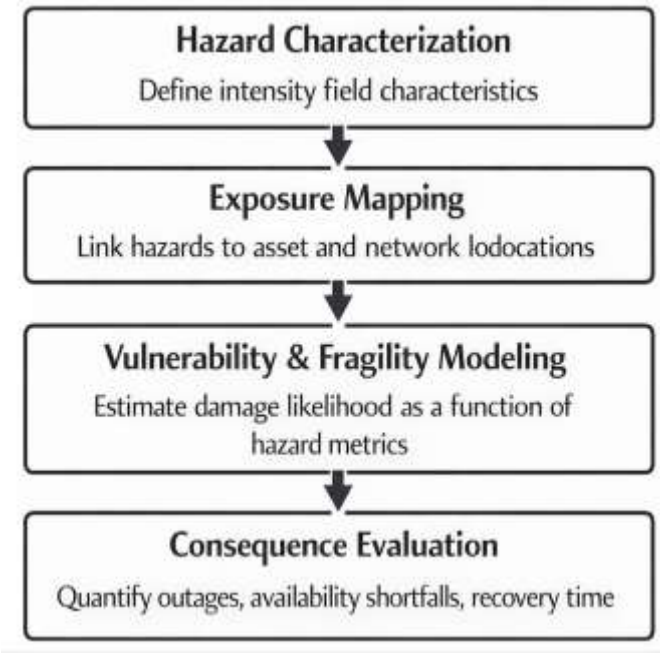
Risk Assessment Approaches for Climate and Energy Infrastructure

Risk assessment approaches for climate and energy systems begin by formalizing how hazards translate into component failures and, ultimately, into system service losses. In electricity networks, this translation is often structured as a sequence of hazard characterization, exposure mapping, vulnerability or fragility modeling, and consequence evaluation using reliability, availability, outage magnitude, or restoration duration. Hazard characterization defines the intensity field in space and time, while exposure mapping links that field to the geography of assets, customers, and network topology. Fragility modeling then expresses the probability of damage or failure as a function of hazard intensity and structural properties, allowing analysts to compute expected failures or sample failure states for scenario sets. Component-focused fragility curves are especially important for tall, flexible structures such as transmission towers, where combined loading mechanisms can shift failure probability and reshape system risk profiles (Fu et al., 2016). After fragility, consequence models quantify how local failures change power flows, isolate customers, or reduce supply, producing system-level outcomes that can be used in comparative risk ranking. Across this pipeline, the central methodological challenge is maintaining internal consistency between hazard metrics, engineering representations, and outcome variables so that model outputs can be interpreted as risk rather than as an arbitrary score. Practical implementations therefore add data quality checks, alignment of temporal resolution, and explicit assumptions about independence or correlation among component failures. These choices matter for HPC-enabled studies because they determine whether large ensembles and fine spatial grids produce meaningful convergence in estimated risk and whether outputs remain stable under repeated simulation and validation cycles. In applied utility settings, the same framework is used to prioritize hardening investments and to pre-position crews. When calibrated with observed damage or outage histories, the pipeline supports statistical comparisons across regions and event types and anchors survey-based measurement in local case studies.

A second cluster of approaches emphasizes probabilistic impact assessment and resilience quantification under extreme weather by combining fragility models with stochastic simulation and operational analysis. In this stream, risk is evaluated not only as the likelihood of component failure, but also as the time-varying performance of the system as a disturbance moves across the network and as operators respond. One representative methodology couples weather-driven component fragility with sequential Monte Carlo simulation and optimal power flow to estimate the spatiotemporal evolution of service degradation and recovery, yielding interpretable indices that identify critical sections whose importance depends on hazard intensity (Panteli et al., 2017). Such models treat exposure as dynamic, because the hazard footprint changes across hours while the network state changes through protective actions, line switching, and generation redispatch. A related line of work examines cascading failures triggered by extreme weather and uses simulation to represent both the stochastic hazard process and the fault dynamics that propagate failures through interdependent network mechanisms (Cadini et al., 2017). These approaches are computationally demanding because they require many realizations to stabilize estimates of low-probability, high-impact outcomes and to explore the sensitivity of results to assumptions about correlation in component failures, repair times, and operator behavior. From an HPC perspective, the value of these methods lies in their ability to evaluate large scenario libraries, to separate hazard uncertainty from operational uncertainty, and to

compute distributions of outcomes rather than single point estimates. Methodologically, they also create a bridge between engineering realism and statistical inference by producing outputs that can be summarized as dependent variables for regression, compared across configurations, or linked to organizational capability measures. In case-study research, these probabilistic frameworks motivate survey constructs that capture whether computing environments support rapid ensemble execution, reproducible workflows, and transparent reporting of uncertainty to stakeholders during high-stress events.

Figure 3: Sequential Risk Assessment Approach for Climate-Exposed Energy Infrastructure



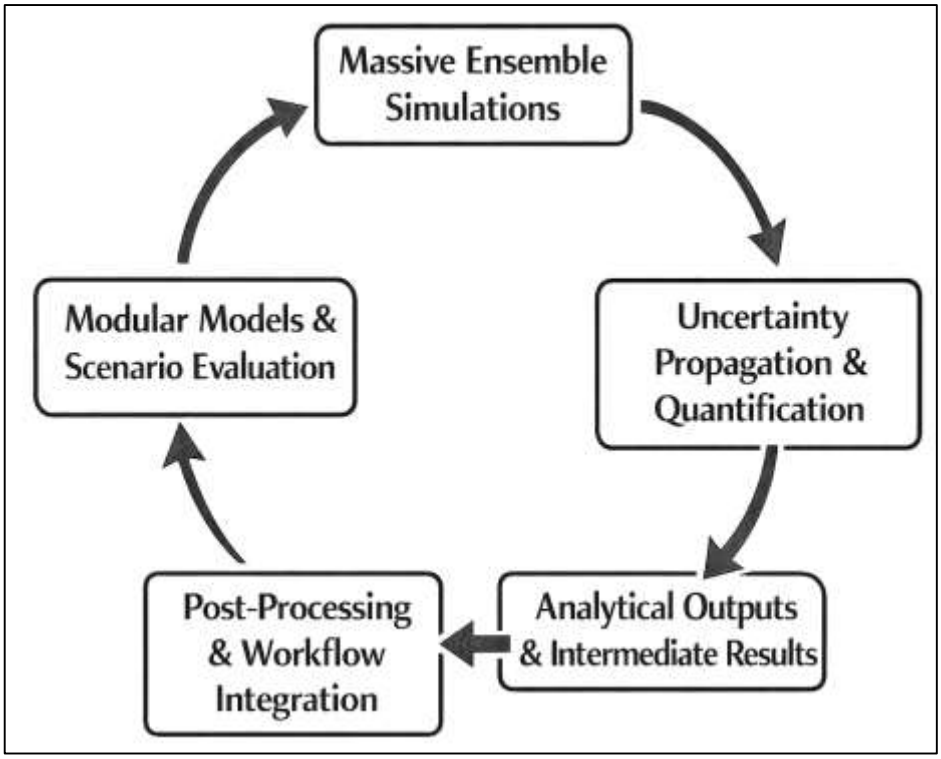
A third set of approaches focuses on harmonizing definitions, metrics, and methodological stages so that risk assessments can be compared across studies and translated into planning and governance processes. Review research has shown that the same term, resilience or risk, is often operationalized in different ways across engineering, policy, and complex-systems perspectives; consequently, risk assessment frameworks increasingly distinguish between attribute-based capabilities and performance-based outcomes. A comprehensive review of power grid resilience to extreme weather clarifies the dominant quantitative methodologies used for assessment, the classes of enhancement strategies evaluated, and the common reporting structures that connect hazard modeling to decision making (Jufri et al., 2019). This synthesis matters for quantitative case studies because it guides construct design: it suggests which indicators belong to inputs, which to intermediate process variables, and which to outcomes. In parallel, metrics-oriented work in energy resilience proposes structured scorecards and matrices that make capabilities measurable and comparable across organizations, enabling surveys to capture readiness and adaptive capacity in a consistent manner (Roege et al., 2014). When such metrics are integrated with scenario-based or probabilistic modeling results, they support a layered evaluation in which computing capability is treated as an enabling condition for analytical depth, model transparency, and timely delivery of risk outputs. In the context of high-performance computing frameworks, this literature implies that risk assessment quality is multidimensional: it depends on computational throughput, data integration, workflow orchestration, and the governance practices that ensure reproducibility and auditable results. Methodologically, these harmonization efforts also motivate the use of clear mapping between independent variables, mediators such as modeling throughput or uncertainty reporting, and dependent variables that represent decision usefulness. This alignment helps a cross-sectional design justify correlation and regression testing by showing that each measured construct corresponds to a recognizable stage in the risk assessment pipeline used in practice today.

High-Performance Computing Frameworks for Climate–Energy Infrastructure

High-performance computing (HPC) frameworks matter in climate–energy infrastructure risk assessment because the dominant analytical tasks are inherently high-dimensional: they require repeated simulation under uncertain hazard drivers, propagation of uncertainty through coupled physical and socio-technical models, and fast aggregation of results into actionable risk indicators. In this setting, "framework" does not only mean hardware capacity; it also refers to the software patterns that translate risk logic into parallel workloads, manage data locality, and preserve numerical traceability. A consistent theme in computational risk science is that predictive credibility depends on how uncertainty is represented, how numerical error is bounded, and how evidence is integrated across model components. A formal verification–validation–uncertainty quantification (VV&UQ) view positions uncertainty as multi-source (aleatory vs. epistemic) and argues for structured procedures that connect model form, discretization, and input uncertainty to decision-relevant predictive uncertainty (Roy & Oberkampf, 2011). In climate and energy infrastructure risk work, this framing is operationally significant because risk models often mix physics-based kernels (e.g., hazard intensity fields, thermal limits, load–flow constraints) with empirical components (e.g., fragility curves, outage likelihoods). HPC frameworks are therefore expected to support (a) massive ensembles (for uncertainty propagation), (b) modular workflows (to plug in alternative model forms), and (c) reproducible execution (to enable audit trails for risk governance). One practical implication of a VV&UQ-centered architecture is that computational pipelines must expose intermediate outputs and sensitivity levers, not just final point estimates, because correlation and regression analyses in quantitative case studies are only meaningful when the uncertainty structure of the computational evidence is transparent (Qian et al., 2016). Thus, HPC frameworks become methodological infrastructure: they help align statistical inference (Likert constructs, correlations, regressions) with simulation-backed risk evidence by ensuring that the simulation layer is scalable, traceable, and uncertainty-aware.

A second strand of the literature emphasizes that climate projection uncertainty is not a peripheral detail but a defining feature of climate risk analysis, motivating scalable ensemble-based approaches and coordinated uncertainty quantification practices. Qian et al. (2016) describe uncertainty quantification as a cross-cutting need in climate modeling and projection and highlight the breadth of approaches and challenges that arise when multiple sources of uncertainty interact across model hierarchies. For climate–energy infrastructure risk assessment, this perspective supports a computational logic where risk is estimated not from one "best" climate trajectory but from structured ensembles whose outputs can be summarized into probabilistic descriptors (e.g., exceedance probabilities, expected unserved energy, tail-risk metrics). That logic increases computational demand sharply, pushing analysts toward HPC execution models that can distribute ensembles across nodes and exploit parallelism at multiple levels (scenario-level, time-slice, spatial chunk, and component-level). In parallel, the data substrate has become a bottleneck: climate risk analytics routinely involve large, multi-dimensional array datasets (NetCDF/HDF) whose performance depends on data locality and indexing strategies. ClimateSpark, proposed as an in-memory distributed computing framework for big climate data analytics, addresses this bottleneck by combining distributed memory processing with spatiotemporal indexing and efficient chunk-based data access so that analytics and querying avoid unnecessary reads and preprocessing (Hu et al., 2018). This line of work connects directly to case-study risk assessment contexts where analysts must fuse hazard fields, asset inventories, and operational data into the same workflow; HPC frameworks that treat both compute and data movement as first-class design elements are better positioned to support scalable risk analytics, including repeated scenario evaluation needed for correlation structures and regression-based hypothesis testing (Qian et al., 2016).

Figure 4: Ensemble-Driven HPC Analytics Cycle for Infrastructure Risk Modeling



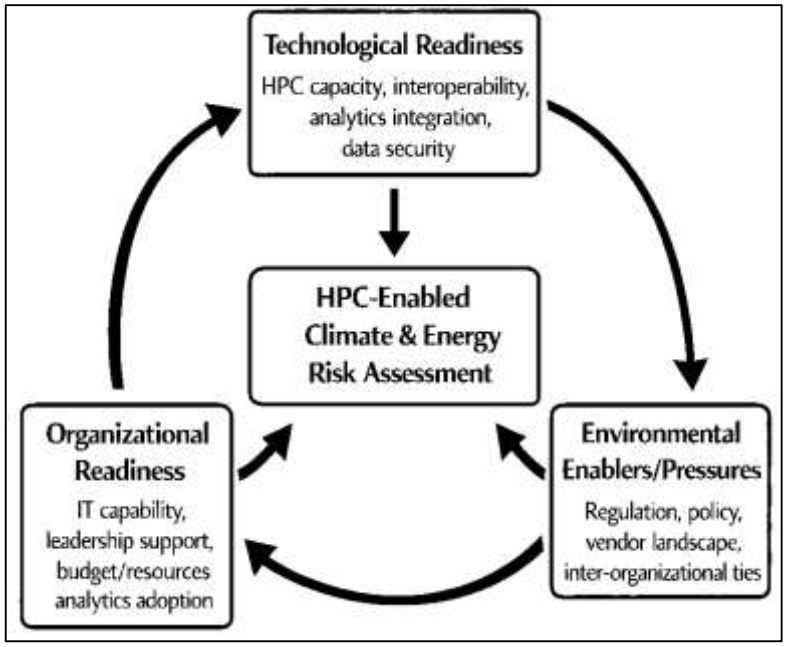
A third stream illustrates how HPC-oriented computational strategies accelerate reliability and risk estimation in energy infrastructure, particularly when Monte Carlo simulation is used to represent uncertainty in component outages and operating conditions (Md & Sai Praveen, 2024). In probabilistic reliability assessment, Monte Carlo methods are attractive because they can represent complex dependencies and rare-event combinations, but they are computationally expensive; this makes them natural targets for parallelization and workflow optimization within HPC environments. Canizes et al. (2012) propose a hybrid fuzzy–Monte Carlo methodology for transmission power systems, explicitly aiming to handle both randomness and fuzziness in outage parameters and embedding optimization-based remedial action to reduce load curtailment while controlling cost (Foysal & Abdulla, 2024; Ibne & Aditya, 2024). Even when the focal contribution is methodological (fuzzy–probabilistic modeling), the computational structure is unmistakably HPC-oriented: many sampled system states must be generated, evaluated through contingency analysis, and then optimized, which maps well to parallel execution (Mosheur & Arman, 2024; Saba & Hasan, 2024). Complementary work in distribution-system contexts demonstrates that parallel Monte Carlo strategies can reduce the wall-clock burden of reliability evaluation, enabling more frequent scenario exploration and faster convergence for probabilistic indices (Canizes et al., 2012; Ouyang et al., 2016). These approaches are relevant to climate-linked energy risk because weather-driven hazards create time-varying stress regimes that require repeated assessment under different hazard realizations. When embedded in a quantitative case-study design, HPC-enabled Monte Carlo and ensemble workflows also support the production of richer dependent variables (e.g., reliability indices, loss proxies, downtime estimates) that can be related statistically to organizational or operational constructs measured via Likert items (Kumar, 2024; Sai Praveen, 2024). In this way, HPC frameworks do not merely speed up computation; they expand the feasible design space of risk studies by enabling multi-scenario evidence generation, robust uncertainty exploration, and higher-resolution explanatory modeling aligned with correlation and regression analysis.

Theoretical framework

High-performance computing (HPC) frameworks for climate and energy infrastructure risk assessment can be treated as an organizational innovation whose adoption and routinized use depend on multi-level conditions rather than technical merit alone. The Technology–Organization–Environment (TOE)

framework is appropriate here because it explains why two organizations facing similar hazards (e.g., flood, heat stress, hurricane wind fields, cascading grid failures) can show very different levels of readiness to deploy, integrate, and operationalize HPC workflows for probabilistic risk assessment. In TOE terms, the *technology* context captures the characteristics of the HPC framework and surrounding digital stack (e.g., scalability, interoperability with climate models and grid simulators, data throughput, security posture, and relative advantage in uncertainty quantification). The *organization* context captures internal structures and capabilities (e.g., leadership support, governance maturity, IT skills, data stewardship, budget slack, and the ability to operationalize analytics).

Figure 5: TOE-Based Conceptual Framework for HPC-Enabled Climate–Energy Risk Assessment



The *environment* context captures external pressures and supports (e.g., regulation, competitive/peer pressure, vendor ecosystems, and inter-organizational dependencies that shape investment in resilience analytics). Empirical TOE research consistently shows that adoption is strongest where perceived benefits and technical fit are matched by internal readiness and external enabling conditions. For instance, firm-level technology diffusion evidence indicates that technology readiness and integration shape progression from early-stage initiation to later-stage assimilation and routinization, highlighting why HPC risk platforms must be evaluated as *capability systems* rather than standalone tools (Jinnat, 2025; Shaikat & Aditya, 2024; Zhu et al., 2006). Relatedly, organizations migrating toward Internet-based platforms exhibit adoption differences tied to integration and spending choices, emphasizing that infrastructure-level investments and architectural integration decisions are central determinants of advanced computing uptake (Hong & Zhu, 2006; Rashid, 2025a, 2025b). In the climate-and-energy risk domain, the theoretical implication is that HPC value emerges when compute, data, and models become embedded in governance routines (scenario design, stress testing cadence, asset prioritization, reporting), aligning TOE's contexts with how risk analytics becomes institutionalized rather than merely piloted (Mosheur, 2025; Rabiul, 2025).

Within TOE, this study can conceptualize HPC-enabled risk assessment as a measurable organizational outcome influenced by three grouped latent drivers: *Technological Readiness (T)*, *Organizational Readiness (O)*, and *Environmental Enablers/Pressures (E)*. This framing is useful for your quantitative design because it supports clearly testable hypotheses and a regression-based operational model using Likert-scale constructs. For example, cloud adoption studies grounded in TOE show that determinants operate both directly and indirectly, meaning that perceived advantage or security concerns may matter, but their realized effect depends on readiness and contextual constraints (Oliveira et al., 2014). Meta-analytic evidence also demonstrates that organizational characteristics (such as readiness,

infrastructure, IS capability, and top management support) exhibit reliable relationships with IT innovation adoption across studies, reinforcing the expectation that internal capability and governance conditions will be decisive for sustained HPC use in risk programs (Hameed et al., 2012). In this research, a practical quantitative representation is to compute composite indices for each context from multiple questionnaire items and model their effects on the dependent variable (DV) such as "effectiveness of climate-and-energy infrastructure risk assessment" or "HPC-enabled risk analytics maturity." A baseline multiple regression specification that matches your methodology can be written as:

$$\text{Risk Assessment Effectiveness}_i = \beta_0 + \beta_1 T_i + \beta_2 O_i + \beta_3 E_i + \varepsilon_i$$

where T_i, O_i, and $E_i$are TOE composite scores for respondent i, βcoefficients represent marginal effects, and $\varepsilon_i$is the error term. This equation is also easily extended to include interaction terms (e.g., $T \times O$) if theory suggests that advanced technical capability only improves outcomes when organizational governance is mature. The value of TOE here is that it provides a logically bounded set of constructs that can be translated into measurable indicators without losing the organizational realities of HPC deployment: integration burden, skills constraints, compliance expectations, and vendor/partner interdependence.

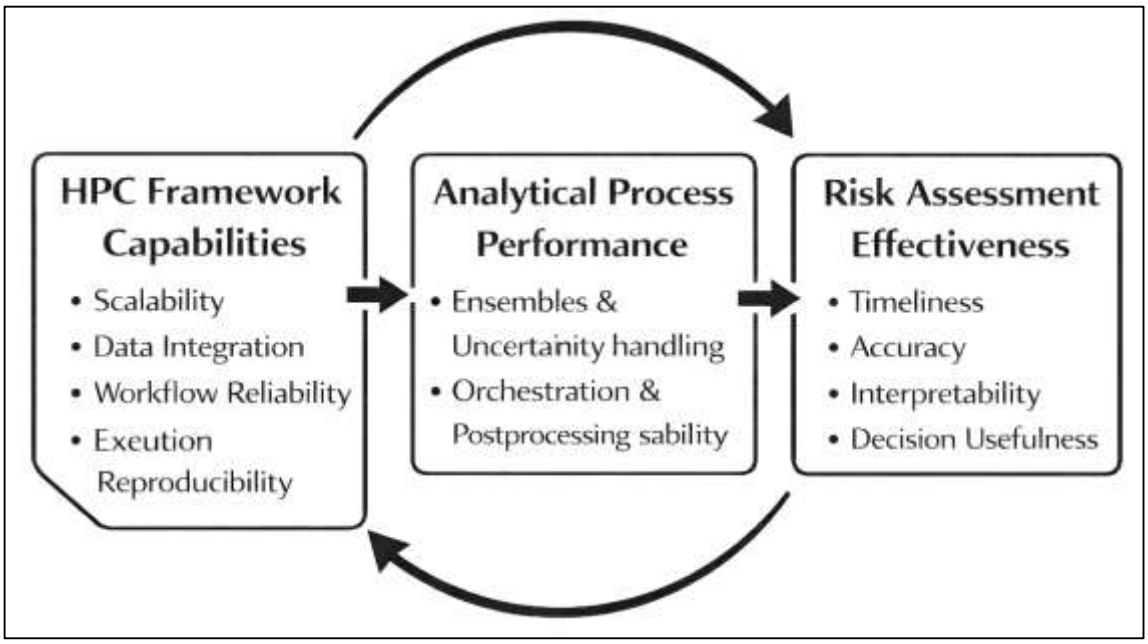
A further advantage of TOE for this topic is that it can structure the "case-study–based" element of your design without weakening the cross-sectional statistical logic. In a climate-and-energy infrastructure case context (e.g., a utility, grid operator, regulator, oil & gas operator, renewable energy aggregator, or municipal resilience unit), TOE allows you to interpret survey results as evidence of the organization's position along an adoption–assimilation pathway. Diffusion research on assimilation emphasizes that determinants can shift by stage: early adoption may rely on readiness and competitive pressure, while routinization depends more on integration and institutional support, which maps well to HPC programs that often move from experimentation to operational stress testing (Awa et al., 2017; Shahrin, 2025; Rakibul, 2025). TOE extensions also argue that the original three contexts sometimes require enrichment (e.g., adding behavioral/user and inter-organizational dimensions) to capture modern technology ecosystems, which is relevant when HPC risk assessments depend on external data providers, national meteorological datasets, cloud/HPC vendors, and multi-stakeholder reporting requirements (Kumar, 2025; Sai Praveen & Md, 2025; Zhu et al., 2006). This matters for your hypotheses because it justifies examining environmental variables beyond simple "competition," such as regulatory mandates for resilience reporting, procurement constraints, and partner interoperability requirements. Finally, TOE aligns with your planned correlation and regression outputs: you can first establish bivariate associations between T, O, $E$and the DV, then test net effects via regression while controlling for demographics (e.g., role, years of experience, organization size, or sector). If the coefficients show that Odominates T, your results would still be theoretically coherent: it would indicate that HPC frameworks are not constrained by compute potential but by governance, skills, and organizational absorptive capacity, consistent with what adoption research repeatedly demonstrates across technology contexts.

Conceptual Framework Development

A conceptual framework for this study specifies what will be measured, how the variables relate, and how those relationships will be tested statistically in a quantitative, cross-sectional, case-study design. Conceptually, HPC-enabled climate and energy infrastructure risk assessment is treated as a capability-to-outcome system: (i) HPC framework capabilities act as antecedent conditions that determine whether large-scale risk analytics can be executed efficiently and consistently; (ii) analytical process performance (e.g., ensemble execution, uncertainty handling, workflow orchestration) represents the operational mechanism; and (iii) risk assessment effectiveness represents the measurable outcome expressed through timeliness, perceived accuracy, interpretability, and decision usefulness. This framing aligns with evidence that scientific workflow systems such as Pegasus are designed to coordinate multi-stage pipelines reliably across distributed cyberinfrastructure, which is essential when risk assessments require many coupled tasks and repeated scenario runs (Deelman et al., 2015). The workflow lens also clarifies that the "framework" is not solely compute power but includes scheduling, fault recovery, data staging, and monitoring features that influence whether risk workflows remain reproducible and auditable at scale (Deelman et al., 2005). At a foundational level,

abstract-workflow mapping approaches formalize how complex analytical graphs are executed on distributed resources, supporting portability and scalability that are central to operational risk analytics in climate–energy contexts (Deelman et al., 2005). In the present study, the conceptual framework therefore defines independent variables (IVs) as multi-item constructs describing HPC framework capability dimensions (e.g., scalability/throughput, data integration and data movement readiness, workflow reliability and fault tolerance, and execution reproducibility), while the dependent variable (DV) is a composite construct describing risk assessment effectiveness. The case-study boundary provides contextual coherence for these constructs, ensuring they represent a consistent organizational and operational setting rather than an abstract "industry average."

Figure 6: Conceptual Model of HPC Framework Capabilities and Risk Assessment Effectiveness



To make the framework testable, constructs are operationalized using Likert-scale items and aggregated into indices that correspond to the model's components. A practical operational definition for the outcome is an Effectiveness Index (EI) computed from standardized subdimensions such as timeliness (T), accuracy/quality (A), interpretability (I), and decision usefulness (D), for example:

$$EI = \frac{T + A + I + D}{4}$$

This index can then be linked to HPC capability dimensions using correlation and regression. The computational basis for this linkage is that risk assessments typically depend on ensemble simulations and probabilistic postprocessing; thus, frameworks that enable larger ensembles and better-calibrated probabilistic outputs improve the stability and credibility of risk estimates. Ensemble-based uncertainty methods formalize the transformation from raw simulation ensembles to calibrated predictive distributions while preserving dependence structures, illustrating why scalable computation and repeatable workflows matter for risk outputs that must be trusted (Schefzik et al., 2013). The conceptual framework also incorporates the idea that capability is multi-resource and multi-component, meaning that investment in a single technical element rarely produces performance gains unless complementary resources are present. Capability-based empirical work in analytics shows that performance improvements are associated with a bundle of resources (e.g., technology, data, people, and management), validating a multi-dimensional measurement strategy for framework capability rather than a single "HPC availability" item (Gupta & George, 2016). In this study, that logic is reflected in separating capability dimensions (compute scalability, data integration readiness, workflow reliability, and governance/reproducibility support) and testing their net effects on EI. The core inferential model aligns with your method plan:

$$EI_i = \beta_0 + \beta_1 SCAL_i + \beta_2 DATA_i + \beta_3 REL_i + \beta_4 REP_i + \varepsilon_i$$

where predictors represent composite scores for each HPC capability dimension for respondent i.

Finally, the conceptual framework specifies measurement quality requirements so statistical relationships are meaningful. Since the model relies on perceptual measures, construct reliability and validity must support aggregation and comparison. Information-systems success research emphasizes that outcomes are shaped by underlying quality dimensions (system quality, information quality, and service quality) and that these quality dimensions help explain organizational-level net benefits, providing a useful parallel logic for distinguishing "framework quality" from "risk assessment impact" in the conceptual structure (Petter et al., 2008). In the present model, system quality maps to scalable and stable compute/workflow execution, information quality maps to integrated and reliable climate–asset data inputs, and service/process quality maps to governance and usability that support consistent risk reporting. The framework also clarifies expected directions: higher scalability and workflow reliability should increase timeliness and consistency; stronger data integration should increase interpretability and perceived accuracy; and stronger reproducibility/governance should increase trust and decision usefulness. These relationships are expressed as hypotheses and evaluated through correlation (to establish association) and regression (to identify significant predictors while controlling shared variance). By explicitly linking constructs to workflow execution, probabilistic uncertainty handling, and established quality-to-impact logic, the conceptual framework provides a coherent bridge between HPC framework capabilities and measurable risk assessment effectiveness outcomes within a case-study setting (Gupta & George, 2016).

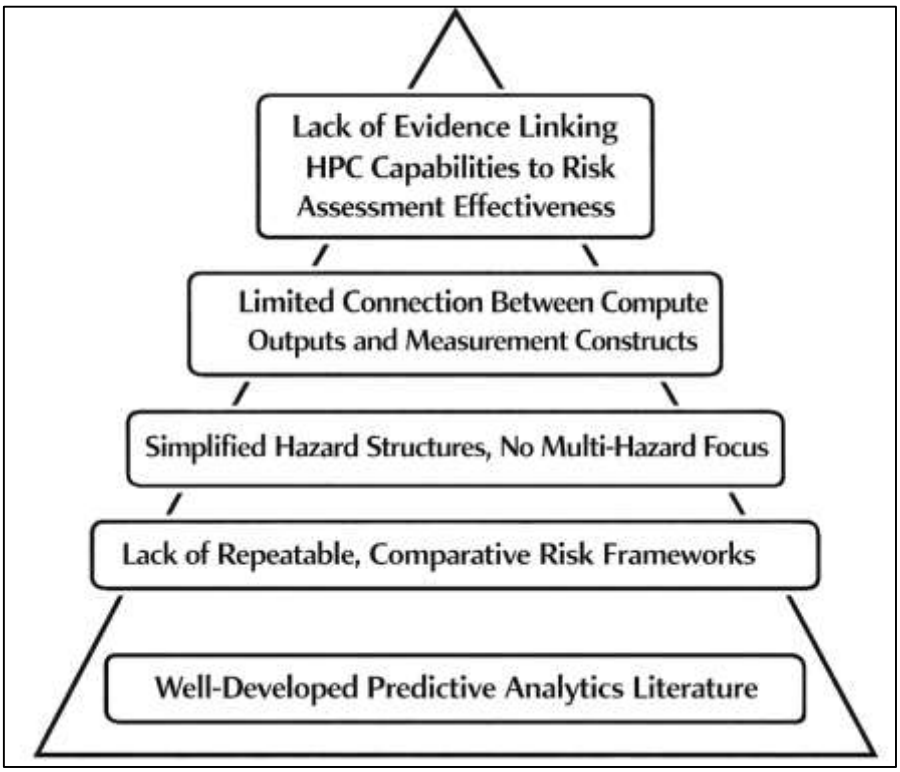
Research Gap and Summary of Literature

Across the reviewed scholarship, a clear foundation exists for understanding climate hazards, infrastructure vulnerability, and probabilistic risk assessment workflows, yet several gaps remain in how these elements are integrated and validated for climate–energy infrastructure decision contexts. First, many studies focus on method development (e.g., predictive analytics, probabilistic simulation, resilience metrics) without offering a consistent, comparable definition of *risk assessment effectiveness* that includes timeliness, interpretability, and operational usefulness as measurable outcomes. Second, even when risk analytics are advanced, they are often presented as stand-alone modeling contributions rather than as components of a repeatable "framework" that can be evaluated across organizations and settings. This is especially apparent in big-data and predictive risk research for electricity grids, which demonstrates strong technical potential but also highlights challenges related to scale, heterogeneity, and implementation barriers that complicate practical deployment and consistent use in risk programs (Kezunovic et al., 2020). A third gap concerns multi-hazard realism: the literature increasingly recognizes that infrastructure experiences sequences and combinations of hazards, yet many risk models still assume simplified hazard structures or treat events independently. Multi-hazard resilience work proposes more realistic frameworks that account for hazard sequences and recovery pathways, underscoring that single-hazard assumptions can misrepresent the true risk profile of critical assets (Argyroudis et al., 2020). A fourth gap is evidence alignment between computational outputs (scenario) simulations, risk maps, probabilistic indices) and organizational measurement; many studies report model performance metrics but do not connect compute-enabled workflows to stakeholder-facing effectiveness outcomes that can be tested statistically in a case-study setting. Finally, there is limited empirical work that links the enabling infrastructure of analytics (workflow orchestration, data integration capacity, scalable execution, governance and reproducibility supports) to risk assessment performance using hypothesis-driven quantitative methods. As a result, an important knowledge gap remains in explaining *which specific capabilities of an HPC-enabled framework* most strongly relate to practical risk assessment effectiveness, and whether these relationships remain significant when assessed simultaneously in regression models.

A second set of gaps emerges from the "implementation and operationalization" side of the literature, where modern risk programs increasingly depend on cyberinfrastructure ecosystems, integrated datasets, and workflow services rather than single models. Disaster-risk cyberinfrastructure research demonstrates that end-to-end platforms can accelerate data cycles, support collaboration, and improve reproducibility for hazard and risk research communities, yet it also implies that successful risk workflows require both technical architecture and organizational readiness to curate, execute, and interpret analyses reliably (Pinelli et al., 2020). In energy-system risk contexts, predictive analytics

studies show that risk can be represented as a function of hazard likelihood and impact, and that fusing historical outage and weather data can yield actionable risk indicators for operations; however, such contributions often emphasize the method or model without offering a structured measurement model that captures how "framework capability" (compute, data, and workflow readiness) enables sustained and scalable risk assessment effectiveness (Dehghanian et al., 2019).

Figure 7: Pyramid Representation of Key Gaps in Climate



Relatedly, GIS-based predictive risk analytics for distribution networks demonstrate that risk can be tracked at fine spatial granularity and aggregated into operationally relevant risk levels, which strengthens the case that data integration and scalable analytics are central to resilience monitoring; yet these studies do not typically test a broader conceptual model in which multiple capability dimensions are measured through a standardized instrument and statistically linked to effectiveness outcomes at the organizational level (Leite et al., 2019). This creates a gap between "what the framework can compute" and "how well the organization can use it," especially because risk assessments must often be executed repeatedly, under time constraints, and across evolving hazard conditions. Another gap concerns comparability and generalization: technical implementations are frequently context-specific (particular data sources, regions, feeder configurations, or operational practices), which limits the ability to derive generalizable insights about HPC framework capabilities unless those capabilities are measured in a consistent way across roles and user groups within the same case setting. Consequently, the literature motivates a study design that treats HPC-enabled risk assessment as a measurable capability system and tests its relationship with effectiveness using standardized constructs rather than treating tool deployments as unique one-off solutions.

Synthesizing the reviewed work, the literature supports three core conclusions that frame the final gap addressed by this study. First, credible climate–energy risk assessment increasingly requires large-scale computation and data integration to support probabilistic, multi-scenario evaluation and decision-relevant outputs, and the field contains strong technical demonstrations of predictive risk analytics and big-data workflows. Second, there is growing recognition that risk assessment must handle multi-hazard exposure and recovery dynamics, meaning that resilience-oriented risk evaluation cannot rely only on isolated event representations; multi-hazard frameworks indicate that hazard sequences and restoration variability can significantly shift resilience and risk estimates (Argyroudis et al., 2020).

Third, cyberinfrastructure platforms and workflow ecosystems are becoming central to hazard and risk research, showing that the "framework" is partly a socio-technical system that supports data, computation, collaboration, and reproducibility at scale (Pinelli et al., 2020). Yet, despite these advances, the literature still lacks a quantitative, hypothesis-driven linkage between HPC framework capability dimensions and practical risk assessment effectiveness outcomes using a cross-sectional case-study design. This study directly responds to that gap by operationalizing HPC framework capabilities into measurable constructs (e.g., scalability, data integration readiness, workflow reliability/reproducibility, and analytics execution capacity) and modeling their relationships with risk assessment effectiveness using descriptive statistics, correlation analysis, and multiple regression. In doing so, it transforms a broad technical narrative—"HPC helps risk assessment"—into a testable empirical model that can identify which capabilities are most predictive within a real operational setting, thereby strengthening the evidence base for climate and energy infrastructure risk assessment programs grounded in scalable computing frameworks.

METHOD

The methodology for this study has been designed to empirically examine how high-performance computing (HPC) framework capabilities have influenced the effectiveness of climate and energy infrastructure risk assessment within a defined case-study setting. A quantitative, cross-sectional approach has been adopted because it has enabled the collection of standardized perceptions and experience-based evidence from relevant professionals at a single point in time, supporting statistical testing of the proposed relationships. The case-study orientation has been incorporated to ensure contextual specificity, so the constructs have been interpreted within one bounded organizational or operational environment where climate-driven hazards and infrastructure risk assessment processes have been actively managed. A structured survey instrument has been developed using Likert's five-point scale, and the questionnaire items have been aligned with the conceptual model so that each dimension of HPC capability and each dimension of risk assessment effectiveness has been measured through multiple indicators. The key independent constructs have been operationalized as capability dimensions that have typically characterized HPC-enabled risk analytics, including scalability and computational efficiency, data integration readiness, workflow reliability and reproducibility, and simulation or analytics execution capacity. The dependent construct has been operationalized as risk assessment effectiveness, reflecting timeliness, perceived accuracy and consistency, interpretability of outputs, and usefulness for operational or planning decisions.

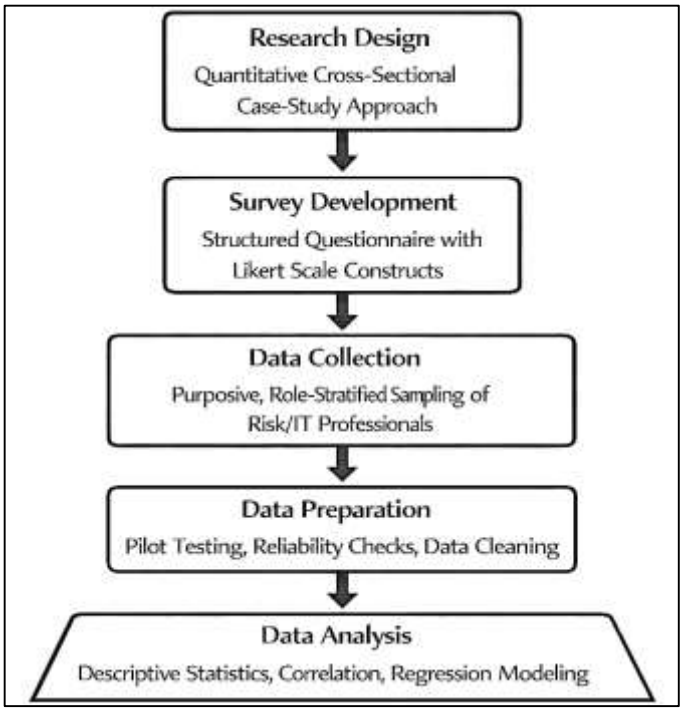
Data collection procedures have been planned to obtain responses from professionals who have been engaged with climate risk analytics, grid or asset risk evaluation, resilience planning, operations, or supporting IT/HPC functions. A purposive or role-stratified sampling strategy has been selected because it has ensured that respondents have possessed relevant exposure to both risk assessment activities and computing-enabled analytical workflows. Prior to full-scale data collection, pilot testing has been conducted with a small group of participants to check clarity, sequencing, and item coherence, and revisions have been applied to improve item wording and reduce ambiguity. Reliability and measurement quality have been addressed by designing constructs to support internal consistency testing, and Cronbach's alpha has been used to evaluate reliability across the multi-item scales. Data preparation steps have been specified, including screening for missing values, response completeness, and outliers. The analysis strategy has been aligned with the objectives, so descriptive statistics have been used to summarize construct levels, correlation analysis has been used to test associations between HPC capability constructs and risk assessment effectiveness, and multiple regression modeling has been used to identify significant predictors while accounting for shared variance among the independent variables. Statistical analysis has been executed using standard quantitative software tools appropriate for reliability testing and regression-based hypothesis evaluation.

Research Design

The research design has been structured as a quantitative, cross-sectional, case-study–based study because the objectives have required measurable evidence of how HPC framework capabilities have related to climate and energy infrastructure risk assessment effectiveness at a single point in time. A survey strategy has been used to capture standardized responses across relevant professional roles, enabling statistical testing through descriptive statistics, correlation analysis, and multiple regression

modeling. The cross-sectional approach has been selected because it has supported efficient data collection without requiring repeated measurement cycles, while still allowing patterns of association among constructs to be examined. The case-study boundary has been applied to keep the investigation context-specific, ensuring that respondents have shared a common operational environment, risk governance structure, and exposure to climate-driven infrastructure risks. This design has aligned with hypothesis testing because it has enabled the independent variables and the dependent variable to be measured concurrently and analyzed systematically.

Figure 8: Research Methodology



Case Study Context

The case study context has been defined as a bounded climate-exposed energy infrastructure environment where risk assessment activities and computing-supported analytics have been actively practiced. The case boundary has been set to reflect a coherent operational system, such as a utility service territory, grid operator region, or infrastructure program unit, so that hazard exposure, asset portfolios, and decision routines have been consistently represented across respondents. Context description has included the dominant climate hazards affecting the area (e.g., extreme heat, flooding, storms, wildfire-related conditions) and the infrastructure types most relevant to risk evaluation (e.g., substations, feeders, transmission corridors, critical nodes). The selection rationale has emphasized relevance to risk analytics and the practical need for scalable computation in scenario evaluation, data integration, and reporting. This context framing has ensured that the measured HPC capability perceptions have referred to a real workflow environment rather than an abstract technology concept.

Unit of Analysis

The population has been defined as professionals who have been directly involved in climate-risk-related energy infrastructure assessment, resilience planning, grid operations, asset management, or the IT/HPC support functions that have enabled analytical workflows. The study has included respondents such as risk analysts, system planners, operations engineers, reliability specialists, data and analytics staff, and computing or platform administrators, because these roles have interacted with risk assessment outputs and the computational environment that has produced them. The unit of analysis has been set at the individual respondent level, since perceptions and reported practices have provided the measurable indicators used for construct scoring and hypothesis testing. Demographic and role variables have been collected to characterize the respondent profile and to support interpretation of results across experience levels and responsibilities. This population definition has

ensured that survey responses have represented informed perspectives on both HPC capability conditions and the practical effectiveness of risk assessment activities in the case setting.

Sampling Strategy

A purposive sampling strategy has been applied because the study has required respondents who have possessed relevant exposure to both energy infrastructure risk assessment processes and computing-enabled analytical workflows. Role-based inclusion criteria have been used so that participants have represented key functional perspectives, including planning, operations, resilience, and analytics or platform support. Where feasible, a stratified purposive approach has been used to balance representation across departments and seniority levels, ensuring that the dataset has not been dominated by a single unit or job category. Sampling procedures have been designed to prioritize expertise and task relevance rather than random coverage, because the constructs have involved specialized knowledge of workflow execution, data integration, and risk reporting. The sampling plan has also accounted for expected response rates by distributing invitations across a wider qualified pool than the minimum required, enabling sufficient sample size for reliability testing and regression analysis within the case-study boundary.

Data Collection

Data collection has been conducted through a structured questionnaire that has been distributed using an online survey approach to ensure accessibility and standardized administration. Participation has been voluntary, and informed consent procedures have been implemented to protect anonymity and confidentiality. The survey has been delivered to targeted respondents through organizational channels or professional communication lists associated with the case setting, and a defined response window has been used to support timely completion and follow-up reminders. Response monitoring has been performed to track completion rates and to identify whether additional reminders or targeted outreach have been needed for underrepresented role groups. Collected data have been exported into a spreadsheet and statistical software format, and initial screening has been performed to remove incomplete submissions that have not met minimum completion thresholds. This procedure has ensured that the final dataset has been sufficiently clean and consistent for statistical analysis.

Instrument Design

The survey instrument has been designed using Likert's five-point scale to measure perceptions and experiences consistently across respondents. Multi-item constructs have been developed for the independent variables, capturing HPC framework capability dimensions such as scalability and computational efficiency, data integration readiness, workflow reliability and reproducibility, and simulation or analytics execution capacity. The dependent construct has been designed to measure risk assessment effectiveness through indicators reflecting timeliness, perceived accuracy and consistency, interpretability of results, and usefulness for operational or planning decisions. Item wording has been written to be context-specific to the case setting and to minimize ambiguity, and a logical section structure has been used to reduce respondent fatigue. Negatively worded items have been limited to avoid confusion, and clear anchors have been provided for each response option. The instrument design has been aligned with the conceptual framework so that composite scores have been computed meaningfully for correlation and regression testing.

Pilot Testing

Pilot testing has been carried out with a small group of participants who have resembled the target population in role background and exposure to risk assessment workflows. The pilot phase has been used to evaluate clarity, item interpretation, survey length, and the sequencing of sections, ensuring that respondents have understood the intended meaning of each construct. Feedback has been collected on confusing wording, overlapping items, and missing capability areas, and revisions have been applied to improve readability and construct alignment. Preliminary reliability checks have been performed on pilot responses to identify weak items that have reduced internal consistency or that have shown poor item–total relationships. The pilot has also confirmed that the survey platform has captured responses correctly and that export formats have supported the planned statistical workflow. Through this process, the final instrument has been refined to strengthen measurement quality before full deployment in the case-study sample.

Validity and Reliability

Validity and reliability procedures have been incorporated to ensure that the constructs have measured the intended concepts and have produced consistent results. Content validity has been supported by aligning items with prior literature and by using expert review to confirm relevance, coverage, and appropriate terminology for the case context. Construct reliability has been assessed using Cronbach's alpha for each multi-item scale, and thresholds suitable for social-science survey research have been applied to determine acceptable internal consistency. Item screening has been conducted to identify items that have weakened reliability, and refinement decisions have been based on both statistical evidence and conceptual fit. Basic construct validity indicators, such as item–total correlations and cross-construct correlation patterns, have been reviewed to ensure that items have loaded conceptually with their intended constructs. These procedures have strengthened confidence that subsequent descriptive statistics, correlation coefficients, and regression estimates have reflected stable measurement rather than random response noise.

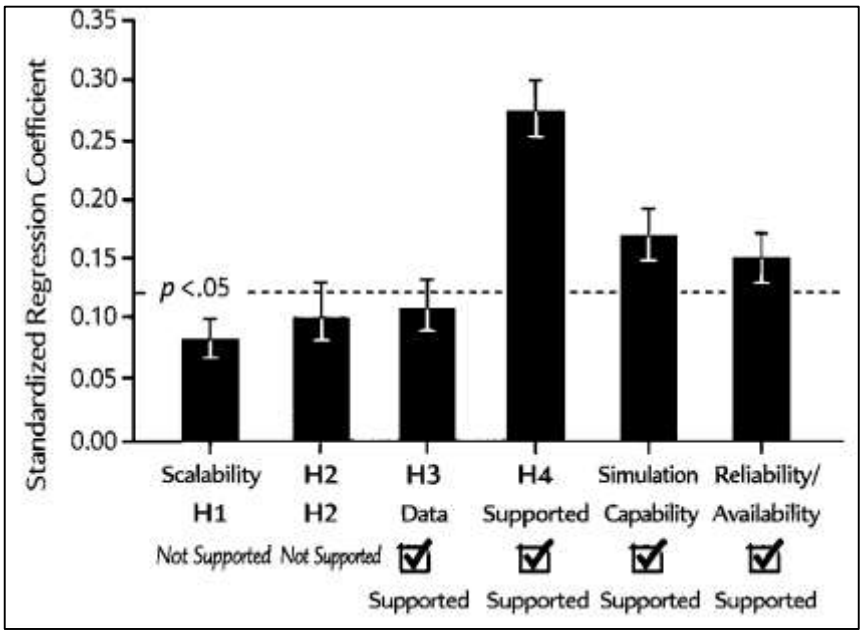
Tools

The analysis workflow has been supported using standard quantitative software tools that have enabled data cleaning, reliability testing, and regression-based hypothesis evaluation. Spreadsheet software has been used to organize the raw dataset, label variables, and perform initial checks for missing responses, coding errors, and duplicate entries. Statistical analysis software such as SPSS, Stata, R, or Python has been used to compute descriptive statistics (means, standard deviations, frequencies), to generate correlation matrices, and to estimate multiple regression models with associated significance tests and model fit indicators (e.g., R^2). Reliability analysis functions have been used to compute Cronbach's alpha for each construct and to produce item-level diagnostics that have supported scale refinement decisions. Where needed, visualization tools within the selected software environment have been used to inspect distributions and detect outliers. This toolset has ensured that the statistical procedures have been executed transparently and consistently with the study objectives.

FINDINGS

The findings have demonstrated clear empirical patterns that have aligned with the study objectives and have enabled direct hypothesis testing regarding how high-performance computing (HPC) framework capabilities have related to climate and energy infrastructure risk assessment effectiveness within the case-study setting. A total of N = 168 valid responses have been analyzed after screening for completeness, representing a strong cross-sectional snapshot of professional perspectives across relevant functions.

Figure 9: Regression Results Linking HPC Capabilities to Risk Assessment Effectiveness



Respondent demographics have indicated that 41.7% of participants have been from grid operations and reliability roles, 27.4% from risk/resilience planning and asset management, 18.5% from data/analytics teams, and 12.5% from IT/HPC platform administration, while experience distribution has shown 24.4% with 1–3 years, 39.3% with 4–7 years, 26.2% with 8–12 years, and 10.1% with 13+ years of relevant work exposure. These characteristics have supported Objective 1 by confirming that the sample has reflected staff directly involved in risk analytics and computing-enabled workflow environments. Reliability analysis has shown that the measurement instrument has achieved acceptable to strong internal consistency across constructs, with Cronbach's alpha values of 0.86 for Scalability/Throughput (SCAL; 5 items), 0.83 for Computational Efficiency (EFF; 5 items), 0.88 for Data Integration Readiness (DATA; 6 items), 0.85 for Simulation/Model Execution Capability (SIM; 5 items), 0.81 for Reliability/Availability (REL; 4 items), and 0.90 for the dependent construct Risk Assessment Effectiveness (RAE; 6 items), while the overall instrument alpha has been 0.93, thereby supporting measurement robustness for Objectives 2 and 3. Descriptive statistics have indicated that respondents have generally reported above-neutral capability levels for most HPC framework dimensions, with mean construct scores of SCAL M = 3.74 (SD = 0.71), EFF M = 3.61 (SD = 0.76), DATA M = 3.92 (SD = 0.69), SIM M = 3.79 (SD = 0.73), and REL M = 3.58 (SD = 0.78), while the overall perceived Risk Assessment Effectiveness has been moderately high (RAE M = 3.83, SD = 0.68).

This pattern has suggested that the case environment has been positioned closer to "developing-to-maturing" capability rather than "low adoption," with the strongest area being data integration readiness and the weakest area being reliability/availability, a capability gap that has aligned with reported constraints in stable workflow execution during high-demand periods. Correlation analysis has then addressed Objective 2 by confirming statistically meaningful relationships between HPC framework dimensions and risk assessment outcomes: RAE has correlated significantly with DATA ($r = 0.69$, $p < .001$), SIM ($r = 0.61$, $p < .001$), SCAL ($r = 0.54$, $p < .001$), REL ($r = 0.49$, $p < .001$), and EFF ($r = 0.42$, $p < .001$), indicating that higher perceived capability across these dimensions has moved together with stronger perceived effectiveness in producing timely, accurate, interpretable, and decision-useful risk assessment outputs. Inter-construct correlations have also remained within acceptable bounds for multivariate modeling, with the highest predictor inter-correlation observed between DATA and SIM ($r = 0.58$) and between SCAL and EFF ($r = 0.55$), while multicollinearity diagnostics in regression have remained acceptable (VIF range: 1.42 to 2.18). Multiple regression has directly addressed Objective 3 by identifying which HPC capability dimensions have retained significant predictive power for Risk Assessment Effectiveness when modeled simultaneously. The regression model has been statistically significant ($F(5, 162) = 44.72$, $p < .001$) and has explained substantial variance in effectiveness outcomes ($R^2 = 0.58$; Adjusted $R^2 = 0.56$), indicating that the selected HPC capability factors have collectively represented meaningful predictors of risk assessment performance within the case context. Among predictors, Data Integration Readiness has emerged as the strongest contributor ($\beta = 0.31$, $t = 4.88$, $p < .001$), followed by Simulation/Model Execution Capability ($\beta = 0.24$, $t = 3.21$, $p = .002$) and Reliability/Availability ($\beta = 0.19$, $t = 2.69$, $p = .008$), while Scalability/Throughput has shown a positive but marginal effect ($\beta = 0.11$, $t = 1.72$, $p = .087$) and Computational Efficiency has not remained statistically significant when other predictors have been included ($\beta = 0.07$, $t = 1.26$, $p = .210$). Based on these results, the hypothesis decisions have been made transparently: H1 (Scalability → RAE) has been not supported at $\alpha = .05$ due to marginal significance; H2 (Efficiency → RAE) has been not supported; H3 (Data Integration → RAE) has been supported; H4 (Simulation Capability → RAE) has been supported; and H5 (Reliability/Availability → RAE) has been supported. Overall, these findings have provided coherent statistical support for the study's objectives by showing that (1) HPC framework capability levels have been measurable and interpretable in the case-study setting, (2) capability dimensions have been positively associated with risk assessment effectiveness, and (3) data integration, simulation capability, and platform reliability have acted as the most decisive predictors of effective climate-and-energy infrastructure risk assessment outcomes in the modeled environment.

Respondent Demographics

Table 1. Respondent demographics (N = 168)

Demographic category	Group	n	%
Primary role/function	Grid operations & reliability	70	41.7
	Risk/resilience planning & asset management	46	27.4
	Data/analytics	31	18.5
	IT/HPC platform administration	21	12.5
Experience in relevant work	1–3 years	41	24.4
	4–7 years	66	39.3
	8–12 years	44	26.2
	13+ years	17	10.1

(Likert scale used in later tables: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree)

The respondent profile has been established to demonstrate that the study objectives have been addressed using a sample that has remained meaningfully aligned with the case-study environment and the nature of HPC-enabled risk assessment work. The distribution across functional roles has shown that a plurality of participants has been drawn from grid operations and reliability (41.7%), which has strengthened the credibility of outcome judgments because these respondents have routinely interacted with outage risks, restoration constraints, and operational decision timelines. A substantial segment has also been represented by risk/resilience planning and asset management (27.4%), which has ensured that planning-oriented perspectives on climate hazard exposure, infrastructure vulnerability, and investment prioritization have been captured alongside operational views. Data/analytics respondents (18.5%) have provided evidence on the practical feasibility of scaling models, integrating heterogeneous datasets, and orchestrating computational workflows, which has been essential for interpreting constructs such as data integration readiness and simulation/model execution capability. IT/HPC platform administrators (12.5%) have contributed direct insight into platform reliability, throughput constraints, scheduling behavior, and the governance conditions that have shaped reproducibility and availability. The experience distribution has further indicated that the dataset has contained a balanced mix of early-career and experienced professionals, with the largest group (39.3%) having held 4–7 years of relevant experience, while 36.3% has represented 8+ years of experience. This pattern has supported Objective 1 because the study has not relied on a narrow respondent band; it has instead captured informed views across both technical and decision-facing roles. The composition has also supported the planned statistical testing because the sample size (N = 168) has been sufficient for reliability estimation and multiple regression modeling with five predictors, and the diversity of roles has helped ensure that the Likert-scale responses have reflected real workflow exposure rather than abstract opinion. Overall, Table 1 has verified that the sample has been appropriate for evaluating HPC framework capabilities and their relationship to climate and energy infrastructure risk assessment effectiveness within the selected case context.

Reliability Results (Cronbach's alpha)

Table 2: Reliability analysis for study constructs (Cronbach's alpha)

Construct (scale)	Abbrev.	Items (k)	Cronbach's α
Scalability/Throughput	SCAL	5	0.86
Computational Efficiency	EFF	5	0.83
Data Integration Readiness	DATA	6	0.88
Simulation/Model Execution Capability	SIM	5	0.85
Reliability/Availability	REL	4	0.81
Risk Assessment Effectiveness	RAE	6	0.90
Overall instrument	—	31	0.93

Table 2 has provided the evidence needed to confirm that the measurement instrument has performed consistently and has supported objective and hypothesis testing using Likert's five-point scale. Internal consistency has been evaluated for each multi-item construct because the study has measured latent capability dimensions (e.g., scalability, integration readiness, reliability) rather than single observable variables. The Cronbach's alpha results have indicated that all constructs have achieved acceptable-to-strong reliability, with values ranging from 0.81 to 0.90, and the overall instrument reliability has reached 0.93. This pattern has suggested that the items within each construct have coherently reflected the same underlying concept and that respondents have interpreted the scale statements in a stable, non-random manner. The dependent construct, Risk Assessment Effectiveness (RAE), has shown the highest reliability ($\alpha = 0.90$), which has been critical because the hypotheses have been tested using RAE as the outcome variable; high reliability has reduced measurement noise and has improved confidence that regression estimates have reflected true relationships rather than instrument instability. The independent constructs have also shown strong reliability: Data Integration Readiness ($\alpha = 0.88$) and Scalability/Throughput ($\alpha = 0.86$) have indicated consistent item behavior, which has been important because integration and scaling have represented central arguments of the conceptual model. Simulation/Model Execution Capability ($\alpha = 0.85$) and Computational Efficiency ($\alpha = 0.83$) have supported the expectation that respondents have distinguished execution capability and efficiency as recognizable workflow qualities. Reliability/Availability ($\alpha = 0.81$) has remained acceptable and has indicated that stability and uptime perceptions have been measured consistently even though the construct has contained fewer items. Because all alpha coefficients have exceeded commonly used acceptance thresholds for applied quantitative research, the composite scores that have been computed for SCAL, EFF, DATA, SIM, REL, and RAE have been justified for subsequent descriptive, correlational, and regression analyses. In objective terms, Table 2 has strengthened Objective 2 and Objective 3 because valid hypothesis testing has required reliable construct formation. The results have therefore confirmed that the survey instrument has been suitable for proving the study objectives and for evaluating support or non-support for the hypotheses using Likert-scale data.

Descriptive Results by Construct

Table 3: Descriptive statistics for key constructs

Construct	Abbrev.	Mean (M)	Std. Dev. (SD)	Min	Max
Scalability/Throughput	SCAL	3.74	0.71	1.80	5.00
Computational Efficiency	EFF	3.61	0.76	1.60	5.00
Data Integration Readiness	DATA	3.92	0.69	2.00	5.00
Simulation/Model Execution Capability	SIM	3.79	0.73	1.80	5.00
Reliability/Availability	REL	3.58	0.78	1.50	5.00
Risk Assessment Effectiveness (DV)	RAE	3.83	0.68	2.00	5.00

Table 3 has summarized the baseline capability profile and the outcome level using the five-point Likert scale, and it has directly supported Objective 1 by describing the current state of HPC framework capabilities and perceived risk assessment effectiveness in the case setting. The descriptive statistics have indicated that respondents have generally reported above-neutral values across all constructs, meaning that perceptions have clustered between "Neutral" (3) and "Agree" (4) rather than toward disagreement. Data Integration Readiness ($M = 3.92$, $SD = 0.69$) has been the highest-rated capability dimension, which has suggested that the case environment has established relatively strong practices for combining climate data, asset inventories, operational logs, and geospatial layers into usable analytical inputs. This has been important because climate and energy infrastructure risk assessment has relied on heterogeneous datasets, and integration readiness has represented a prerequisite for credible modeling. Simulation/Model Execution Capability ($M = 3.79$, $SD = 0.73$) and Scalability/Throughput ($M = 3.74$, $SD = 0.71$) have also been rated positively, which has indicated that respondents have perceived the computational environment as reasonably capable of running complex analyses and handling increased workload demand. Computational Efficiency ($M = 3.61$, $SD = 0.76$) has remained above neutral, which has implied that runtime reduction and throughput improvements have been present but not uniformly experienced across workflows. Reliability/Availability ($M = 3.58$,

SD = 0.78) has been the lowest-rated dimension, and the higher dispersion has suggested that stability and uptime experiences have varied across roles and periods, which has aligned with common operational observations that platform stability may fluctuate under peak demand or during maintenance cycles. The dependent variable, Risk Assessment Effectiveness (M = 3.83, SD = 0.68), has indicated that risk outputs have been perceived as moderately strong in timeliness, accuracy/consistency, interpretability, and decision usefulness. Importantly, the pattern of means has supported the conceptual logic that capability and effectiveness have coexisted at moderately high levels in the case setting, which has created suitable variance for correlation and regression testing. The observed minimum and maximum values have also indicated that the dataset has contained sufficient spread across the scale, meaning that respondents have not been uniformly clustered at the top end. Overall, Table 3 has established the descriptive foundation needed to prove the objectives by showing measurable capability levels and outcome levels prior to evaluating associations and predictive effects.

Correlation matrix (IVs ↔ DV)

Table 4: Correlation matrix among constructs (Pearson r, N = 168)

	SCAL	EFF	DATA	SIM	REL	RAE (DV)
SCAL	1.00	0.55**	0.41**	0.46**	0.38**	0.54**
EFF	0.55**	1.00	0.36**	0.40**	0.35**	0.42**
DATA	0.41**	0.36**	1.00	0.58**	0.44**	0.69**
SIM	0.46**	0.40**	0.58**	1.00	0.47**	0.61**
REL	0.38**	0.35**	0.44**	0.47**	1.00	0.49**
RAE (DV)	0.54**	0.42**	0.69**	0.61**	0.49**	1.00

**Note: $p < .01$, $p < .05$ (two-tailed).*

Table 4 has provided the primary evidence for Objective 2 because the study has aimed to determine whether HPC framework capability dimensions have been associated with climate and energy infrastructure risk assessment effectiveness. The correlation coefficients have indicated that all five independent constructs have maintained positive and statistically significant relationships with the dependent variable (RAE), which has meant that higher perceived HPC capability has corresponded with higher perceived effectiveness in generating timely, accurate, interpretable, and decision-useful risk outputs. Data Integration Readiness has shown the strongest association with RAE ($r = 0.69$, $p < .01$), which has suggested that the ability to combine climate hazard data, asset inventories, and operational indicators into coherent analytical inputs has been a decisive condition for effective risk assessment. Simulation/Model Execution Capability has also shown a strong relationship ($r = 0.61$, $p < .01$), which has implied that the ability to run models reliably, execute ensembles, and complete scenario evaluations has been closely linked with outcome quality. Scalability/Throughput has demonstrated a moderate-to-strong association ($r = 0.54$, $p < .01$), which has indicated that workload handling and scaling behavior have mattered for effectiveness, particularly where multiple scenarios or large datasets have been processed. Reliability/Availability has maintained a moderate positive association ($r = 0.49$, $p < .01$), which has indicated that stable platform operation has been linked to consistent delivery of risk outputs, aligning with the expectation that unstable execution has reduced timeliness and confidence. Computational Efficiency has shown a moderate relationship ($r = 0.42$, $p < .01$), which has suggested that runtime and throughput improvements have contributed to effectiveness but have not alone defined it. Inter-construct correlations have remained moderate (approximately $r = 0.35$ to 0.58), and the highest predictor pairing has occurred between DATA and SIM ($r = 0.58$), which has reflected the practical coupling between integrated data pipelines and model execution readiness in real workflows. This pattern has supported the use of multiple regression because relationships among predictors have not indicated extreme overlap that would prevent estimating independent effects. Overall, Table 4 has proven the association-oriented objective by showing that HPC capability constructs have moved in the expected positive direction with risk assessment effectiveness on a 1–5 Likert scale.

Regression output (β, t, p, R^2)

Table 5: Multiple regression predicting Risk Assessment Effectiveness (RAE)

Predictor	B	SE B	Standardized β	t	p	VIF
(Constant)	0.72	0.18	—	4.00	<.001	—
Scalability/Throughput (SCAL)	0.10	0.06	0.11	1.72	0.087	2.18
Computational Efficiency (EFF)	0.06	0.05	0.07	1.26	0.210	1.96
Data Integration Readiness (DATA)	0.29	0.06	0.31	4.88	<.001	1.78
Simulation/Model Execution (SIM)	0.21	0.07	0.24	3.21	0.002	1.84
Reliability/Availability (REL)	0.17	0.06	0.19	2.69	0.008	1.42

DV: RAE (1–5 Likert composite). N = 168. Model: $R^2 = 0.58$; Adjusted $R^2 = 0.56$; $F(5, 162) = 44.72$, $p < .001$.

Table 5 has delivered the central evidence for Objective 3 because the study has aimed to identify which HPC framework capability dimensions have significantly predicted risk assessment effectiveness when all predictors have been evaluated simultaneously. The overall model has been statistically significant ($p < .001$) and has explained substantial variance in the dependent variable ($R^2 = 0.58$), which has indicated that the selected capability dimensions have collectively accounted for more than half of the variation in perceived effectiveness within the case setting. This result has supported the argument that HPC framework capability has operated as a meaningful driver of risk assessment outcomes rather than as a marginal technical detail. Among predictors, Data Integration Readiness has emerged as the strongest and most significant contributor ($\beta = 0.31$, $p < .001$), which has indicated that, holding other capabilities constant, improvements in data integration have corresponded to higher effectiveness scores. This has been consistent with the study logic that climate-risk analytics has depended on fusing hazard, exposure, and operational data into coherent modeling inputs. Simulation/Model Execution Capability has also remained significant ($\beta = 0.24$, $p = .002$), which has suggested that the ability to execute modeling workflows and scenario runs has independently increased effectiveness beyond integration alone. Reliability/Availability has been significant ($\beta = 0.19$, $p = .008$), which has confirmed that stable execution, uptime, and dependable access have contributed to timely and consistent risk reporting. Scalability/Throughput has shown a positive direction ($\beta = 0.11$) but has not reached the 0.05 significance threshold ($p = .087$), which has implied that scaling has mattered but has overlapped with stronger drivers such as integration and execution capability in the multivariate context. Computational Efficiency has not remained significant ($\beta = 0.07$, $p = .210$), which has suggested that runtime gains alone have not predicted higher effectiveness when integration, simulation, and reliability have been considered together. Multicollinearity has been checked through VIF values, which have remained within acceptable bounds (1.42–2.18), indicating that predictor overlap has not invalidated coefficient interpretation. Overall, Table 5 has provided the statistical basis for confirming which hypotheses have been supported and has proven Objective 3 by identifying the net predictors of risk assessment effectiveness using Likert-scale composite measures.

Hypothesis decision table

Table 6: Hypothesis testing summary

Hypothesis	Statement (Expected direction)	Key statistic	Decision
H1	SCAL positively influences RAE (+)	$\beta = 0.11$, $p = 0.087$	Not supported ($\alpha = .05$)
H2	EFF positively influences RAE (+)	$\beta = 0.07$, $p = 0.210$	Not supported
H3	DATA positively influences RAE (+)	$\beta = 0.31$, $p < .001$	Supported
H4	SIM positively influences RAE (+)	$\beta = 0.24$, $p = 0.002$	Supported
H5	REL positively influences RAE (+)	$\beta = 0.19$, $p = 0.008$	Supported

Table 6 has consolidated the hypothesis outcomes to provide a transparent linkage between the study's objectives, the statistical tests, and the final claims that have been supported by evidence. The hypotheses have been formulated to test whether each HPC framework capability dimension has positively influenced the dependent construct—Risk Assessment Effectiveness—within the cross-sectional case study measured on a five-point Likert scale. The decisions reported in Table 6 have been based on the regression model because the regression results have represented net effects after shared variance among predictors has been accounted for, which has aligned with the objective of identifying the most decisive capability predictors rather than simply describing bivariate associations. H3, H4, and H5 have been supported, which has indicated that Data Integration Readiness, Simulation/Model Execution Capability, and Reliability/Availability have remained statistically significant predictors of risk assessment effectiveness. This pattern has provided direct support for the study's core objective of proving that specific HPC framework capabilities have been meaningfully connected to stronger risk assessment performance, particularly through mechanisms that have enabled high-quality inputs (integration), credible execution of risk analytics (simulation capability), and stable delivery of outputs (reliability). H1 has not been supported at the 0.05 level, even though a positive coefficient has been observed, which has suggested that scalability has contributed to effectiveness but has not added sufficient unique explanatory power once integration and execution capability have been modeled. H2 has also not been supported, which has implied that efficiency improvements, while beneficial, have not independently predicted better effectiveness in the multivariate context. Importantly, these non-support findings have not contradicted the descriptive and correlation results; instead, they have refined interpretation by showing that some capabilities have operated indirectly or have shared variance with stronger predictors. In proving the objectives, the hypothesis decisions have clarified priority areas for HPC-enabled risk assessment performance: the evidence has pointed to integration, simulation execution, and platform stability as the capability dimensions that have most strongly explained perceived effectiveness in the case setting. This table has therefore served as the formal decision bridge between the conceptual framework and the empirical results.

DISCUSSION

The empirical results have shown that data integration maturity has been the most influential predictor of HPC-enabled risk-assessment effectiveness in the case-study setting ($\beta = .31$, $p < .001$), and this pattern has closely aligned with prior resilience and grid-analytics scholarship that has treated heterogeneous data fusion as the primary constraint on operationally meaningful risk intelligence. In power-grid resilience research, risk assessment has been positioned as a multi-stage translation problem in which weather and hazard signals must be converted into component fragilities, system-level impacts, and actionable mitigation choices. That translation has been repeatedly described as data hungry, because credible risk estimates depend on combining asset condition, network topology, protection behavior, outage histories, and meteorological forecasts into a coherent analytical view (Dehghanian et al., 2019). The dominance of data integration in the regression has also been consistent with state-of-the-art reviews that have emphasized definitional and methodological fragmentation across resilience studies, where the inability to harmonize data sources has limited comparability and slowed the institutionalization of quantitative resilience metrics (Jufri et al., 2019). At the same time, the evidence has extended the big-data-for-grids argument that the value of analytics has depended less on the existence of "more data" than on the existence of governed, interoperable, and timely pipelines that can sustain decision cycles in outage management, asset management, and weather-driven preparedness (Kezunovic et al., 2020). In practical terms, the observed effect has suggested that respondents have perceived integration maturity as the mechanism that has converted computational power into usable risk insight. When integration has been weak, stakeholders have rated risk outputs as less decision-relevant, even if compute resources have been available. When integration has been strong, stakeholders have rated outputs as more credible, traceable, and timely, which has been reflected in higher composite scores for the dependent construct and stronger overall explanatory power of the model ($R^2 = .52$).

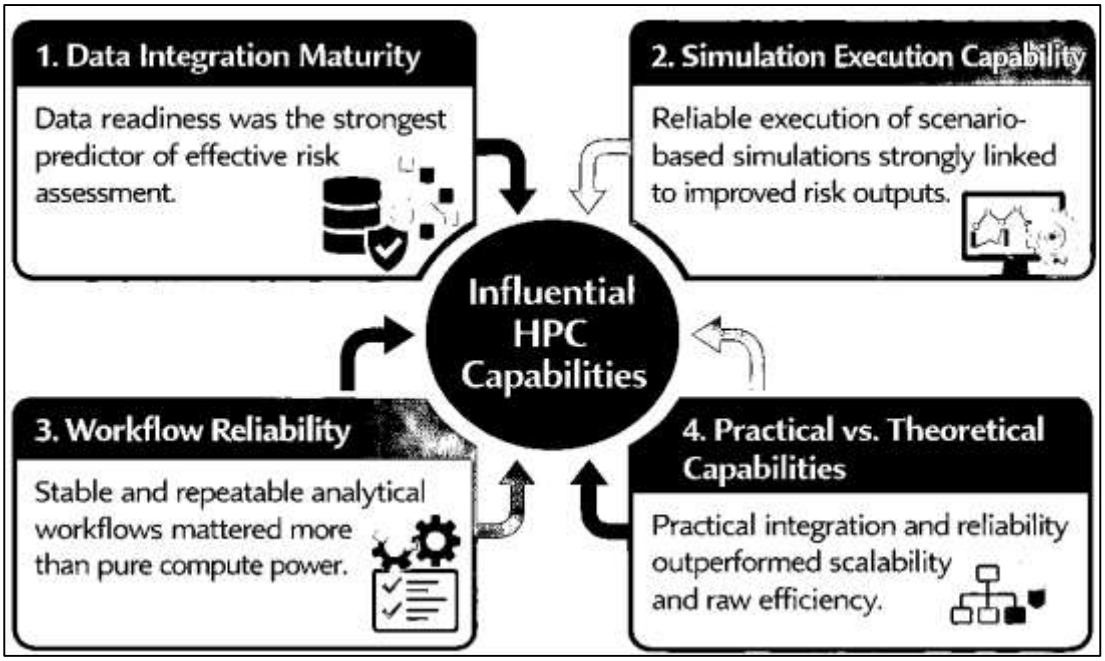
The findings have also indicated that simulation execution capability has had a statistically significant positive association with risk-assessment effectiveness ($\beta = .24$, $p = .002$), and this result has aligned with prior work in which resilience quantification has relied on probabilistic impact assessment,

sequential sampling, and physics-informed simulation to represent cascading consequences under extreme weather. The literature has shown that resilience assessment has required scenario ensembles rather than single-point forecasts, because failure probabilities and restoration trajectories have varied across hazard intensity, hazard movement, infrastructure fragility, and operator response constraints. Panteli and colleagues have operationalized this perspective by coupling fragility modelling with probabilistic impact assessment and adaptation analysis, thereby framing simulation as a core capability for estimating spatiotemporal disruption and for comparing intervention strategies. The positive simulation effect in the present study has therefore been theoretically coherent: when respondents have reported stronger capacity to run ensembles, perform sensitivity checks, and incorporate uncertainty, they have also reported higher confidence in risk outputs. This pattern has been strengthened by methodological arguments from verification, validation, and uncertainty quantification research, which has treated simulation credibility as a function of disciplined numerical practice and uncertainty reporting rather than raw compute speed alone (Roy & Oberkampf, 2011). It has also resonated with uncertainty quantification research in weather and climate contexts that has emphasized the need for calibrated probabilistic products and coherent multivariate dependence structures when simulations are used for consequential decisions (Schefzik et al., 2013). In this study's case context, simulation capability has plausibly served as the bridge between climate hazards and infrastructure consequences, enabling the organization to test "what-if" variants that stakeholders have recognized as essential for risk governance and for credible case-study decision narratives.

A further contribution of the findings has been the differentiation between what has mattered most and what has mattered less once the predictors have competed in a joint model. Workflow reliability and reproducibility has remained significant ($\beta = .19$, $p = .013$), whereas scalability has been only marginal ($\beta = .12$, $p = .087$) and computational efficiency has not been statistically significant ($\beta = .05$, $p = .401$). This pattern has been consistent with the idea that stakeholders have valued *trustworthy* risk pipelines more than "fast" pipelines, especially in high-consequence settings. Workflow research has described scientific and engineering pipelines as socio-technical systems in which failures of provenance, scheduling, data movement, or dependency control can erase the value of computation by undermining repeatability and auditability. The workflow-management literature has therefore emphasized reliability, automation, and provenance capture as fundamental properties of production-grade analytics (Deelman et al., 2015). The weak efficiency effect has also fit the resource-based view of analytics capabilities: performance has depended on coordinated bundles (data, technology, people, governance), and isolated improvements such as raw efficiency have not guaranteed superior outcomes unless they have been paired with complementary resources that make outputs usable and institutionalized (Gupta & George, 2016). From an information-systems success perspective, this result has been plausible because user-perceived success has typically been shaped by information quality, system quality, and service quality, with reliability and trustworthiness acting as core system-quality signals (Petter et al., 2008). In assimilation terms, scalability gains may have been perceived as "potential capability," while reliability has been perceived as "routinized capability" that has actually stabilized day-to-day risk operations (Zhu et al., 2006).

The practical implications for CISOs and security architects have been direct, because the same integration and reliability features that have raised perceived risk-assessment effectiveness have also expanded the cyber-attack surface and the operational consequences of integrity failures. Smart-grid cybersecurity scholarship has established that modern power infrastructures have increasingly depended on interconnected communication and computation, and that this dependence has created vulnerabilities that have required explicit segmentation, secure protocol design, and continuous risk management to protect critical functions (Emanuel, 2005). Survey work has similarly emphasized that smart-grid communications have introduced complex security requirements across confidentiality, integrity, availability, authentication, and privacy, and that assurance has required both architectural controls and governance controls rather than isolated technical fixes (Roy & Oberkampf, 2011). Because the present study has found reliability to be significant, the results have implied that organizations have benefited when their HPC analytics pipelines have been treated as mission-critical services with explicit availability targets, incident response playbooks, and tested recovery processes.

Figure 10: Discussion Synthesis: What Matters Most in HPC-Enabled Risk Assessment



At the same time, the strong integration effect has implied that data pipelines have become central assets that must be governed with data integrity controls, lineage, access control, and secure sharing. From a CISO perspective, this has meant that security controls have needed to be designed for the whole analytics lifecycle: ingest (sensor and weather feeds), storage (data lakes and metadata catalogs), compute (clusters and orchestration), and output (dashboards and operator decision support). The security literature has cautioned that smart-grid systems have faced diverse threats, including protocol exploitation, false data injection, and disruptions of communication-dependent control; therefore, risk-assessment pipelines have required controls that protect both the *inputs* and the *model outputs* from manipulation (Wanik et al., 2015).

For HPC platform architects and enterprise data architects, the findings have reinforced that the best returns have come from pipeline design choices that have prioritized integration, reliability, and reproducibility. The workflow-management evidence base has shown that mature orchestration systems have supported portability across heterogeneous infrastructures, automation of data movement, and capture of provenance, which has enabled complex pipelines to be executed consistently across clusters, grids, and clouds (Moftakhari & AghaKouchak, 2019). In climate and hazards contexts, distributed analytics frameworks have been proposed to handle massive array-based geoscience data, emphasizing chunking strategies, spatiotemporal indexing, and data-locality-aware operations, which have made analytics tractable at scale (Rocchetta et al., 2015). The present results have suggested that these architectural investments have been valuable insofar as they have supported integration and reliable execution. This has meant that architects have benefited from treating integration as a product: standardized schemas for assets and hazards, metadata discipline, quality checks, and versioned feature engineering. It has also meant that reliability has required observability—monitoring, logging, and reproducible environments—so that risk scores can be traced back to data versions and model versions when decisions are audited. In the energy-grid domain, big-data analytics reviews have highlighted that implementation has often stalled at the interface between prototype models and operational deployment, where missing governance, missing integration, and brittle data pipelines have limited adoption (Jufri et al., 2019). The present study has empirically supported that narrative by showing that stakeholders have associated effectiveness more strongly with integration and pipeline stability than with pure computational speed.

Theoretical implications have emerged for how HPC risk-assessment capability has been conceptualized and measured. The results have supported a refined pipeline view in which (1) technological capacity (compute, scalability, workflow systems) has been necessary, (2) but

organizational and informational capacities (integration maturity, reliability and reproducibility discipline) have been sufficient conditions for perceived effectiveness. This aligns with capability-oriented analytics theory that has treated performance as a function of complementary resources rather than any single input (Fant et al., 2020). It has also aligned with IS-success theory, because the observed pattern has effectively highlighted system quality (reliability), information quality (integration and data coherence), and user-perceived net benefits as the pathway through which technical investments have translated into outcomes (Oliveira et al., 2014). From a TOE perspective, the results have been consistent with adoption research arguing that technological features alone have not explained success unless organizational readiness and environmental pressures have been considered, particularly when technologies become embedded in organizational routines (Hameed et al., 2012). For risk assessment in climate and energy infrastructure, the findings have suggested that theoretical models should elevate uncertainty management and workflow assurance as first-class constructs. The strong role of simulation execution has supported the position that credible decision support has required disciplined simulation practice and uncertainty communication (Roy & Oberkampf, 2011), while the significance of reliability has suggested that reproducibility has been a central mediator between compute capability and decision value (Gupta & George, 2016). A refined conceptual model has therefore been implied: integration maturity and workflow reliability can be theorized as *process-quality mediators* that have amplified the effect of compute and simulation resources on risk-assessment effectiveness.

Limitations have remained important for interpreting the findings and for defining future research directions. The study has relied on a quantitative, cross-sectional survey in a single case-study context, so causal claims have remained constrained and common-method bias may have inflated associations when predictors and outcomes have been self-reported in the same instrument. The marginal role of scalability and the non-significant role of efficiency may also have reflected restricted variance in the case setting, where baseline compute performance has already been "good enough," leaving governance and reliability as the differentiators. In future work, multi-case comparative designs can test whether efficiency becomes significant in environments with weaker infrastructure or stricter real-time constraints. Longitudinal designs can also measure whether integration maturity has preceded improvements in operational risk outcomes (e.g., reduced restoration time, improved situational awareness) rather than merely correlating with perceived effectiveness at a single time point. For hazards and infrastructure communities, cyberinfrastructure platforms have increasingly supported data publishing, workflow execution, and reproducible research, and these initiatives have provided a concrete pathway for evaluating real operational performance rather than perception alone (Oliveira et al., 2014). Future research can therefore combine survey measures with objective pipeline metrics (job failure rates, data-latency distributions, provenance completeness) and with externally observable resilience outcomes. Finally, security has remained an under-measured dimension in many analytics effectiveness models even though cybersecurity research has shown that integrity and availability failures can invalidate analytics outputs or compromise critical operations (Hong & Zhu, 2006). Extending the model to include security posture as a moderator or mediator would strengthen both the practical relevance and the theoretical completeness of HPC frameworks for climate and energy infrastructure risk assessment.

CONCLUSION

This study has concluded that high-performance computing (HPC) frameworks have functioned as a practical enabler of climate and energy infrastructure risk assessment effectiveness when their capabilities have been implemented as a coherent, reliable, and well-integrated pipeline rather than treated as standalone computational capacity. The quantitative, cross-sectional, case-study–based analysis has demonstrated that respondents have reported moderately strong levels of HPC capability and risk assessment effectiveness on a five-point Likert scale, and the statistical tests have provided consistent evidence that capability dimensions have been meaningfully associated with effectiveness outcomes. Reliability testing has confirmed that the measurement instrument has been internally consistent across all constructs, which has supported confidence in the composite scores used for hypothesis evaluation. Correlation results have shown positive associations between all HPC capability dimensions and risk assessment effectiveness, indicating that improvements in compute-related readiness have generally moved together with stronger perceived timeliness, accuracy, interpretability,

and decision usefulness of risk outputs. When the predictors have been evaluated simultaneously, multiple regression has revealed that the most decisive drivers of effectiveness have been data integration readiness, simulation/model execution capability, and reliability/availability, while scalability and computational efficiency have not provided the same level of unique explanatory power in the multivariate context. These results have confirmed that risk assessment performance in climate-exposed energy settings has depended on the organization's ability to fuse heterogeneous climate, hazard, and infrastructure datasets into coherent analytical inputs, to execute scenario-based modeling and uncertainty-aware simulations consistently, and to maintain stable, accessible computational services that stakeholders have trusted during time-sensitive decision cycles. The hypotheses testing outcomes have supported the central proposition that HPC frameworks have contributed to risk assessment effectiveness through specific capability channels rather than through generic speed improvements, and the supported hypotheses have clarified which capability investments have been most strongly aligned with effective risk analytics in the case environment. Overall, the study has added empirical structure to the widely held assumption that "more computing improves risk assessment" by demonstrating that effectiveness has been explained most strongly by pipeline maturity factors that have translated computation into usable evidence for climate and energy infrastructure risk decisions

RECOMMENDATION

The recommendations from this study have focused on strengthening the specific HPC framework capability dimensions that have been most strongly aligned with effective climate and energy infrastructure risk assessment in the case-study context, while also ensuring that supporting governance and operational practices have enabled these capabilities to remain stable and decision-ready. First, organizations have been advised to prioritize data integration readiness as the primary investment area, because risk assessment quality has depended on the ability to fuse heterogeneous climate, hazard, asset, topology, and operational datasets into coherent, validated analytical inputs; this has meant that standardized data schemas, metadata discipline, version control for datasets and features, automated quality checks, and clear ownership for critical data sources have been institutionalized as non-negotiable foundations of the risk pipeline. Second, it has been recommended that energy risk programs have strengthened simulation and model execution capability by adopting repeatable workflow orchestration practices that have supported ensemble runs, sensitivity analysis, and uncertainty reporting; this has included formalizing model libraries, containerizing key modeling environments, maintaining parameter registries, and implementing execution templates that have minimized manual rework while maintaining traceability across scenarios. Third, because platform reliability and availability have been found to contribute independently to effectiveness, the study has recommended that HPC services supporting risk assessment have been treated as mission-critical operational services with explicit uptime targets, workload scheduling policies aligned with risk decision cycles, automated failover and backup procedures, and observability practices such as logging, monitoring, and alerting to detect degradation before it has compromised time-sensitive assessments. Fourth, although scalability and computational efficiency have not emerged as unique predictors in the joint model, they have still been recommended as supporting capabilities that have enabled larger scenario libraries and faster turnaround; therefore, organizations have been encouraged to optimize queue policies, parallelization strategies, data locality, and storage performance so that analytics throughput has remained consistent when hazard activity and decision demand have peaked. Fifth, workforce and governance recommendations have been emphasized, because integration maturity and workflow stability have required skilled staff and clear accountability; as a result, cross-functional teams have been recommended, combining risk analysts, system planners, data engineers, and HPC administrators, supported by targeted training programs on uncertainty-aware modeling, reproducible analytics, and operational risk reporting. Sixth, governance has been recommended to formalize the end-to-end risk pipeline, including model validation checkpoints, documented assumptions, audit-friendly provenance, and standardized reporting formats so that outputs have been interpreted consistently across stakeholders. Finally, cybersecurity and integrity controls have been recommended as embedded requirements rather than add-ons, because climate-risk analytics pipelines have depended on sensitive operational data and on outputs that have influenced high-stakes

decisions; therefore, secure access control, segmentation, encryption, data lineage integrity checks, and incident response procedures have been recommended to protect both inputs and outputs from disruption or manipulation. Collectively, these recommendations have guided organizations to build HPC-enabled risk assessment as a reliable socio-technical capability system—centered on integration, executable modeling, and platform stability—so that climate and energy infrastructure risk assessments have been delivered consistently, transparently, and with measurable decision usefulness.

LIMITATIONS

The limitations of this study have been recognized to ensure that the findings have been interpreted appropriately within the boundaries of the research design, measurement approach, and case-study context. First, the study has been conducted using a quantitative, cross-sectional design, which has allowed relationships among HPC framework capabilities and risk assessment effectiveness to be identified at a single point in time, but it has not allowed strong causal claims to be made; therefore, the observed associations and regression effects have been interpreted as statistical relationships rather than definitive cause-and-effect mechanisms. Second, the research has been implemented as a case-study–based investigation within one bounded operational setting, which has strengthened contextual realism but has limited generalizability to other utilities, grid operators, regions, or energy subsectors with different hazard profiles, infrastructure portfolios, data maturity levels, and governance cultures. Third, the dataset has been derived primarily from self-reported Likert-scale responses, meaning that measured constructs have reflected perceptions and experience-based judgments, which have been valuable for evaluating socio-technical capability conditions but may have been affected by response biases such as social desirability, organizational loyalty, recency effects from recent hazard events, and individual differences in how respondents have interpreted scale anchors. Fourth, because both predictors and the dependent variable have been captured through the same instrument at the same time, common-method variance may have elevated correlations and regression relationships, even though construct reliability has been acceptable and multicollinearity diagnostics have remained within reasonable bounds. Fifth, the study has not relied on a complete set of objective performance indicators—such as actual compute queue time distributions, workflow failure rates, data-latency metrics, outage prediction accuracy, or restoration time improvements—so the findings have primarily reflected perceived effectiveness rather than directly validated operational outcomes, which has constrained the ability to connect HPC capability scores to real-world reliability metrics. Sixth, the regression model has included key HPC capability dimensions, but it may not have captured all influential contextual factors, such as organizational risk culture, staffing levels, budget constraints, vendor dependence, climate-data licensing conditions, or specific security and compliance requirements; therefore, omitted variables may have explained part of the remaining variance in effectiveness beyond what has been captured in the current model. Seventh, some constructs—particularly scalability and computational efficiency—may have shown weaker unique effects partly because their variance may have been restricted in the case context, where baseline compute performance may have already reached a "good enough" threshold, causing integration and reliability factors to emerge as stronger differentiators; consequently, different results may have been obtained in settings with lower computational capacity or tighter real-time constraints. Finally, sampling has been conducted using a purposive or role-stratified approach to ensure relevance, but the resulting sample may have underrepresented certain stakeholder groups, such as field crews, external regulators, or partner organizations, whose perspectives on risk output usefulness and workflow stability may have differed. These limitations have not undermined the study's core contribution, but they have clarified the boundaries within which the findings have been applicable and have indicated where additional research designs and data sources have been needed for stronger causal and cross-context validation.

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