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Review

Measuring Resilience to Sea-Level Rise for Critical Infrastructure Systems: Leveraging Leading Indicators

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Abstract: There has been a growing interest in research on how to define and build indicators of resilience to address challenges associated with sea-level rise. Most of the proposed methods rely on lagging indicators constructed based on the historical performance of an infrastructure sub-system. These indicators are traditionally utilized to build curves that describe the past response of the sub-system to stressors; these curves are then used to predict the future resilience of the sub-system to hypothesized events. However, there is now a growing concern that this approach cannot provide the best insights for adaptive decision-making across the broader context of multiple sub-systems and stakeholders. As an alternative, leading indicators that are built on the structural characteristics that embody system resilience have been gaining in popularity. This structure-based approach can reveal problems and gaps in resilience planning and shed light on the effectiveness of potential adaptation activities. Here, we survey the relevant literature for these leading indicators within the context of sea-level rise and then synthesize the gained insights into a broader examination of the current research challenges. We propose research directions on leveraging leading indicators as effective instruments for incorporating resilience into integrated decision-making on the adaptation of infrastructure systems.

Keywords: leading indicators; resilience measures; structure-based resilience; critical infrastructure; adaptation; sea-level rise; climate adaptation

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1. Introduction

Over the last century, eustatic sea-level rise (SLR) has increased more rapidly than it has at any time over the past three millennia [1]. This rapid change, compounded by additional changes in relative vertical elevation at specific locations due to subsidence and isostatic effects, poses a significant threat to coastal communities. The potential impacts to communities include coastal and inland flooding, salt-water intrusion, and coastal erosion. These risks, which are expected to be exacerbated by continuing and accelerating rates of SLR in the future, have precipitated a need to design and implement adaptation measures to curtail future losses and make communities more resilient [2]. Maintaining communities that are resilient necessitates holistic and proactive approaches. Among the stakeholders within these communities, there has been a call for a shift from ad hoc, disaster-driven, and reactive systems and policies to a proactive, threat-driven, and mitigative focus. This call has fueled the rising interest in urban resiliency research [3,4].

Quantifying resilience is crucial for effective adaptation strategies. It provides a comprehensive understanding of system vulnerabilities and capacities, enabling the identification of effective adaptation strategies. Quantifying resilience allows for comparing adaptation options, assessing costs and benefits, and informing resource allocation decisions. It also enables monitoring and evaluating implemented adaptation measures. Existing frameworks for quantifying resilience generally fall into two categories: data-driven (performance-based) or structure-driven (design-based or physical) approaches. The data-driven approach relies on "lagging indicators" and assesses systems as resilient based on their past performance and observed data. On the other hand, structure-driven approaches proactively assess systems' responses to current and future disturbances based on their inherent design and structure. The latter approach relies on "leading indicators".

The use of lagging indicators often necessitates a significant amount of historical data on past events, which may not always be available. In contrast, leading indicators are practical options for assessing resilience, particularly in the context of adaptation and decision-making [5]. By definition, leading indicators are utilized to measure the reliability of a certain process or system function and can be used to predict future performance. When one or more of these measures indicate that a process or system's safety or continuity is weak or deteriorating, interventions can be implemented to improve the process before negative consequences occur [6]. It is imperative to gain a comprehensive understanding of the structure of a system, its interactions and dependencies on other interconnected systems, and the surrounding environment in order to identify leading indicators related to its resilience. Mapping the system structure and identifying potential hazards and the risks associated with those hazards makes it possible to model all potential system failure modes, understand why and how systems might fail, and what system characteristics are most critical to shaping its response to identified risks.

In the context of resilience, an indicator can be regarded as a leading indicator if it satisfies the following three key criteria; (i) it must be *measurable*, which may represent distances, percentages, counts, flow rates, etc.; (ii) its interpretation must be *system-specific* and *risk-driven*. Since resilience must be specific to a context and addressed in relation to a given risk, a leading indicator must be specific to a given system and type of disruption; and (iii) it must be *structure-based* since leading indicators are proposed as leading indicators reflect the system's capacities, design, and relationship with other interdependent systems and are not predicted based on historical performance. For example, when modeling the resilience of road networks to risks due to coastal flooding, the underlying indicators may include the number of links located in high-risk flood zones, the criticality of links represented by the peak traffic volume, the number, and size of recovery crews, etc. Other measures based on the network's architecture can also be used to assess the degree of connectivity, accessibility, and redundancy in the network. We refer to the indicators that satisfy these criteria as the *resilience-leading indicators* or *resilience-critical indicators*. Their primary function is to measure a system's resistive, adaptive, and restorative capacities in responding to threats caused by climate change such as SLR.

Clearly, resilience is a multi-dimensional concept and as such cannot be captured by a single indicator, especially in the context of complex infrastructure systems that interact with people and environment and serve societal needs. As such, in most cases, resilience must be assessed by means of multiple indicators, which necessitates a framework that aggregates them into a unified function of resistive, adaptive and restorative capacities that can effectively incorporate people–environment–infrastructure relations. Built on deductive rationale, leading indicators can be instrumental in achieving such aggregation and developing composite metrics that can be used in policy analysis decision making [7]. Following the seminal paper authored by Cutter et al. [8], which introduces a disaster-focused composite Social Vulnerability Index (SoVI), there has been an increase in the application of composite indicator methodologies in measuring vulnerability and resilience to climate-related risks [9]. With this understanding, this study aims to review and contribute to the existing literature on operationalizing resilience by (1) conducting an extensive review of the resilience-critical indicators for various infrastructure systems subject to a range of risks caused by SLR, (2) classifying the identified measures according to their contribution to each of the system's three response capacities, and (3) identifying research gaps and offering recommendations for future research on integrating these critical measures into a unified resilience measure that can inform adaptation decision-making. The literature that introduces resilience-critical indicators as either a single variable or a composite measure is the specific area of attention.

This review utilized popular scholarly databases such as Scopus, Google Scholar, Taylor & Francis Online, and Springer Link, among others. More than 271 articles and reports were gathered and filtered using a set of relevant keywords, including "sea-level rise", "resilience assessment", "resilience measures", "critical infrastructure", "climate adaptation", "operationalizing resilience", "adaptation", "risk", and "vulnerability". Following this filtering process, 130 articles and reports were shortlisted as directly relevant to resilience indicators. These articles were analyzed and deconstructed to synthesize information on the proposed resilience-leading measures for critical infrastructure systems that are highly vulnerable to SLR including water supply, agriculture and farming (Agri), transportation (Transp.), wastewater drainage and treatment, and energy generation and transmission [10]. The selected articles were then classified according to three possible response capacities of a coastal community's infrastructure, namely, *resistive*, *adaptive*, and *recovery* capacities.

The distribution of these capacities among the reviewed publications is depicted in Figure 1. Each bar chart in the figure corresponds to a capacity type combination and displays the number of articles associated with various infrastructure systems in descending order. As shown by the charts in diagonal, majority of the articles examined resilience for only one system response capacity, more so for the resistive or adaptive capacities. Only seven of these articles explicitly incorporate all three system capacities in their resilience metrics (as shown on the top right of the figure).

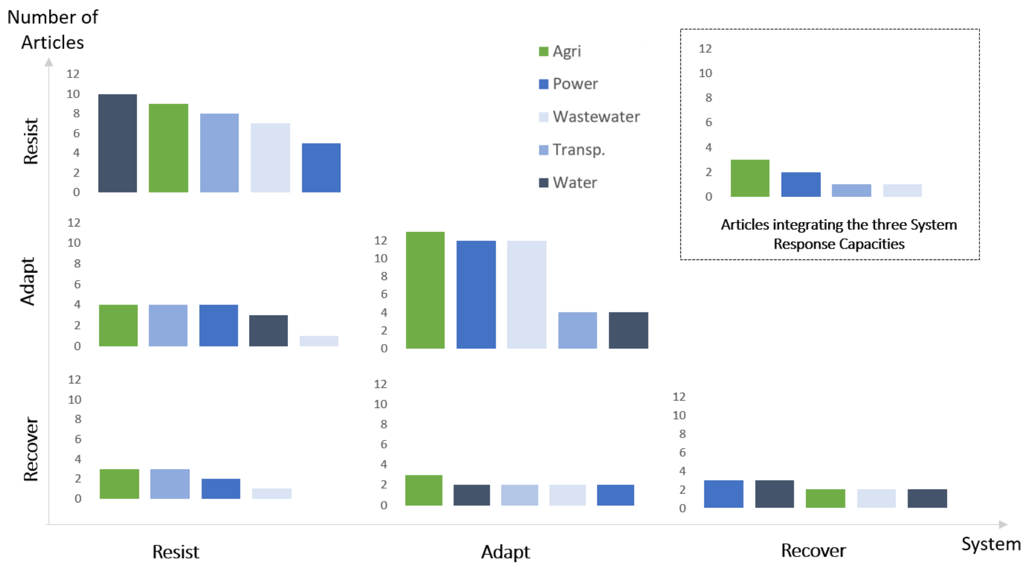

Figure 1. Distribution of articles proposing resilience-leading indicators to model a single (shown on the diagonal sub-graphs) or multiple system response capacities for different infrastructure systems.

In addition to the methodological papers, we identified eight systematic reviews on resilience measures as the most relevant to the subject of interest. These articles either survey quantitative resilience measures [11–14] or address both quantitative and qualitative resilience metrics [15,16]. While some of the review articles examined multiple critical infrastructure systems [12,13,16,17], others were specific to a particular system such as transportation networks [18], water supply and distribution resources [14,19], agriculture infrastructure [15], or energy systems [20]. While these papers provide a comprehensive review with a general focus on risks due to generic and multiple hazards, they present limited coverage on measuring risks caused by rising sea levels, namely, coastal flooding, inland flooding, coastal erosion, and saltwater intrusion. Furthermore, they provide limited information on the proposed resilience-critical measures for various infrastructure systems. The work of Bruneau et al. [12] represents an exception, where the authors identify and classify resilience indicators based on four response capabilities of a system, referred to as the 4Rs, standing for *robustness*, *redundancy*, *resourcefulness*, and *rapidity*, in the context of seismic resilience. However, the majority of the identified sub-indicators are qualitative and thus lack the identification of the critical leading indicators for measuring resilience, which is a key focus of the present study.

We acknowledge that resilience is a vast and multi-faceted research field, and it is not possible for a single review article to cover all aspects and dimensions of the topic. Given the complexity of integrating resilience assessment methodologies, specific infrastructure systems, types of risks, and the system's response capacity, our review focused on complementary articles that addressed particular systems, risk types, assessment methodologies, or response capacities. In the following sections, we begin by examining the risks associated with SLR, which serves as the basis for identifying leading indicators. Subsequently, we provide a comprehensive review of leading indicators proposed in the literature for various infrastructure systems. Drawing on these insights, we conclude the paper by discussing the existing challenges and suggesting future research directions for operationalizing resilience using leading indicators.

2. Delineating Risks in the Context of Sea Level Rise

Since the resilience of a system is associated with its exposure to risks, a risk assessment must constitute an integral part of the decision-making process to effectively adapt and respond to climate change. As such, risk is the main reference point for the formation of resilience indicators. It is typically computed as a function of anticipated hazards and their likely consequences in damages and losses. Consequently, quantifying risk involves both exposure levels and likelihood of hazardous events. On the one hand, *exposure* is mainly assessed by analyzing the localities of systems and the conditions under which these systems become adversely exposed to undesirable events. In this regard, Geographic Information Systems (GIS) has emerged as a useful and practical tool for conducting such assessments [21–23]. On the other hand, future climate change scenarios translate the *likelihood* of occurrence of adverse physical events. In the context of SLR, these adverse events include (1) coastal flooding, (2) inland flooding, (3) saltwater intrusion, and (4) coastal erosion. In what follows, we discuss these risk-triggering adverse events associated with SLR and how they are modeled and quantified in the literature.

Coastal Flooding—Recent studies project increased frequency of flooding events with rising sea levels [24]. Coastal flooding occurs when water levels or waves surpass critical thresholds for low-lying shorelines and defense structures [25–27]. Flood intensity assessment employs static and dynamic models. Static models use a "bathtub" approach to estimate flood depths and spatial extent based on projected relative sea level rise (SLR) scenarios [28]. Non-linear hydrodynamic response models consider coastal topography, land use, storm characteristics, wave effects, and storm surge to generate more accurate predictions. These models incorporate damage functions related to flood water depth, accounting for SLR, land subsidence, and flood surge [23,29,30]. Some models consider additional factors like hydrodynamics, landforms, relief, geology, and shoreline displacement [31]. Studies focusing on specific regions, such as Australia [32], Canada [33], and the USA [34], highlight high-risk shorelines with low resilience to coastal flooding due to low relief, erodible substrate, subsidence, and high wave energies.

Inland Flooding—In addition to coastal flooding, rising sea levels are associated with rising groundwater tables, which extend the risks of inland flooding for low-lying areas located further inland from shorelines. As such, the response of groundwater tables to sea levels, precipitation, and water extraction and use is an essential input for assessing risks due to inland flooding. This relation is generally predicted through process simulation models such as MODFLOW. The predicted response is then incorporated to evaluate the exposure and potential impacts on various systems and communities [21,35]. For a further detailed analysis of the process simulation models predicting groundwater response to sea levels, we refer the interested reader to the detailed review conducted in [35].

Coastal erosion—Also known as "shoreline retreat", coastal erosion is another projected risk caused by SLR. It is a change in the morphology of coasts due to several factors, which include, in addition to SLR, the sediment supply, wave energy, tidal currents, and wind action. Prediction of shoreline response to SLR has been challenging due to the highly dynamic nature of the process and the undetermined interactions between the contributing factors. One of the early approaches to quantifying shoreline change is known as the "Bruun Rule". This method was developed by Bruun in 1954 [36] and has been extensively used in shaping societal responses to future sea levels. The Bruun Method proposes a linear relationship between SLR and shoreline recession based on equilibrium profile theory, as visually presented in Figure 2. Several refinements were later published by Bruun and other researchers and are incorporated as the basis for recent models aiming to capture shoreline change, including GENESIS and SBEACH. For more details on these models, we refer the reader to a review of the history of this method, its applications, and drawbacks provided in [37].

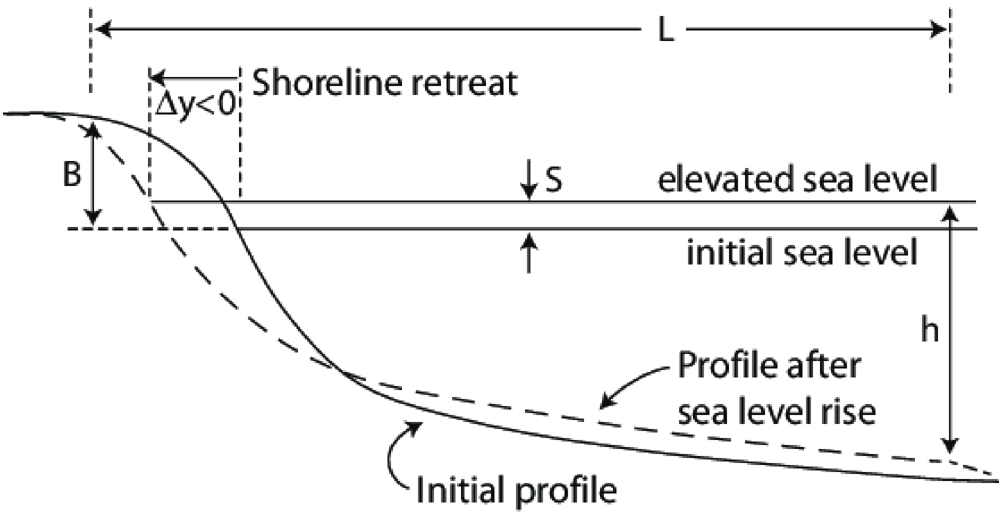

Figure 2. Bruun Rule of shoreline retreat.

Saltwater intrusion—Saltwater intrusion is the encroachment of saline water into fresh groundwater regions in coastal aquifers, leading to a reduction in freshwater availability. Saltwater is pushed upstream from the ocean with forces exerted by rising sea levels. These forces, coupled with the decreasing volumes of freshwater due to periodic dry seasons and increased pumping activities, cause the saltwater to intrude even further into the fresh aquifers.

To model saltwater intrusion as a result of the rising seas, Willem Badon-Ghijben and Alexander Herzbergin proposed the first physical formulation to approximate the saltwater intrusion known as the Ghyben–Herzberg relation [38]. Typically, the "toe length (t)" and the "depth of the interface from sea-level (h)" are two measurable indicators that represent the extent of saltwater intrusion (Figure 3). Due to the complexity of modeling the saltwater–freshwater boundary response to SLR, reliance on process simulation and experimental models, such as MODFLOW—SWI Package and SEAWAT, has become popular in recent years. These models involve a high level of integration between different interdependent hydro-geological parameters, including the boundary conditions and the influences of tidal fluctuation and groundwater exploitation through pumping and extraction [39]. Several researchers provide reviews of a wide range of saltwater intrusion modeling techniques in recent literature [40,41].

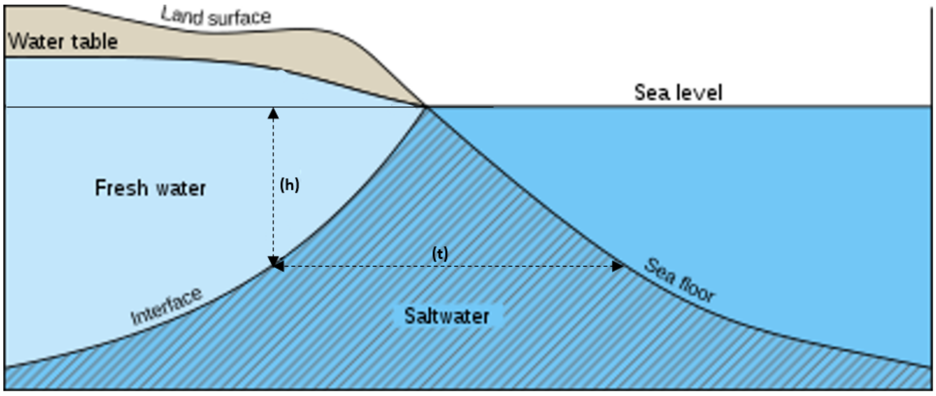

Figure 3. A diagram of a coastal aquifer showing the main seawater intrusion (SWI) metrics.

3. Resilience-Critical Indicators

As emphasized in the previous section, the identification of risks and their impacts to the environment–people–infrastructure nexus informs the formation of indicators or measures for resilience. These identified risks provide reference points and thresholds in assessing the state of the system and hence, deducing the leading indicators for resilience. In this section, we review resilience measures proposed and employed in the extant literature for infrastructure systems that are exposed to the aforementioned SLR-associated risks. The scope of our study encompasses transportation, water supply and distribution, wastewater collection and treatment, energy generation and transmission, and agricultural infrastructure systems. The resilience indicators elicited from the literature and presented in this study are primarily leading indicators that are consistent with the definition and attributes discussed in Section 1. They have been proposed either as a uni-dimensional measure of resilience or part of a composite indicator. In addition, they have been presented in the context of assessing risks, vulnerability, or resilience to various SLR-related risks. We categorize these indicators according to how they relate to a system's resistive, adaptive, or recovery capacities.

3.1. Transportation Infrastructure

SLR poses various risks to transportation infrastructure systems, including inundation of roads in coastal areas, erosion of road base, bridge scours, and reduced clearance under bridges [42]. According to the PESETA-II project [43], flooding due to sea-level rise and storm surges encompasses 50% of the risk factors threatening the operability of transportation networks caused by all climate stressors. Therefore, coastal flooding is one of the most addressed sources of risk for transportation infrastructure in the extant literature [44–47] with very few articles addressing other sources of risks such as inland flooding [48]. Resilience metrics for transportation infrastructure in the context of coastal and inland flooding risks are primarily driven by the robustness of the system components, including roads, bridges, pavements, etc., the architecture of the network, and the connectivity among these components.

Measuring Resistivity—The resistive capacity of road networks is often determined by the structural integrity/robustness of the network foundations and surface material, its ability to drain excess surface runoff, and the robustness of the flood defense structure protecting the network. The structural integrity of pavement structures plays a crucial role in determining the ability of road networks to resist SLR-related risks, including heavy rainfall and surface flooding. The resilient modulus, structural number (SN) of different pavement layers, pavement moisture content, International Roughness Index (IRI), and extent of rutting and cracking, as measured by rut and crack depths and lengths, are some of the identified resilience-leading indicators to quantify the strength of pavement structures [49]. In addition to the surface robustness, the robustness of the foundations and other critical components of transportation systems, including bridges and bridge crossings, has drawn particular attention in the context of resilience assessment studies. In this regard, various measures have been proposed, including the actual condition of exposed bridges, as determined by the National Bridge Inspection Standards (NBIS) [50], as well as some design-related features that may accelerate future bridge scouring, such as geometry (skew), length of maximum span, scour critical rating, the presence of channel protection measures (such as steel sheeting or riprap), and cross-sectional area that may exacerbate the potential for erosion (or scouring) of the streambed [50]. On the water side, the amount of high and lowland flooding could reduce the top clearance between ships and bridges and thus, also disturb the operations of maritime transportation systems. Such measures are utilized to assess the ability of ports to resist inundation events [51].

In addition to the structural integrity of the system components, the capacity of transportation infrastructure to efficiently drain excess surface water is a vital aspect of its resilience to coastal flooding and intense rainfall. The landscape's morphology and connectivity, surface permeability and roughness [52,53], as well as the efficiency and robustness of the stormwater and urban drainage systems [54], are some of the identified resilience-critical factors that measure the transportation infrastructure's capacity to drain excess surface water. For instance, a transportation infrastructure located in a flat, low-lying area with limited vegetation and poor surface permeability will be less resistant to surface flooding than one located in a hilly, vegetated area with good surface permeability and an efficient stormwater and urban drainage system. Another resilience-critical measure that is commonly used to assess the robustness of existing flood defense structures is the probability of overtopping of seawalls, which is computed based on the road elevation profile and defense crest heights relative to the highest astronomical tide [55].

Measuring Adaptability—The adaptability of a transportation network is a key determinant of its serviceability during adverse events. Various metrics have been developed to quantify the adaptive capacity of transportation networks, most of which are derived from the principles of graph theory. They focus on measures such as connectivity, accessibility, mobility, and redundancy. While these metrics have been widely discussed in the literature, few studies have considered them in the context of SLR. For details on these measures, we refer the reader to work reported by Geurs and van Wee (2004) [56], Leobons et al. (2019) [57], and Sun et al. (2020) [58].

The concept of *accessibility* in the context of transportation networks refers to the ease with which individuals can reach a node from a specific location using a particular mode of transportation [59]. The ease of access can be quantified in various ways, such as by assessing the cost (or burden) of travel in terms of distance, travel time, and traffic volume between two nodes [60], or by evaluating the attractiveness (importance) of the origin and/or destination nodes, as represented by population size or the regional Gross Domestic Product (GDP) [61]. On a network-wide level, measures such as the number of impassable links and/or nodes, the total number or length of roads subject to disruptions [47,62], and the Hansen accessibility Index and its variations [46,63] have been proposed in the literature [47,62]. Other accessibility measures that are less commonly considered in assessing the resilience of transportation infrastructure to SLR but could potentially be incorporated in future studies include the regional accessibility index, the daily accessibility index, and the gravity-based network efficiency (ease-of-access) indicator [64].

In addition to accessibility, *connectivity* is a key aspect of adaptability in transportation networks. Generally, the degree of connectivity within a network determines the additional distance a motorist would need to travel to reach a destination node in case of a disruptive event. A network with high connectivity has higher residual capacity, such as alternative links connecting various origin–destination (O/D) nodes, and therefore, higher resilience to disruptions. As connectivity is associated with the availability of backup resources, there is a degree of overlap between connectivity and redundancy measures for a network. To assess connectivity, measures such as the cyclomatic index, detour index, and network density indicator are commonly used in the literature [61]. Availability of spare (or backup) capacity, which can be computed by the clustering coefficient (also known as the transitivity index) [61], the quality margin [65], and the redundancy ratio [66] are proposed to measure redundancy. In addition, diversity of travel modes and routes between origin–destination pairs are also considered for assessing *redundancy*. Diversity indices based on the availability of multiple travel modes and routes are recommended as complementary measures [67]. Redundancy measures have also been employed for assessing the adaptability of port systems to failures caused by sea-level rise or other disruptions. The proposed redundancy measures include levels of backup energy and utility sources for contingency, availability of reserve capacity for physical support (such as cranes [68]), and presence of nearby ports for substitution [69].

Another pillar of adaptability is *criticality*, which pertains to identifying the network components that are most vital for maintaining uninterrupted flows during planned or unplanned disruptions. Commonly used measures to capture the criticality of nodes and edges include the node-betweenness index and the edge-betweenness centrality. They indicate the likelihood of a node or edge to be used for transportation between any given pair of nodes [61,62,70]. Other criticality measures based on traffic volume and flow rate have also been proposed in the literature such as the aggregated Network Vulnerability Index (NVI) [45,71]. Criticality can also be evaluated in terms of the Zone Importance Factor, computed as the ratio between trips flowing into a specific zone and all trips originating from the zone [46], the Network Robustness Index (NRI) [72], and the Detour Length [50]. From the social perspective, criticality measures that take into account the historical significance of specific network components, such as bridges [50], or assign equity weights to transportation activities based on the attributes, motives, and characteristics of commuters [73] have also been proposed. For a more comprehensive list of measures and models that can be utilized to assess the criticality of networks, we refer the reader to the interdiction optimization models, which are usually employed in network-disruption analysis [74]. In the context of maritime transportation systems, several criticality measures are proposed reflecting the different functionalities of ports. Such measures include annual revenue, number of jobs supported, occupancy rate, and metric tons or twenty-foot equivalent units (TEU) imported and exported [75].

Measuring Recovery—Recovery capacity of transportation infrastructure in the context of SLR has not been widely addressed in the literature. Nonetheless, several measures developed by earlier researchers in the context of generic disruptions are relevant and worth mentioning. For instance, Chang et al. [76] evaluated post-disaster system performance of network coverage and transport accessibility and proposed metrics for the urban rail and highway transportation systems. They based their analysis on the 1995 Hyogoken–Nanbu Earthquake that devastated Kobe, Japan. Similarly, Peeta et al. [77] developed a post-disaster connectivity index between origin–destination nodes in transportation networks. While many studies have assessed post-disaster recovery efforts in the transportation sector, limited attention was given to pre-disaster adaptation in the context of recovery.

Table 1 summarizes the surveyed literature related to resilience-critical indicators in the context of transportation infrastructure.

Table 1. Summary of studies encompassing resilience leading indicators for transportation infrastructure.

		Resilience-Critical Indicators							
		Resistive			Adaptive				
Ref.	Risk Type	Age/Condition	Drainage Capability	Protection Measures	Connectivity	Accessibility	Redundancy	Criticality	Recovery
[47]	CF				✓	✓			
[45]	CF				✓	✓		✓	
[44]	CF						✓		✓
[46]	CF					✓		✓	
[61]	CF				✓	✓	✓	✓	
[78]	CF					✓			
[79]	CF	✓			✓				
[50]	CF	✓						✓	
[55]	CF			✓					
[49]	CF	✓							
[71]	CF							✓	
[54]	CF	✓	✓						
[62]	CF							✓	
[48]	IF	✓							
[53]	CF	✓	✓						
[80]	CF					✓			
[70]	CF							✓	✓

3.2. Water Supply and Distribution Infrastructure

Urban water infrastructure systems are vulnerable to SLR on both the supply and distribution sides. On the supply side, SLR may result in saltwater intrusion, which increases the salinity of freshwater resources in surface water and groundwater thereby reducing the availability of freshwater resources. SLR also indirectly impacts water quality by accelerating the erosion of coastal wetlands, which play a critical role in reducing excess nutrients such as phosphorus and nitrogen by providing a natural filtering process. The adverse consequences of declining water quality include water infrastructure malfunctioning during floods and overloading on water treatment plants during extreme rainfall events [81]. On the distribution side, SLR results in a rising underground water table, causing inflow into water infrastructure components and increasing the frequency of backlogs and overflows [39]. The rising water table causes increased stress on the foundations of underground infrastructure. Additionally, wave run-up and overtopping can destroy water management infrastructure and other assets for a considerable distance inland [82].

Our review of resilience-critical indicators for water supply and distribution infrastructure systems incorporates the aforementioned risk types. It is also inclusive of the indicators proposed for assessing the systems' resilience to generic risks that cause a reduction in freshwater availability. Although the latter indicators are not directly presented in the context of SLR, they are relevant to risks caused by SLR. On a general note, most of the articles in the extant literature utilize the measures proposed in the seminal paper by Hashimoto et al. [83], where the authors characterize the resilience of water supply systems in mathematical form. For a comprehensive review of these and similar measures, the reader is referred to [19,84].

Measuring Resistivity—Aquifers and sources of freshwater supply constitute an integral component of the water supply infrastructure, and their disruption can have a significant impact on the entire system. As such, their ability to resist disruptions resulting from SLR, mainly due to saltwater intrusion, has gained attraction in research in recent years. Various indicators have been proposed in the literature to evaluate the aquifer's resistance to saltwater intrusion, including the type of aquifer, its hydraulic conductivity, thickness, depth to groundwater, and perpendicular distance inland from the shoreline. Generally, those indicators are measured using process simulation models, such as the GALDIT Model [85]. In addition to the aquifer characteristics, the saltwater-freshwater interface characteristics are utilized to assess the potential of saltwater intrusion. Conceptual saltwater intrusion models such as the Ghyben-Herzberg approximation are employed to determine the position of the freshwater-saltwater transition zone based on the ratio of the thickness of the freshwater zone to the depth below the mean sea level. For more detailed mathematical formulations of these measures, we refer the interested reader to the studies conducted by Werner et al. [39,86].

When reservoirs are part of the water supply system, the robustness of the reservoir operations to changing climate, especially to the rising sea level, is an essential factor that influences the availability of freshwater and hence the robustness of the supply resources. Studies have examined the impact of climate risks on small, distributed reservoirs [87] and multi-purpose, integrated reservoirs [88,89]. When multiple small-scale distributed reservoirs are located upstream from a central reservoir, water availability downstream is an important measure to consider. This can be represented by the reservoir yield measured by the constant outflow that can be guaranteed 90% of the year, in addition to the total volume of water stored in the smaller reservoirs located upstream [87]. Although these metrics are primarily used to assess the expected reduction in freshwater availability due to a reduction in precipitation, they can also be deployed in the context of the increased salinity and contamination associated with the SLR. Other measures assess the reservoir's robustness to flooding events, including the expected amount of water discharge during flooding, known as reservoir spill [88,90].

On the distribution side, the robustness of critical network components affects the network's ability to resist disruptions. Proposed metrics in this scope include material, age, and condition of the water pipes and the number of breakage incidents resulting from pipes' deterioration [91].

Measuring Adaptability—The ability of a water supply and distribution system to adapt to SLR is influenced by how well both the supply sources and distribution network can adapt to disruptions. These disruptions can be localized pipe failures or long-term freshwater shortages affecting the system entirely. On the supply side, the inability to satisfy a minimum daily threshold of freshwater is considered a critical condition for the system; this threshold is estimated to be 50% of the expected water demand [92] or 1000 m^3 per capita. according to the Food and Agriculture Organization (FAO) of the United Nations. To mathematically evaluate this ability, the proposed measures focus on evaluating the excess (or redundant) amounts of supply measured relative to the minimum thresholds, such as the shortage Index (SI), Stability Degree (SD) [93], and the expected freshwater availability per capita given the anticipated risks [90,94]. In addition, where reservoirs constitute part of the system, proposed measures include the multivariate resilience index that combines the Inflow-Demand Reliability indicator (IDR) and the Water Storage Resilience indicator (WSR) [95]. These indicators assess the changes in the inflow to reservoirs due to climate conditions, including rising sea levels and the reservoir storage capacity relative to the forecasted demand and the hydrological variability. Although this composite index was deployed in the context of drought, it can also be utilized in assessing resilience to relevant risks due to SLR.

Diversity in supply resources is another measure that reflects redundancy in the water supply system. Modern water supply systems have multiple water sources such as groundwater, surface water, desalinated water, and water diverted from other regions. In these systems, the freshwater supply is not entirely compromised if one source is disrupted. Diversion of water from upstream reservoirs to lower streams helps the downstream regions sustain a specific volume of fresh water and, at the same time, minimize the saltwater intrusion rates, especially during the dry season. In this regard, a measure of the annual water diversion capacity is developed to assess the resilience of upstream water supply resources [96]. The ideal benefits of diversion can be achieved when two regions, namely the original destination and the diverted destination, are in the wetness–dryness alternation, known as asynchronous encounter situations. Thus, indicators measuring the probability of having asynchronous encounter situations between two regions, such as the

Shortage Index (SI), are developed when assessing the effectiveness of the multi-supply process in adapting to risks due to SLR [97].

On the distribution side, various measures have been proposed to assess the network's criticality, connectivity (redundancy), and reliability based on network topology and graph theory. The criticality of a network component can be quantified using metrics such as the average daily flow through a pipe [98], the average outflow rate from a water supply facility [99], the size of the area the water network is serving [100], in addition to other measures including the Loading Rate (LR) and Congestion Frequency (CF) that are developed to identify potential bottlenecks and critical components in a water distribution system [93].

Connectivity across the network is also an essential measure of adaptability that has not been addressed much in the context of SLR. One of the emerging research tracks in this context extends the concepts of the Structural Vulnerability Theory (SVT) proposed by Wu et al. [101]. SVT is utilized to identify the vulnerable parts of a network based on analyzing its structural form and connectivity. One of the proposed measures includes the nodal connectivity index that measures the availability of alternative (redundant) water supply paths between a branched cluster and the rest of the network [102]. Other measures include link density, path length, clustering coefficient, Meshedness coefficient, etc. [103,104]. We note although none of these measures have been presented specifically in the context of SLR, they can be tailored to and used in this context. For further studies on resilience measures based on the application of the SVT and network topology to generic disruptions, we refer the reader to [91,98].

In addition to criticality and connectivity, the reliability of a network is also utilized to measure its adaptive capacity. one of the proposed measures is the resilience index [105] that assesses the amount of surplus pressure in the network. Basically, networks with excess pressure are more capable of meeting customers' demands under disruptive events. Another measure, the nodal uniformity metric, is founded on the understanding that reliable sections of the network can be attained if the pipes connected to a node are not widely varying in diameter [106,107]. To the best of our knowledge, none of the articles in this track address failures precisely due to SLR, which remains to be an interesting potential research direction.

Measuring Recovery—Compromising the water quality due to saltwater intrusion and pollution is a major threat caused by SLR. Therefore, measures assessing the extent of water pollution have been proposed to assess the ability of water supply systems to recover following possible disruptions. Some of the proposed leading indicators include the percentage of rivers and stream miles that meet applicable water quality standards [90]. Other measures integrate the social element by accounting for the size of the population and the level of economic development (Gross Domestic Product) in the areas serviced by the supply source under study. These measures could also be used to reflect the criticality of the system as they are direct projections for the expected demand, hence the amount of effort required to adapt to possible disruptions.

Although risks due to SLR may impact the water supply and distribution network at various levels, the literature mostly focuses on the supply side by mainly addressing the risks of saltwater intrusion and the indirect contamination of freshwater resources. On the distribution side, although several measures are proposed in the extant literature to assess the resilience of water distribution infrastructure, they are often conceptualized as generic disruptions. As such, most of the proposed measures are yet to be tailored to the context of SLR.

Table 2 summarizes the surveyed literature related to resilience-critical indicators in the context of water supply and distribution infrastructure.

Table 2. Summary of studies encompassing resilience leading indicators for water supply and distribution infrastructure.

			Resilience-Critical Indicators								
			Resistive				Adaptive				
Ref.	**Risk Type** [1]	**System Component**	**Age/Condition**	**Reservoirs Robustness**	**Supply Robustness**	**Hydrological Response**	**Connectivity**	**Reliability**	**Redundancy**	**Criticality**	**Recovery**
[95]	WS	S		✓					✓		✓
[99]	WS	S/D	✓						✓		✓
[90]	CF	S		✓					✓	✓	✓
[92]	WS	S								✓	
[105]	CF	S							✓		
[107]	Generic	D						✓	✓		
[98]	Generic	D							✓	✓	
[91]	Generic	D	✓				✓			✓	
[94]	Generic	D						✓	✓	✓	
[104]	Generic	D					✓	✓	✓		
[103]	Generic	D					✓	✓	✓		
[85]	SWI	S				✓					
[39]	SWI	S				✓					
[96]	SWI	S			✓						
[97]	Generic	S			✓						
[87]	Generic	S		✓							
[88]	CF	S		✓							
[102]	Generic	D					✓		✓	✓	

[1] WS: Water Scarcity, SWI: Saltwater Intrusion, S: Supply-Side, D: Distribution-Side.

3.3. Wastewater Collection and Treatment Infrastructure

Typically, wastewater is handled under two broad categories: (1) decentralized systems (septic systems and holding tanks) and (2) centralized systems, including pipes, manholes, and pumps that convey wastewater from local areas to treatment facilities and disposal locations. In both systems, wastewater network components are either buried or located in low-lying lands close to the shoreline, which makes them highly vulnerable to risks due to SLR. The direct impacts of SLR on wastewater infrastructure include: (1) degradation of underground utilities, (2) sewage overflow, and (3) inundation of low-lying treatment facilities [10]. In addition to the direct impacts, indirect impacts could be more subversive. These impacts include infiltration and inflow into the collection system due to the rising water table, increased precipitation, and storm surges [108]. Infiltration and inflow can stress the sewage system as it is forced to transport more flow than its design capacity, causing subsequent failures in the distribution or treatment functions of the system. In addition, infiltration can also cause pipe structure failures due to erosion of soil support and ground subsidence due to underground soil erosion. For the decentralized systems, on the other hand, the rising groundwater, increased precipitation, and surface flooding caused those systems to experience hydraulic failures or contamination of groundwater. These failures are a result of the partially treated wastewater seeping into groundwater through cracked components or insufficient treatment conditions for the septic systems. Both cases result in aggravated health and environmental problems.

Measuring Resistivity—Various leading measures are introduced in the literature to assess the ability of the different system components to resist risks associated with SLR. Some of the proposed measures assess the robustness of the system components, such as the elevation of a wastewater treatment facility or its critical components such as pump motors, aeration tanks [99], and outlet pipes (discharge points) [108,109]. Other measures evaluate the robustness of the existing flood defense structures [99].

On the collection side, whether a system is composed of a combined sewer/storm mechanism governs the measures regarding the system's response to flooding. Combined sewer systems may send runoff groundwater to a wastewater plant during storms and excess rainfall. This might cause overflow when the plant's inflow capacity is exceeded [99].

Other measures, such as the frequency of sewer overflowing from manholes, are also developed to reflect the network's ability to resist additional stresses caused by flooding events [108]. Generally, assessing pipes' condition and deterioration rate is a complex process determined by various factors. Although not considered explicitly in studies assessing the resilience of wastewater collection systems, some indicators identified in the extant literature have good potential for future consideration in the context of resilience assessment studies and are worth mentioning. Such indicators include pipe length, age (in years), gradient, depth, and material (in Manning's roughness coefficient). For additional details on other factors affecting pipe deterioration, we refer the interested reader to [110]. Besides the centralized wastewater collection and treatment systems, a few studies address the resilience of onsite wastewater systems (OSTDS) in the context of SLR. Some of the developed resistivity measures include depth to groundwater level (the vertical separation distance between the bottom of the drain field and the high-season water table), soil moisture content, and base flood elevation at a given OSTDS location [111,112].

Measuring Adaptability—The literature on measuring the adaptability of wastewater collection and treatment systems focuses on the criticality, redundancy, and connectivity of the system's components. The criticality of a wastewater treatment facility can be evaluated through various measures, including the population it serves and the Discharge Monitoring Reports (DMR) violations index. The DMR violations index measures the percentage of effluent violations and serves as an indicator of the facility's ability to adapt to daily stress and increased vulnerability to flooding events [21,113]. Another measure employed to evaluate criticality is the elevation of pipes and manholes in relation to the expected future groundwater levels. According to Friedrich et al. [108], network elements with an elevation between 0 and 2 m are considered critical under a worst-case scenario of a 2.8-meter rise in sea level. Additionally, the network clustering coefficient, measured as a function of the total length of pipes and the number of manholes within a region [108], and proximity to other critical infrastructure systems [110] are employed to evaluate an unfavorable and critical situation, where regions with high densities of network components lead to a diminished ability to adapt to failure. In assessing the criticality of OSTDS, measures such as proximity to other infrastructure systems, including public or private drinking water wells, waterbodies, and surface drainage lines (watersheds), which can function as channels that accelerate transferring the effluent to nearby freshwater sources, are proposed in the literature [111].

Indicators associated with connectivity within the wastewater network primarily rely on the type of network structure (tree vs. loop networks) [114]. Studies show that loop networks are considered more resilient to disruptions since the proportion of critical hydraulic pipes is relatively less significant compared to tree networks [114]. Other connectivity measures include the betweenness centrality index computed based on Dijkstra's shortest path algorithm, degree distribution, and the number of connected network components [115].

Redundancy in the system can be assessed by the overload capacity of a pump station [108], the existence of underground tunnel systems, availability of backup facilities in the neighboring areas, and the availability of additional onsite storage provided by the volume of lakes in a given zone [113]. Also, redundancy in a treatment facility can be assessed by measuring the permitted inflow relative to the facility's design, which provides a measure of how close the plant is to its capacity [99,113], or the maximum amount of untreated wastewater to be bypassed to secondary treatment facilities [99]. Treatment plants with the ability to bypass untreated sewage from primary to secondary treatment facilities are observed to be more capable of adapting to excessive damages that can be caused by the increased flow during flooding.

Measuring Recovery—To assess the recovery of wastewater treatment and collection systems, a few leading indicators, including the availability of multiple backup parts, such as pump motors [99], and the resourcefulness resiliency index [113] are proposed. For the OSTD systems, the resilience index proposed by [111] employs leading indicators that reflect the ease with which adaptations can be made in the event of failure. The adaptation options in this context include structural improvement of the existing system or extension to the existing sewer network. Specific measures in this context include distance to existing and planned sewer lines, distance to sewer overflow locations, and the moratorium status of the pump station basin to which the on-site system belongs. Moreover, socio-economic conditions, measured by the median household income, are also incorporated into the proposed metric.

Table 3 summarizes the surveyed literature related to resilience-critical indicators in the context of wastewater collection and treatment infrastructure.

Table 3. Summary of studies encompassing resilience leading indicators for wastewater collection and treatment infrastructure.

			Resilience-Critical Indicators							
			Resistive				Adaptive			
Ref.	**Risk Type** [1]	**System Component**	**Age/Condition**	**Robustness of Collection System**	**Robustness of Treatment System**	**Protection Measures**	**Connectivity**	**Redundancy**	**Criticality**	**Recovery**
[110]	Generic	C	✓							
[99]	CF	C/T	✓	✓		✓				✓
[108]	CF/IF	C/T	✓				✓	✓	✓	
[113]	CF	T	✓				✓	✓	✓	✓
[21]	CF/IF	T	✓		✓	✓			✓	
[109]	CF/IF/SWI	T			✓					
[111]	CF/IF	OSTDS	✓	✓	N/A.		N/A.	✓	✓	✓

[1] CF: Coastal Flooding, IF: Inland Flooding, SWI: Saltwater Intrusion, C: Collection System, T: Treatment System, OSTDS: On-Site Wastewater Treatment and Disposal System (Septic).

3.4. Energy Generation and Transmission Infrastructure

Like many wastewater treatment facilities, power generation facilities were initially constructed near shorelines for cost-efficient water intake and cooling-water discharge operations. Locating such facilities at lower elevations and near shoreline exposes them to increased risk of flooding associated with SLR [116]. Moreover, salt-water intrusion may accelerate substructure erosion, resulting in higher maintenance costs, shorter equipment replacement cycles, and more frequent and prolonged power outages. These risks have significant cascading impacts on other critical infrastructure systems that primarily rely on energy for maintaining an uninterrupted level of services.

Several studies have reviewed the impacts of climate change on energy infrastructure [117,118]. The extant literature primarily highlights the effects of temperature and precipitation changes on energy infrastructure, particularly emphasizing the increasing frequency of windstorms as a major threat to power transmission lines. Limited research has been conducted on the stressors caused by SLR on energy infrastructure. Nevertheless, specific contributions within this literature merit mention as they further our understanding of resilience-critical metrics in the energy sector that can be applied to the context of SLR.

Measuring Resistivity—The response capacities of energy infrastructure are assessed at the supply (S) and transmission (T) component levels. On both the power generation and transmission sides, damages resulting from SLR are primarily attributed to flooding and inundation of critical system components such as power plants, substations, distribution circuits, and buried cables. The literature has extensively examined the ability of the existing energy infrastructure to resist inundation. Proposed resilience-critical metrics are based on a system's structural integrity, a base elevation of its critical equipment relative to the expected flood levels, and the likelihood of failure of flood defense structures [119–121]. Additionally, higher salinity levels accelerate the processes of corrosion, fouling, and scaling along the surfaces of the cooling tower and the condenser; thereby, decreasing thermal performance, leading indicators capturing the ability of the cooling systems to resist failures caused by salinity are also proposed [122].

The aging of physical assets, notably timber poles and overhead cables, is the main cause of the brittleness of transmission infrastructure components. To address this issue, resilience-critical indicators based on age-based strength measures are proposed [123]. These measures include initial fiber strength, age-dependent capacity loss factor, geometric features, and modulus of rapture. Additionally, as wooden poles are made of natural material prone to absorbing moisture, which accelerates degradation, the rate of in-service degradation is also computed as a function of soil moisture and humidity as a resistivity measure. Although these measures are primarily used in the context of windstorm-caused risks, they can also be applied in the case of SLR, which may result in flooding events resulting in increased precipitation and stresses to poles.

Measuring Adaptability—Diversification of energy supply, including fuel mix and multi-sourcing, is one of the essential strategies to hedge against energy supply risks [124] and as such, related indicators have been employed to capture their resilience. In this regard, the proposed leading indicators assess the diversity of energy supply sources by means of three key elements: (1) "variety" represented by the number and nature of sources, (2) "balance" represented by the spread across different sources, and (3) "disparity" signifying the degree to which the sources are different [125]. While metrics have been commonly referenced to the first two elements, no clear metrics are reported in the literature to measure disparity in energy supply [126]. Among the proposed metrics are the fuel import dependence, calculated based on net imports or the Shannon index introduced by the Asian Pacific Energy Research Center (APERC) [102], the Herfindahl-Hirschman Index as a measure of market concentration [127], and the degree of dependence on reserves of energy sources to assess energy security [128].

Diversity in generation is recommended as a pertinent metric in addition to supply diversity [128]. Diversification in power generation can be assessed by the availability of on-site energy production such as solar energy for individual buildings or relatively small communities [129]. For communities that rely heavily on fossil oil as their primary energy source, Oil Vulnerability Index (OVI) is proposed to assess the supply efficiency [130]. OVI is computed as a function of the ratio of oil imports value to GDP, oil share in total energy supply, domestic reserves to the oil consumption ratio, and net oil import dependence.

Redundancy is another indicator that reflects the system's adaptability. In energy systems, redundancy can be represented by the amount of spare capacity, the number of redundant (or backup) components such as generators and pumps [98,131]. Other measures are mostly based on the network topology as reviewed in detail by Watts and Strogatz [132]. The authors proposed several interesting models in this context. They include dynamic flow models, shortest path models, power flow entropy models, etc. These models are constructed using a variety of topology-based metrics that assess the resilience of the connected power networks, including average path length, clustering coefficient, betweenness centrality, hybrid flow betweenness [133], centrality [134], and criticality measures including maximum link flow [135]. As mentioned earlier, although the theory behind these models can be applied to assess the resilience of power grids to risks due to SLR, the reviewed literature does not include this aspect explicitly as a focal point. We refer the interested reader to [136–139] for detailed discussions on resilience indicators designed for power grid architecture.

Measuring Recovery—The ability of energy systems to rebuild after disruptions can be assessed through the use of financial, technical, and governance-related indicators. These indicators include the availability of financial resources measured in GDP per capita, the amount of private investment into energy infrastructure, the percentage of technically qualified personnel in the energy sector and electric utilities, and the average outage times [140]. Additional indicators include the availability of recovery resources that are quantified by the number and size of recovery crews working in the energy sector [126]. When historical data is available, lagging indicators such as Mean Time to Repair (MTTR) and Random Time to Repair (RTTR) can also be utilized [126].

Table 4 summarizes the surveyed literature related to resilience-critical indicators in the context of wastewater collection and treatment infrastructure.

Table 4. Summary of studies encompassing resilience leading indicators for energy generation and transmission infrastructure.

			Resilience-Critical Indicators								
			Resistive				Adaptive				
Ref.	**Risk Type [1]**	**System Component**	**Age/Condition**	**Robustness of Supply**	**Robustness of Transmission**	**Protection Measures**	**Diversion in Supply/Generation**	**Reliability**	**Redundancy**	**Criticality**	**Recovery**
[134]	Generic	T								✓	
[130]	Generic	S					✓	✓			
[121]	CF	S/T				✓					
[102]	Generic	S					✓				
[127]	Generic	S					✓				
[128]	Generic	S					✓		✓		
[123]	W	T	✓		✓						
[129]	Generic	S					✓				
[131]	Generic	T							✓		
[119]	CF	S	✓								
[133]	Generic	T							✓	✓	
[135]	Generic	T								✓	
[139]	Generic	T						✓		✓	
[118]	Generic	T	✓		✓						
[126]	Generic	S/T					✓				✓
[122]	SWI	S									
[140]	Generic	S/T		✓	✓		✓	✓	✓		✓

[1] CF: Coastal Flooding, W: Wind, SWI: Saltwater Intrusion.

3.5. Agricultural Systems

Agriculture systems and crop yields are susceptible to the adverse effects of climate change, which is projected to threaten food security by 2050 as global agricultural production must be doubled to meet rising demand [141,142]. Increased surface and inland flooding, exacerbated by rising sea levels, has negatively impacted the yield of non-water tolerant crops [143]. For example, the projected rise in groundwater in Qingpu county in China is expected to significantly reduce wheat production by 2050 unless electric pumping capacity is increased to maintain a vertical distance of greater than 0.5 m between the surface and groundwater [144]. In addition to inundation, increased salinity resulting from saltwater intrusion poses a significant risk to both water and soil elements, disrupting nutrient flow and negatively impacting the production of crops with low salinity tolerance, such as rice [145]. Another detrimental effect, soil erosion, poses additional constraints on agricultural yield. On the one hand, the eroded shorelines lead to fewer shoals for reclamation and, thus, a reduction in the total agricultural land. On the other hand, agricultural soil erosion impacts soil health and agricultural yield by removing the fertile topsoil. Soil erosion can be assessed using various models, such as the EPIC and APSIM models [146].

Simulation tools that utilize crop growth models are commonly employed to evaluate the effects of SLR on crop production. These models aim to analyze the response of crops to future climate stressors by integrating field experiments and statistical analyses of past and projected future climate data into simulations of crop growth dynamics [147]. These models typically incorporate factors such as soil and cultivar characteristics, crop management practices, irrigation schedules, nutrient supply, and weather information including temperatures, rainfall, and solar radiation [146]. Additionally, some crop growth models also incorporate the effect of waterlogging on crop growth. In addition to crop growth models, salinity-impact models are also recommended for assessing the impact of SLR on agricultural production. Salinity in soil primarily affects root water uptake, the process by which plants absorb water, and the quality of nutrients obtained from the soil. Salinity-impact models can capture water uptake in relation to the average salt concentration in the root zone [145].

Measuring Resistivity—The resistive capacity of agricultural lands is governed by their ability to resist excess water, waterlogging, and increased salinity. The ability to resist waterlogging is shaped by the drainage capacity, soil moisture content, and availability of efficient flood defense structures that can keep water out of the fields [144]. Drainage systems help maintain the groundwater at an adequate level that sustains the productivity of the agricultural land. Therefore, the importance of maintaining the drainage infrastructure, including the associated equipment and machinery, is emphasized in the literature. The drainage capacity with respect to the expected inundation levels and the maintenance frequency of the drainage infrastructure is used as leading indicators for resistivity [144]. Additionally, soil water (moisture) percentage [148] and the Standard Precipitation Index (SPI) [149] are other proposed leading indicators that can assess the reduction in crop yield as a result of the increased moisture content measured relative to the soil saturation capacity [150]. Although soil moisture is generally used to assess the response of agricultural fields to projected drought conditions, it can also be used in the context of flooding to assess resistance to excess water. Actual soil moisture data can be obtained from several national and global soil moisture database such as the surface satellite soil moisture dataset provided by the Soil Moisture and Ocean Salinity (SMOS). Another source is the root zone soil moisture dataset made available by the Canadian Meteorology Center's Regional Deterministic Prediction System (RDPS) [151]. In addition to the soil moisture content, depth to groundwater table is also proposed to measure the likelihood of diminished yield due to inland flooding [152].

Besides tolerance to increased water contents, a crop's tolerance to increased soil salinity can also be used as an indicator for resistivity [153]. We refer the interested reader to a detailed review by Maas and Hoffman [154] on various measures employed to assess the tolerance of crops to increased salinity.

Measuring Adaptability—The majority of the studies within this category examine adaptability to SLR from the perspectives of the community and household rather than solely from the agricultural field. Proposed indicators include the ratio of rice production in a region to its gross domestic product (GDP), the number of employees engaged in the agriculture sector, the number of households with a primary income source from agriculture, the average net income per household from agricultural production, the percentage of households with alternative livelihood options besides agriculture, the percentage of paddy land in the total area, the percentage of rural population per square kilometer, and the percentage of rain-fed fields compared to irrigation-dependent fields [145]. With a special focus on agricultural fields, Antle et al. [155] have proposed a spatial heterogeneity indicator, which utilizes physical characteristics of the soil, such as biogeochemistry, moisture, and texture, and measures the endowment capacity of resources by assessing the proportion of farmers with access to alternate technology and other resources.

Measuring Recovery—The majority of the recovery measures published in the body of literature are community-centric, which is in tune with the adaptation measures. These measures are mostly socio-economic in nature, including the literacy rate, represented by the proportion of individuals who possess reading and writing proficiency, the poverty rate, represented by the percentage of individuals below the poverty line, and the agricultural income share, represented by the percentage of crop production in relation to the region's Gross Domestic Product (GDP) [145].

Table 5 summarizes the surveyed literature related to resilience-critical indicators in the context of agricultural systems.

Table 5. Summary of studies on assessing the resilience of agricultural systems.

		Resilience-Critical Indicators							
		Resistive					Adaptive		
		Crop Tolerance to Excess Water							
Ref.	**Risk Type** [1]	**Depth to Groundwater**	**Soil Conditions**	**Drainage Capacity/Efficiency**	**Protection Measures**	**Crop Tolerance to Excess Salinity**	**Resources Endowments**	**Criticality**	**Recovery**
[144]	CF/IF/SWI/SE	✓		✓	✓		✓		
[148]	Generic		✓						
[150]	CF/IF		✓						
[151]	PT		✓						
[145]	CF/IF/SWI/SE					✓		✓	✓
[152]	CF/SWI	✓				✓	✓		
[155]	Generic		✓			✓	✓		✓
[153]	SWI					✓			
[149]	Generic		✓						

[1] CF: Coastal Flooding, IF: Inland Flooding, SWI: Saltwater Intrusion, SE: Shoreline Erosion, PT: Precipitation.

4. Results and Insights: Operationalizing SLR Resilience with Leading Indicators

This paper reviews various indicators that have been introduced in the literature to quantitatively assess resilience in the face of sea-level rise (SLR) risks. These indicators, categorized based on the system's capacity to respond, namely resistive, adaptive, and restorative capacities, contribute to the overall resilience of different systems. Given the complexity of infrastructure systems and the scarcity of adequate or readily available data, multi-variate leading indicators for resilience have emerged as promising tools for enabling resilience assessment and adaptation decision-making for infrastructure systems. Such indicators can be useful to form a baseline for making adaptation decisions in both spatial and temporal domains. The review of the extant literature provides us with insights pertaining to potential areas for future research.

One crucial research area relates to multidimensionality of resilience. As indicated in Figure 1, previous studies have focused on various aspects of resilience capacities. However, a majority of the reviewed works concentrate on a single dimension of resilience: 37 on resistive capacity, 40 on adaptive capacity, and 12 on recovery capacity. Only 41 out of 130 papers consider some combinations of capacities, with a mere 7 incorporating all capacity domains. This observation highlights the need for holistic methods to capture the overall resilience of infrastructure systems. These approaches should integrate multidimensional measures and indicators of resilience into metrics that facilitate decision-making for adaptation. One effective strategy involves developing composite metrics in functional forms that can serve as fundamental elements in decision models.

Another notable finding is that the majority of research papers in this field focus on the resilience of specific infrastructure systems or their components. Exploring resilience metrics for systems composed of multiple infrastructure elements, such as urban or regional systems, presents an interesting and promising research avenue. In this respect, leading indicators can be studied as instruments of integrating resilience metrics and adaptation efforts across different infrastructures and geographical regions. Furthermore, there is significant potential for studying coordination mechanisms that employ leading indicators and establishing links between infrastructure resilience and community resilience. This aspect has been largely overlooked in existing literature.

Building upon these insights, the following discussion explores these potential research directions in greater detail and addresses the associated challenges.

4.1. Multidimensionality and Composite Indicators

The reviewed work suggests and demonstrates that multiple metrics can be used to mathematically measure resilience and, consequently, facilitate its integration into adaptation planning. One effective way to achieve this integration is to develop mechanisms that aggregate multiple dimensions inherent in resilience into a single, multi-variate, composite indicator. Composite indicators ideally combine multidimensional concepts in some manner to produce a baseline. The quality of such an indicator, as well as the soundness of its underlying premises, depend not only on the methodology used in its construction (i.e., the aggregation methodology) but also on the validity of the underlying theory and the quality of the data used to reflect that theory (i.e., the selection of variables) [7].

While the use of composite indicators in policy analysis is growing, its application to climate-based resilience, particularly in informing decision-making rather than global comparisons, is still nascent. Developing effective composite indicators alongside advancements in data analytics and prediction models can significantly contribute to ongoing research on operationalizing resilience. A key challenge in this endeavor is identifying resilience-leading indicators. Throughout this paper, we emphasize the importance of selecting indicators based on their relevance and criticality in shaping system resilience, rather than solely relying on data availability. Given the complexity and dynamic nature of infrastructure systems, adopting a systems thinking approach can enhance understanding of how systems respond to climate threats and evolve under different adaptation strategies. Concepts such as causal hypotheses can be employed to establish the theoretical foundation for operationalizing resilience using the identified leading indicators. This process involves identifying and linking various indicators and sub-indicators, as depicted in Figure 4.

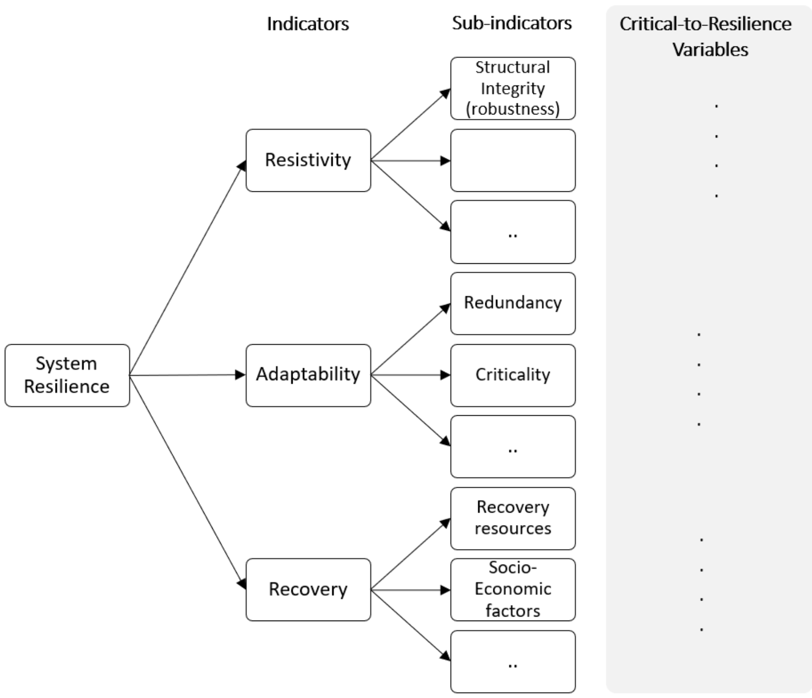

Figure 4. Hierarchical structure of resilience indicators, sub-indicators, and resilience-critical variables.

The second major challenge in constructing a composite resilience index is aggregating the leading indicators into a single multidimensional index. In the context of climate resilience, the most commonly used method for aggregation is linear addition of variables using equal weights [17,156]. Some examples include PEOPLES [157] and BRIC [8]. Other aggregation techniques include "fuzzified rules" such as min-max IF-THEN logic for conjunctive and disjunctive reasoning, weighted multi-criteria overlay analysis, and Analytic Hierarchy Process (AHP) [7]. The fuzzy inference models generally specify explicit input conditions to generate an output. These conditions hinder the aggregation strategy from robustness while also assigning the same importance to all the fuzzified factors. AHP and weighted multi-criteria overlay analysis are mainly utilized to prioritize criteria based on the assigned weights. However, decision-making based on weighted comparisons, for the most part, relies on the judgment of the decision-maker and often results in the assignment of arbitrary weights. Moreover, in AHP, pairwise comparisons must be established to determine the weights since the main goal is to order factors in their importance. This process becomes computationally expensive with a potentially large number of variables, and the complexity of the process is further exacerbated by the selection of scale and range for the weights from an arbitrary spectrum.

Some statistical techniques for dimensionality reduction, such as Principal Component Analysis (PCA) and Factor Analysis (FA), are also proposed to aggregate the selected indicators into a composite index (proxy). For instance, in the PCA method, the first principal component is calculated as a linear combination of all the variables while preserving as much variation within the data as possible [158,159]. When applied to real cases with data imperfections and deficiencies, this approach may result in poorly constructed principal component(s) and provide misleading reflections of the underlying indicators. In general, such methods often result in a measure that does not reflect the established theory behind which multiple causal pathways are initially constructed. In that respect, there is a significant niche in the literature for novel aggregation methods specific to the context of measuring resilience to sea-level rise risks. For instance, an axiomatic fault-driven resilience metric has been proposed to bridge this gap in the context of SLR in a recent study [111]. The axioms of the proposed framework are developed using a deductive (formative) construct based on the conditions essential for systems' survival during and after disruptions. As such, the resulting composite metric does not require the assumption of statistical homogeneity of data and does not resort to weights to map the system capacities to resilience.

4.2. Integration: From Local View to Global Perspective

Urban critical infrastructure systems are densely collocated and reliant on each other to function effectively. Overall, the interdependence of urban critical infrastructure systems underscores the need for a holistic and integrated approach to their management and maintenance. Any disruption or failure in one system can have cascading effects on the others, highlighting the importance of an integrated approach in sustaining resilient and adaptive urban infrastructure systems. As such, both the direct and indirect impacts of SLR on a system must be assessed and incorporated in associated resilience measures (Figure 5). In that respect, leading indicators can be employed to reflect not only the resilience of the components of a system but also their interaction with multiple systems. For instance, leading indicators are used in a recent study that focuses on onsite wastewater treatment and disposal systems to incorporate the impact propagation of these systems failing on freshwater resources in resilience metric generation process [111]. In another study, a vulnerability assessment is proposed to address physical interdependencies between infrastructures, where the output at one node serves as an input for another [160]. Besides the physical interdependence, other forms of infrastructure interdependencies were identified by Rinaldi et al. [161]. These include: (1) cyber interdependency mapping the communication or information links and (2) geographic interdependency representing interactions between neighboring geographic locations. To our knowledge, these different forms of infrastructure inter-dependencies are yet to be addressed in the context of measuring resilience.

Even though the extant literature offers a rich mix of resilience measures, as exemplified by the leading indicators listed in Tables 1–5, they are introduced with narrow scope, focusing on a particular system component or limited to a certain type of risk. Although it is essential to understand the marginal influence of specific risk types, more comprehensive and inclusive modeling approaches are needed for capturing resilience of systems to multiple risks in the context of developing holistic adaptation solutions. For example, in the context of SLR, all potential risks, such as coastal flooding, inland flooding, saltwater intrusion, and coastal erosion, must be inclusively addressed and reflected in the constructed resilience index. A noteworthy example is a study due to Snoussi et al. [162], where the authors investigate the impacts of SLR on a coastal zone by quantifying and integrating measures related to both coastal erosion and flooding. Additionally, the study by Ciscar et al. [163] proposes a comprehensive and holistic model for a collection of climate risks by fusing a variety of process models, such as flood models, various forecast models for coastal erosion, and rising groundwater levels under a collection of SLR scenarios. Extending such models to build metrics that capture the resilience of an overall urban system is a promising area for research. Leading indicators can offer the "joining points" to connect metrics across multiple systems (local models) within a larger system of systems framework (global model).

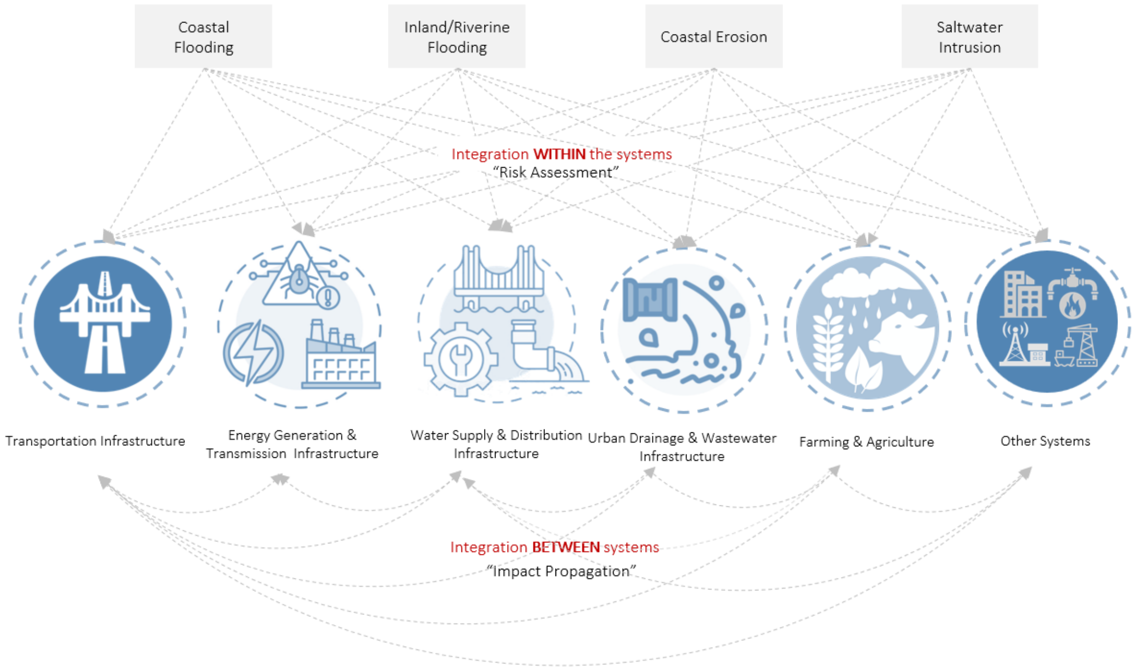

Figure 5. A diagrammatic representation of interdependencies across infrastructure systems (inclusive of other systems such as harbor, residential, communications, etc.) in the context of SLR impact.

4.3. Inclusion and Coordination: from Infrastructure-Centered Resilience to People-Centered Resilience

Most of the resilience metrics pertaining to infrastructure systems tend to focus on the engineering aspects of the risks and often ignore the social and economic impacts. Therefore, solutions based on such metrics often overlook the uneven distribution of costs and impacts across social classes. Integrating the social determinants into the construction of resilience metrics will help prioritize addressing the needs of those on the front-line and those who already suffer from a range of social challenges and develop more equitable solutions. Such integration must be reflected in the adaptive and restorative capacities of the engineered systems and the communities they serve. People-centric indicators typically relate to social connectedness, equity and social justice, health and well-being, economic security and cultural preservation. Developing an inclusive methodology must account for community or region-wide resilience, which incorporates such factors as well as the inter-dependencies between multiple systems and regions. Only a small group of studies such as [70,90,111,140] can be cited from the extant literature that explicitly integrates socioeconomic factors into infrastructure resilience modeling.

Climate adaptation is of relevance and interest to a wide range of stakeholders and policymakers. Their engagement and participation can offer support during the planning and implementation stages. From the policy-making perspective, it is imperative to integrate multiple objectives and stakeholder incentives into the decision-making process to ensure actionable solutions. For example, some stakeholders are so risk-averse that the decision makers, acting on their behalf at the negotiations, are willing to invest heavily into infrastructure to minimize expected damages [164], whereas decision-makers representing fiscally conservative stakeholders would argue for low investment-cost solutions. In either case, a traditional single-objective function masks these trade-offs leading to a locally optimal solution that could be inconsistent with these stakeholders' preferences [165]. In this regard, reaching a global optimal adaptation policy that addresses the stakeholders' visions, which in some cases might be conflicting, is a challenging problem that needs further research. This challenge is exacerbated by the need for resilience metrics that can be aptly incorporated into objective functions.

Stakeholder coordination is crucial at the very early stages; when the theory behind the resilience metric is formulated, expert opinions, community needs, and concerns should be reflected in the metric by designing appropriate leading indicators that inclusively address the different perspectives on resilience. Such coordination ensures that leading indicators are grounded in the lived experiences and perspectives of community members, rather than being imposed from above by outside experts or authorities. Developing metrics with communities can help to identify and prioritize the factors that are most important for building resilience in a particular context. The indicators identified by such processes will have a higher chance of collective understanding, acceptance, ownership, and building trust. Several community engagement and community disaster resilience frameworks proposed in the literature [166,167] can be leveraged to develop methodologies for identifying indicators and co-constructing metrics that can be integrated into infrastructure resilience modeling.

5. Conclusions

In contrast to lagging indicators that are characterized based on historical performance, leading indicators aim to capture the state of a system to predict its future performance. In this respect, they focus on "what drives results" and as such, their construct is structure-based, formative, and deductive. They are especially useful for assessing complex systems or when adequate or readily available data are scarce. As such, leading indicators offer practical options for assessing infrastructure and community resilience developing measures, particularly in the context of adaptation and decision-making. When adequately mapped to the system variables, leading resilience indicators can guide assessing and monitoring the resilience of systems across time and space. They can guide communities in taking adaptation actions at the right time, at the right location, and with the right scope. Likewise, they can be instrumental in setting thresholds and priorities for adaptation actions. More importantly, they can be used in shaping adaptation actions as components of the decision-making process.

We provide a review of leading indicators employed to assess the resilience of a selection of critical infrastructure systems, namely transportation, water supply and distribution, waste water collection and treatment, energy generation and transmission, and agriculture, to sea-level rise. Based on the insights gained from this review, we highlight three research directions to fill the gap in the existing literature on resilience measurements that can aid decision-making on adaptation: (i) aggregating leading indicators into functional composite resilience measures, (ii) leveraging leading indicators to integrate resilience metrics across multiple systems, and (iii) using leading indicators to design mechanisms to coordinate resilience measures across the environment–people–infrastructure nexus. We examine and discuss the pertinent challenges and opportunities for each of these research directions.

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