System-Level Risk Modeling for Critical Infrastructure in Data-Limited Regions

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***Abstract*—Critical infrastructure systems face evolving environmental and socioeconomic pressures, and many fast-developing regions lack reliable, timely data on the condition and location of their distributed system assets. These limitations hinder the assessment of asset functionalities, interdependencies, and risk of disruption. This paper presents a system-level framework for addressing risk under data scarcity by integrating physical-asset information with complementary population, economic, hydrologic, and other datasets. The method applies multi-criteria ordering, scenario-specific factor weighting, and an order-based risk measure to evaluate how infrastructure priorities are influenced by disruptions. By comparing baseline and scenario-adjusted system orders, the framework identifies assets likely to become more vulnerable or more critical over time. The approach is demonstrated for the case of the electrical transmission network of Libya, illustrating how the framework can guide risk-informed planning where comprehensive infrastructure inventories are unavailable.**

***Keywords*—risk analysis, systems engineering, decision-making, multi-criteria analysis, geographic information system (GIS), CMIP6**

I. Introduction

Critical water and energy infrastructure systems face escalating risks driven by aging assets, lack of maintenance, and increasing environmental, social, and economic pressures [1], [2]. These challenges are especially acute in data-limited settings, where asset information is often incomplete, outdated, or inconsistently documented. Such limitations constrain the ability to characterize system interdependencies and complicate risk-informed planning for tightly connected water-energy systems. Because disruptions in one sector can cascade through the other, a systems-level perspective remains essential even when asset data are sparse [1], [3].

Reliable and comprehensive asset data are essential for identifying critical nodes, single points of failure, and opportunities to improve resilience. Yet many resource-constrained or conflict-affected regions lack complete and validated infrastructure datasets describing the location, condition, or functionality of their physical assets. For example, persistent information gaps remain in Libya, where prolonged instability and water insecurity complicate long-term infrastructure planning [4].

Traditional risk assessment and decision-support methods for critical infrastructure typically depend on detailed, validated datasets to support probabilistic assessment [5], [6], making them difficult to apply in contexts characterized by partial or missing information. There is therefore a need for a system risk framework that can integrate heterogenous and incomplete infrastructure data, quantify system vulnerability, and support decision-making and prioritization of infrastructure investments. This work presents methods for assessing system-level risk for critical water and energy infrastructure in data-limited regions. Rather than relying on partial or inaccurate asset inventories, the approach uses limited physical-asset data drawn from the literature and compiled into a geographic information system (GIS) database to infer geographic interdependencies. These asset layers are complemented with traditional demographic and economic datasets, as well as state-of-the-art hydrologic projections to construct the most complete representation of system context possible. Building on this data foundation, a system-order tool ranks assets using physical, environmental, economic, and demographic performance indicators and evaluates the disruptiveness of several projected futures. This work advances risk assessment and system prioritization for infrastructure systems characterized by limited data availability and uncertain future conditions.

II. Background and Literature Review

Water and energy systems are deeply interconnected, a relationship widely known as the “water-energy nexus.” A central challenge at this nexus is efficiently balancing water and energy resources to meet population needs [7]. The energy sector depends heavily on water for fuel extraction, refining, and thermoelectric cooling, while water distribution, treatment, pumping, and desalination require substantial energy resources [7], [8], [9]. This interdependence becomes most visible when either resource is scarce, limiting the other's reliability [8]. For example, coastal regions facing freshwater shortages may rely on desalination, which can require up to 100 times more energy than conventional treatment [7], [8], [9]. Projected environmental shifts, such as temperature variability and sea-level rise are expected to intensify pressures [8], underscoring the need for integrated planning.

Water and energy challenges are especially pronounced in Southwest Asia and North Africa (SWANA), a region characterized by chronic water scarcity and heavy dependence on energy production for economic development [9]. Energy production from fossil fuels requires substantial water resources. Limited renewable water supply leaves many countries in the region relying on groundwater withdrawal or desalination to meet growing residential and industrial demands, making water-energy trade-offs central to long-term resilience [9]. The authors of [10] addressed water security risks in SWANA, emphasizing that risk emerges from the interaction of environmental constraints and institutional capacity. They introduced a dual-axis framework that considers regional water security as the joint performance of natural water availability and state investment in infrastructure. Applied to Libya, the results revealed widespread and significant vulnerabilities, with none of the over 20 districts studied achieving even half of the potential water security score. These findings motivate this paper's contribution: a system-level risk assessment framework that integrates environmental and institutional dimensions of critical infrastructure risk to identify and compare the most disruptive scenarios affecting water, energy, and other critical infrastructure systems and assets.

Risk is often defined in traditional frameworks as a function of likelihood, consequences, and vulnerability [5], [6]. While these approaches can effectively estimate the magnitude of predictable or known threats, they may fall short of capturing system-wide impacts or the differing ways that system components respond to shocks. As future conditions become increasingly uncertain due to environmental variability, geopolitical instability, and shifting demographic pressures, system-level approaches offer a more comprehensive basis for decision-making. A systems view extends beyond individual physical assets, considering context, resources, network topology, and the users that depend on their services [11]. In data-limited regions, contextual and complementary datasets become especially important for inferring interdependencies and risk exposure.

The authors of [11] proposed a six-step process for system-level risk assessment of climate-threatened critical infrastructure systems: 1) analyze climate variables; 2) characterize system assets; 3) assess network-level effects; 4) identify cascading impacts; 5) evaluate service-loss risk; and 6) implement adaptation measures. The methods introduced here directly address steps 1–3 by leveraging limited physical-asset data alongside broader environmental and socioeconomic datasets. The results lay the groundwork for the deeper analyses proposed by steps 4–6. Similarly, in the context of disaster recovery and emergency management, [12] proposed a four-phase approach: identifying stakeholder needs, identifying system assets, collecting relevant data, and assessing the resilience of assets and systems. In [13], the authors reviewed data needs for risk analysis across sectors and find that access to high-quality data remains a major barrier. Semi-quantitative models were commonly used to bridge this gap, with ordinal or categorical data applied where numerical data were incomplete or unavailable. The studies reviewed employed diverse data sources, including public datasets, satellite imagery, and expert judgement, highlighting the importance of synthesizing multiple information streams, a strategy adopted in this paper [13].

In this work, system risk is defined as the disruption of system order. Systems can be described by rankings of their components against some measure; for example, districts ordered by population count or power plants ranked by generation capacity. When a disruption occurs, whether a natural hazard, cyberattack, or physical failure, this order may shift. For example, a water treatment plant serving a major hospital may become significantly more critical after a large-scale incident. Risk can then be quantified as the magnitude of change in system order. This definition can be considered complementary to more traditional definitions of risk (i.e., likelihood, vulnerability, and consequence), with the magnitude of system order disruption representing aspects of both vulnerability and consequence. Low-risk scenarios leave priorities largely unchanged, while high-risk scenarios cause substantial reordering. This order-based risk framework has been applied to energy and transportation systems in Iraq [14], [15], [16], energy and water systems in Turkmenistan [17], [18], and regional infrastructure networks in the United States [19], [20]. This work extends these methods to regions where asset-location and operability data are heterogenous and incomplete, using physical-asset data compiled from the literature and supplementing with hydrologic and socioeconomic layers to support comprehensive system-level risk assessment.

This paper advances system-level risk assessment for data-scarce environments, particularly in the context of interdependent critical infrastructure systems. The framework defines system risk as disruption to system order and integrates heterogeneous infrastructure, environmental, and socioeconomic datasets. Scenario analysis compares baseline system orders to several potential future scenarios to identify the most disruptive scenarios and assets most vulnerable or robust to disruption. These outcomes produce actionable priorities for decision-makers facing uncertainty.

III. Methods

This paper introduces a system-level risk assessment that is suited to regions with limited information on the locations and conditions of infrastructure system assets and uncertainty in emerging and future conditions. The method consists of two main parts: asset data collection and a scenario-based system order tool. Sections III.A and III.B describe the data collection process, including the integration of limited physical-asset data with socioeconomic and hydrologic datasets. Section III.C presents the decision-support tool, rooted in the concept of system order, that prioritizes assets based on key indicators and evaluates the disruptiveness of potential future scenarios.

A. Infrastructure Data Collection and Geopspatial Mapping

A literature review of over 50 publications of academic researchers, government agencies, and international aid organizations was conducted to identify geospatially-tagged infrastructure assets, population centers, and energy and water resources of Libya. In total, 19 .shp files, each containing GIS data for a particular system/resource, were generated and uploaded as layers in ArcGIS for visualization. Figure 1 shows a sample of identified map layers including populated towns, airports, road network, electric network nodes and transmission lines, and water supply and treatment plants. A key outcome of the GIS mapping was the ability to identify or infer geographic interdependencies between infrastructure systems, e.g., wastewater facilities within five kilometers of population centers and other critical infrastructure facilities.

B. Hydrology Data Collection and Projections

Uncertain future environmental conditions present a major challenge for infrastructure planning at the water-energy nexus. Hydrologic projections from General Circulation Models (GCMs) help address this challenge by providing contextual information about potential future conditions that may not be evident from current observations. When combined with available infrastructure data, these projections support a more holistic forward-looking risk assessment. The Coupled Model Intercomparison Project Phase 6 (CMIP6) compares and evaluates GCMs of historic and future projected hydrologic conditions [21]. A key feature of the CMIP6 is the consideration of Shared Socioeconomic Pathways (SSPs), which represent different hypotheses of future global development pathways. In this work, two contrasting SSPs were considered: *SSP126,* representing a sustainable development trajectory, and *SSP585*, representing a fossil-fueled, higher emissions pathway. Average annual precipitation and average annual air temperature projections for 2050–2055 were collected from two CMIP6 models: *BCC-CSM2-MR* from the China Meteorological Administration [22] and *IPSL-CM6A-LR* from the Institut Pierre-Simon Laplace [23]. These models project long-term regional environmental conditions relevant to infrastructure exposure. Historical data were compiled for the most recent five full years and averaged to provide a baseline representation of current conditions.

C. System Order and Decision-Support Tool

The decision-support tool adopts a multi-criteria approach similar to that applied in [16]. Risk is defined as the influence of scenarios on system priorities, focusing the methodology on the concept of system order and system order disruption. The model prioritizes the components of the system of analysis using a multi-criteria scoring system that incorporates physical, economic, demographic, environmental, and resource metrics, alongside projected future conditions. These metrics are chosen to represent the key characteristics of a well-functioning infrastructure system, with each metric assigned a numerical weight to reflect its relative importance. These weights are user-defined, with input from stakeholders and published national development goals. The inclusion of metrics beyond simple measures of the physical infrastructure allow the tool to operate effectively even when infrastructure asset data are incomplete, using complementary datasets to fill gaps.

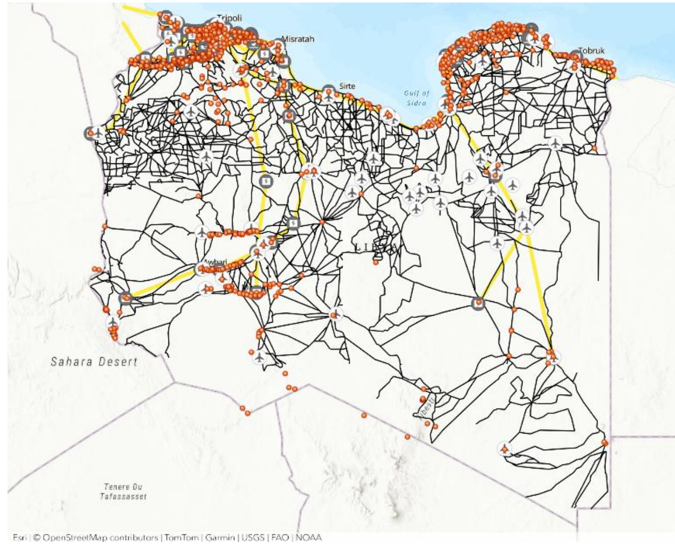

Fig. 1. Sample of infrastrucutre and socioeconomic data layers collected in GIS database

System components are the individual assets or technologies within the larger system. System components are scored against the system metrics to quantify their value within the system or their achievement of stakeholder goals. For example, when assessing system components against a population metric, an asset serving a high-population district would receive a higher score than a similar asset serving a low-population district.

The components are ranked according to their metric scores, establishing a baseline system order. The scoring and ranking process is then repeated for multiple hypothesized scenarios. Comparing these scenario-adjusted system orders to the baseline system order identifies the most disruptive futures and highlights infrastructure investment opportunities that may be particularly vulnerable or resilient to stressors.

Formally, the framework defines:

- System metrics: $M = \{m_1, m_2, \dots, m_p\}$
- System components: $X = \{x_1, x_2, \dots, x_n\}$
- Scenarios: $S = \{s_0, s_1, s_2, \dots, s_q\}$, where s_0 represents the baseline
- Scenario-specific metric weights: w_{jk} for metric $m_j \in M$ and scenario $s_k \in S$
- Component-metric scores: y_{ijk} for component $x_i \in X$, metric $m_j \in M$, and scenario $s_k \in S$

The total score of component x_i under scenario s_k is defined as a weighted sum of its component-metric scores as shown in Eq. 1:

$$V(x_i)_k = \sum_{j=1}^{p} w_{jk}\, y_{ijk} \qquad \forall i \in X,\ k \in S \tag{1}$$

The system components are ranked such that if $V(x_i)_k > V(x_j)_k$ then x_i is ranked higher than x_j. To quantify scenario disruptiveness, the sum of squared differences between the baseline ranking and each scenario's adjusted ranking is calculated. This provides a scenario-level overall measure of how strongly future conditions may affect system priorities.

IV. Demonstration

Libya is one of the world's most water-stressed nations, ranked 11th most water-stressed globally by the World Resources Institute [24]. The country's land area is dominated by the Sahara Desert and population centers are concentrated along the Mediterranean coast. Renewable water resources are scarce, and per capita consumption exceeds regional and global averages [25], [26]. To meet national water demand, Libya relies heavily on non-renewable groundwater, particularly through the Great Man-Made River (GMMR), a vast pipeline network transporting water from the Nubian Sandstone Aquifer System [25]. Population growth is expected to increase pressure on these already limited freshwater resources [26].

Political instability has also greatly impacted water and energy infrastructure systems. Years of fragmented governance have led to mismanagement and deferred maintenance. Conflict has disrupted water infrastructure operations and damaged GMMR pipeline networks, while also hindering data collection and reporting capacities [26], [27], [28]. These environmental and political pressures create a complex landscape for risk assessment, characterized by interdependence, uncertainty, and limited data availability. This demonstration focuses on the electrical transmission infrastructure of Libya, a critical backbone of the energy system that also plays a crucial role in water security.

Table I describes the seven system metrics ($M = \{m_1, m_2, \dots, m_7\}$) assessed to reflect the need to balance energy security, water security, environmental exposure, and long-term socioeconomic development. These metrics represent contextual factors that influence the importance and resilience of transmission lines within the broader water-energy nexus. Metrics include air temperature and annual precipitation as measures of environmental suitability, alongside traditional development goals such as economic development, population health, and water security.

Twenty-five transmission lines (system components) ($X = \{x_1, x_2, \dots, x_{25}\}$) were assessed. Of these, 21 lines are existing (although not necessarily currently operational) and four represent planned future lines. Twenty-two of the lines operate entirely within Libya, while three connect to neighboring countries (one to Egypt and two to Tunisia).

Beyond the baseline, four projection scenarios were formed by combining the two climate models and the two SSPs: *BCC-CSM2-MR SSP126*, *BCC-CSM2-MR SSP585*, *IPSL-CM6A-LR SSP126*, and *IPSL-CM6A-LR SSP585*. Using two models allowed testing whether different representations of climate sensitivity led to different system-order and scenario disruptiveness outcomes.

Each transmission line was scored against each metric. Scores were defined from $\{0, 1/3, 2/3, 1\}$, with 0 representing the lowest score and 1 representing the highest score. Five complete sets of scores were produced: one baseline and one for each CMIP6 scenario.

TABLE I. Metrics for Evaluation of Infrastructure System

Index	System Metric	Definition
m_1	Water security	Water supply and treatment infrastructure within 5km
m_2	Energy security	Power generation sources within 5km
m_3	Environmental health	Proximity to less carbon-intensive generation sources
m_4	Economic development	GDP per capita (2023) of district where component is located
m_5	Population	Population of district where component is located
m_6	Air temperature	District average annual air temperature from historical observations and CMIP6 projections
m_7	Precipitation	District average annual precipitation from historical observations and CMIP6 projections

For metrics based on physical infrastructure or socioeconomic data ($m_1 - m_5$), raw values for each component were collected and grouped into four classes using the Jenks natural breaks algorithm. The resulting class determined each component's score for each metric from $\{0, 1/3, 2/3, 1\}$. The Jenks natural breaks algorithm is widely used in geographic data analysis and identifies meaningful clusters in skewed data distributions such as those in this case [29]. The algorithm minimizes within-class variance while maximizing between-class separation, producing stable and interpretable classes [30]. This allows components with similar raw values to be grouped together while preserving meaningful differences between groups of system components. For example, for m_1—*Water security*, the raw count of water supply and treatment infrastructure assets within 5km of each system component was collected using ArcGIS, and the components were grouped into four classes based on these raw counts. The scores for these metrics were not re-evaluated for the CMIP6 scenarios as the scenarios project only future hydrologic and environmental conditions, and not specific values for socioeconomic shifts.

For the environmental metrics, m_6—*Air temperature* and m_7—*Annual precipitation*, values were first normalized to a 0–100 scale using min-max normalization. The components were then grouped into four classes and assigned a score from $\{0, 1/3, 2/3, 1\}$ according to their quartile. Note that for m_6—*Air temperature*, the scale was reversed so that *lower* temperatures receive higher scores, reflecting better environmental suitability. Because of the continuous and non-clustered values of the historical observations and CMIP6 projections, min-max scaling with quartile classes provided the most consistent and interpretive groupings.

Table II shows the metric importance scores and corresponding numerical weights assigned to each metric in each scenario. These weights reflect how the relative importance of system metrics evolves under different future conditions. In the s_0—*Baseline* scenario, m_1—*Water security* and m_4—*Economic Development* were assigned high priority weights, while environmental metrics (m_6, m_7) were assigned lower weights. For the SSP126 scenarios (s_1, s_3), environmental metrics are given medium weight and m_3—*Environmental health* and m_5—*Population* become highly weighted. For SSP585 scenarios (s_2, s_4), environmental metrics (m_6, m_7) and m_2—*Energy security* were given highest importance, reflecting heightened climate stress.

The overall component scores for the baseline and each CMIP6 scenario were calculated as in Eq. 1, determining five system orders. Figure 2 visualizes the system orders including the baseline rank (black bar), highest rank (blue bar) and lowest rank (red bar) for each system component. Components with shorter bars experienced the least disruption in rank across the scenarios, while those with longer bars experienced greater variability in rank between scenarios.

TABLE II. IMPORTANCE ASSESSMENT AND WEIGHTS FOR METRICS ASSESSING INFRASTRUCTURE SYSTEM RISK

System Metric	s_0—Baseline	s_1—BCC-CSM2-MR SSP126	s_2—BCC-CSM2-MR SSP585	s_3—IPSL-CM6A-LR SSP126	s_4—IPSL-CM6A-LR SSP585
m_1—Water security	high = 6	high = 6	high = 6	high = 6	high = 6
m_2—Energy security	medium = 3	medium = 3	high = 6	medium = 3	high = 6
m_3—Environmental health	low = 1	high = 6	low = 1	high = 6	low = 1
m_4—Economic development	high = 6	high = 6	medium = 3	high = 6	medium = 3
m_5—Population	medium = 3	high = 6	high = 6	high = 6	high = 6
m_6—Air temperature	low = 1	medium = 3	high = 6	medium = 3	high = 6
m_7—Precipitation	low = 1	medium = 3	high = 6	medium = 3	high = 6

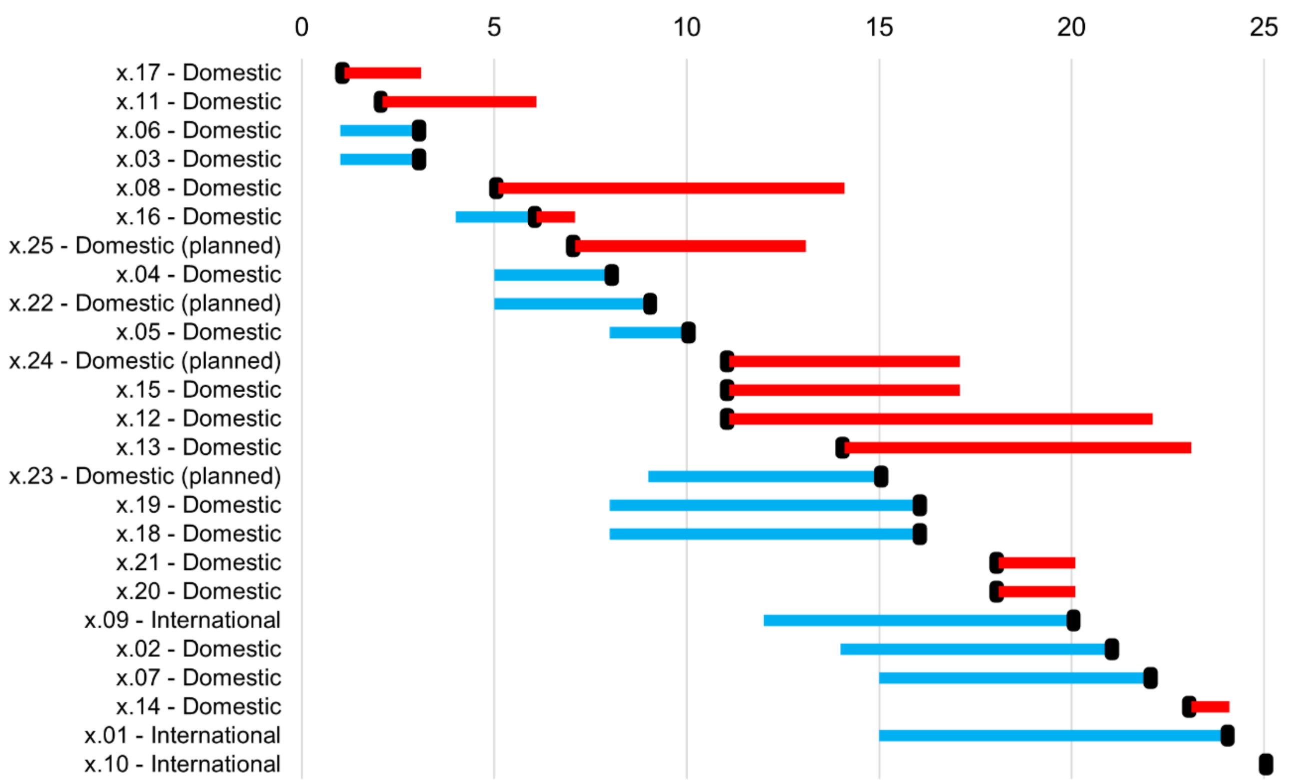

Fig. 2. Rankings of 25 electrical network assets for baseline (black bar) and CMIP6 projection scenarios (blue and red bars). Variability in ranking indicates scenario disruptiveness.

Components that remain highly ranked across all scenarios represent opportunities for investments that are unlikely to lose importance as future conditions evolve. These components are best positioned to broadly support water and energy security, environmental health, and economic development across all of the studied climate projection scenarios. The top four ranked components in the baseline, $x_{17}, x_{11}, x_{06}, x_{03}$, remain highly ranked across CMIP6 scenarios. From a decision-making perspective, these assets are strong candidates for further development and resilience investment as they remain justified across a range of futures. The components ranked between fifth and 16th in the baseline scenario experience relatively significant variability across the scenarios. For example, x_{08}, ranked fifth in the baseline, falls to rank 14th in the projection scenarios. On the other hand, x_{18} and x_{19}, tied for 16th in the baseline, jump up to the 7th position in the projection scenarios. While these assets may be less suitable for high-cost, irreversible or long-term investments today, they may be candidates for enhanced monitoring and/or phased development and resilience investments. Conversely, the lowest ranked component in the baseline, x_{10}, remains the lowest in system order in all analyzed scenarios. This indicates that this transmission line can be deprioritized as it shows limited strategic value in both current and future projected conditions.

Figure 3 presents the normalized scenario disruptiveness scores on a 0-100 scale, where 0 indicates no change from the baseline system order and 100 represents a complete reversal. Overall, disruptiveness is similar between the two CMIP6 models, suggesting that model choice has relatively minor influence on system-level outcomes. However, clear differences emerge between the SSPs. The SSP126 scenarios show lower disruptiveness than the SSP585 scenarios, indicating that system priorities are closer to the baseline under a sustainable development trajectory. In contrast, the SSP585 scenarios that reflect more intense environmental and socioeconomic pressures lead to larger shifts in system order. These results indicate that infrastructure priorities based solely on current conditions are more likely to remain valid when future development resembles SSP126. If the region instead follows a pathway closer to SSP585, current priorities may diverge significantly from those projected for mid-century. This distinction highlights the importance of future conditions in critical infrastructure planning. Decision makers can use these results to evaluate the risk of relying on baseline-only approaches and assess whether additional adaptation pathways are needed.

V. Discussion and Conclusions

This work has demonstrated how system-level risk assessments can be conducted even in regions with limited access to physical-asset data. Even limited data can be complemented with contextual demographic, economic, climate, and other datasets to provide a more holistic analysis. The mapping and integration of available asset data highlights the importance of building as complete a geospatial database as possible in regions where records are sparse. Incorporating future climate projections clarifies how long-term environmental uncertainty may alter infrastructure system performance and priorities, identifying components most resilient and vulnerable under different development pathways.

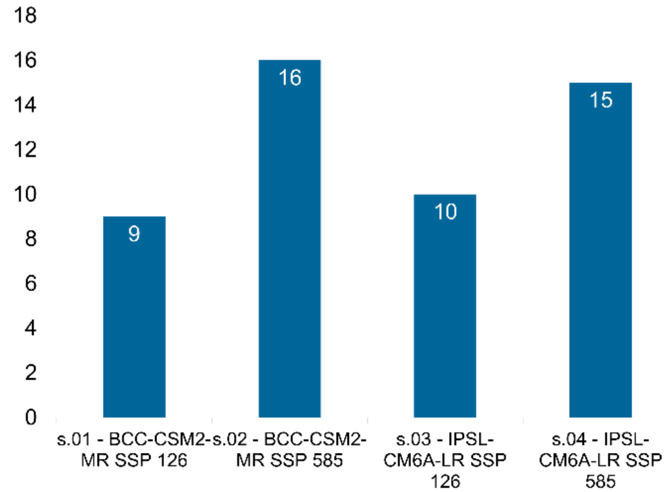

Fig. 3. Disruptiveness score (0-100 scale) of four projected future development pathways, indicating the level of disruption to baseline system order

Systems that are most vulnerable to disruption show significant reordering of system components under different future scenarios. Individual system components most vulnerable to disruption fall in the system order, while those most resilient to disruption move up in the system order. These methods help decision makers assess infrastructure risk by revealing how priorities change under uncertainty. The results can support infrastructure development strategies that remain effective across a range of plausible futures instead of relying strictly on historical or current conditions and events.

Some limitations of this work present several opportunities for future extensions. Infrastructure datasets collected here were unable to be fully verified due to the nature of the region of analysis. Further validation of the accuracy and completeness of the physical infrastructure dataset will enhance the practical usability of these results. The use of expert-defined metric weights introduces potential for bias. Future work will incorporate structured sensitivity analysis of all user-defined values. Future work will further evaluate the impacts of alternative scenario assumptions, including socioeconomic and political scenarios, natural hazards such as floods and droughts, and the co-occurrence of multiple hazards (e.g., a concurrent flood and pandemic).

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