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AI for infrastructure resilience

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Foreword

Around the globe, infrastructure systems are under growing pressure—from extreme weather events and aging assets to the demands of the energy transition, urbanization, and accelerating technological change.
Yet amidst these challenges lies a significant opportunity: **to envision and create infrastructure that is more resilient, intelligent, and adaptable.**

Artificial intelligence (AI) is rapidly transitioning from being experimental to being an important part of the solution. Leaders are recognizing AI not just as a technical innovation, but one of the strategic tools that can be used to make infrastructure systems more resilient. Whether through predictive maintenance, digital twins, or AI-enabled early warning systems, AI is helping public and private sector leaders make faster, smarter and more accurate decisions—and in doing so is helping to mitigate risks, reduce costs, lower recovery times, and maintain vital services to support thriving societies and economies.

Examples are already emerging, like the use of digital twins in city planning to simulate flood occurrences in different extreme weather scenarios, demonstrating what's possible when advanced technology is embedded into infrastructure strategy.

The potential of AI is vast. With the right vision and ecosystem collaboration, it can help leaders build infrastructure that's stronger, more efficient, more sustainable and future-ready. Progress comes when infrastructure stakeholders—including policymakers, planners, operators, investors, technology providers, and insurers—move beyond experimentation and pilots to help scale AI adoption with confidence.

The timing is right. Ecosystems are evolving. Solutions are maturing. The value proposition is clear. AI can be both a tool for innovation and a strategic enabler of resilience.

Explore the insights, draw inspiration from the examples, and consider how your organization can take the next step forward.

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Executive summary

Infrastructure is fundamental to modern society. It can shape how we live, work and move, enabling the flow of people, goods, and information. From energy and water, to healthcare, sanitation, and transportation, infrastructure helps deliver essential services that support human well-being and economic resilience. When infrastructure thrives, societies can flourish.

To remain effective, infrastructure should continually evolve. With accelerating population growth and economic development, the coming decades will likely demand a wave of new infrastructure—systems that are more expansive, intelligent, adaptive, and sustainable. But as infrastructure systems grow in size and value, they also become increasingly vulnerable to the changing environments around them.

Natural disasters alone are projected to cause approximately US$460 billion in average annual losses to infrastructure globally by 2050.[1] For comparison, natural disasters have resulted in more than US$200 billion of average annual damages globally over the last 15 years.[2] Natural hazards are expected to become more frequent and intense in the future due to the changing climate, significantly increasing associated losses.[3]

Resilient infrastructure—so it can absorb these shocks, bounce back quickly, and adapt[4]—is important as continued economic and civil demands put highways, power grids, and water systems under greater stress.[5] Making infrastructure resilient can help protect lives and livelihoods, keep cities running, and enable economic growth despite potential risks.[6]

The transformative power of artificial intelligence (AI) has the potential to significantly enhance infrastructure resilience. Infrastructure resilience unfolds across three stages—planning (prevent), response (detect and react), and recovery—and AI can offer powerful tools at each step. In the planning phase, machine learning can help analyze risk data and simulate scenarios to identify measures that can be taken for prevention and preparedness to improve flood resilience[7] or using fire-resistant materials.[8] During an event, AI-driven early-warning systems and real-time monitoring help accelerate detection,[9] and help guide emergency responses.[10] In the recovery phase, AI can help accelerate recovery by prioritizing repairs through predictive damage assessments and optimized resource allocation.[11] By weaving data-driven insights into planning, response, and recovery, AI can strengthen traditional resilience measures, reduce vulnerabilities, and help infrastructure adapt more effectively to evolving risks.

Numerous real-world applications help demonstrate the effectiveness of AI-enhanced resilience solutions. Digital twins, for example, can simulate and stress-test infrastructure designs, which can lead to more disaster-resilient assets. AI-powered predictive maintenance can help prevent technical failures and ensure operational continuity—for instance, applied to an offshore wind turbine, it has the potential to reduce downtime by 15%, and increase annual revenues by up to 6%, as outlined in this report.[12] AI can also play an important role in hazard mitigation: systems that monitor forest areas for early signs of smoke can detect wildfires in their infancy, enabling suppression before these risks escalate.[13,14] For example, adapting California's early wildfire detection system to Australia's forests could mitigate an estimated US$100 million to US$300 million in annual damages while requiring a one-time investment of approximately US$300 million.[14,15] To support recovery, AI can accelerate post-disaster damage assessments, helping to restore services and reduce economic disruption. For instance, Deloitte Consulting LLP's OptoAI tool for post-disaster inspections can more than double roof reconstruction speeds by helping to identify repair needs after extreme weather events.[12]

The findings in this report show that integrating AI-powered solutions for hazard mitigation and vulnerability reduction alone could yield approximately US$70 billion globally in annual savings in direct disaster costs by 2050—equivalent to 15% of projected average losses, complementing other resilience options.[16] With improved AI capabilities, these savings could exceed US$110 billion annually.[16]

Despite this enormous potential, the path to widespread implementation of AI-enabled resilience in infrastructure systems is challenging. Obstacles include technological limitations, financial constraints, regulatory uncertainty, and institutional inertia. High-quality, diverse datasets contribute to effective AI performance, yet data availability and accuracy remain one of the major concerns.[17] Upfront investment costs—often paired with uncertain short-term returns—can further deter adoption.[18] On the regulatory and security front, as AI-specific frameworks continue to evolve, coupled with cybersecurity and privacy concerns, progress can be slow, particularly in regions with limited digital infrastructure, notably low-income countries. Additionally, a shortage of skilled professionals and organizational resistance to new technologies and ways of working can hinder momentum.[19]

Realizing the potential of AI to enhance infrastructure resilience can require coordinated action across the ecosystem— from policymakers and infrastructure operators to technology companies and the financial services and insurance industries:

- **Policymakers** play a foundational role by helping to shape the enabling environment for the widespread adoption of AI. This can include playing a role in standard setting, offering economic support schemes, and modernizing legacy infrastructure. Beyond regulation and economic support, governments can also help drive coordination across the infrastructure value chain—facilitating cross-sector collaboration and long-term planning.
- **Infrastructure owners and operators**, many of whom are public agencies, should look to embed AI across the planning, design, and operational phases to help unlock efficiency gains and enhance resilience. Early investments in high-impact pilot projects can generate proof points, economies of scale, and a cycle of continuous learning. Modernizing systems to be AI-ready, particularly through adaptable and expandable IT frameworks and interoperability standards, is important.
- **Financial institutions** are key in overcoming the funding gap that AI solutions often face. Through innovative financing tools—such as resilience bonds or targeted credit lines that include AI—they can help support long-term projects with delayed returns. These institutions can also apply AI internally to help enhance risk assessment and investment processes, including credit underwriting and asset evaluations. As co-investors in public-private partnerships, they can help amplify the impact of resilience strategies alongside governments.
- **Insurers** have the opportunity to evolve alongside infrastructure systems by embedding AI into their services. This includes developing new products tailored to AI-enabled assets, offering premium reductions for systems that help integrate trusted AI solutions, and improving risk models through advanced analytics. In doing so, insurers can help incentivize the adoption of AI for resilience while better managing their own exposure to risks associated with natural hazards.
- **Technology companies** are the innovation engine helping to power AI development. Their role extends beyond software and algorithms to include integrated solutions that help combine AI with complementary technologies such as the Internet of Things (IoT) and digital twins. Demonstrating the measurable impact of these solutions on resilience outcomes is important. Equally important is helping to ensure that digital innovation aligns with operational goals, including managing energy consumption through alternative energy sources.
- **Architecture and engineering firms** play a key role in embedding AI tools into the planning and design phases of infrastructure systems early to help enhance their resilience. By integrating tools such as digital twins during planning and helping to ensure compatibility with real-time monitoring systems and predictive analytics, they can help create smarter, more resilient infrastructure. Their close collaboration with technology and service providers can help ensure that emerging innovations translate into scalable, real-world solutions.

Coordinated and decisive action across stakeholders is important to help build infrastructure systems, that are prepared for the challenges of a changing world. By forging an ecosystem that is resilient to disruption and reinforced with AI across the phases of resilience—planning (prevent), response (detect and react), and recovery—a safer, smarter and more resilient future awaits.

1. Introduction

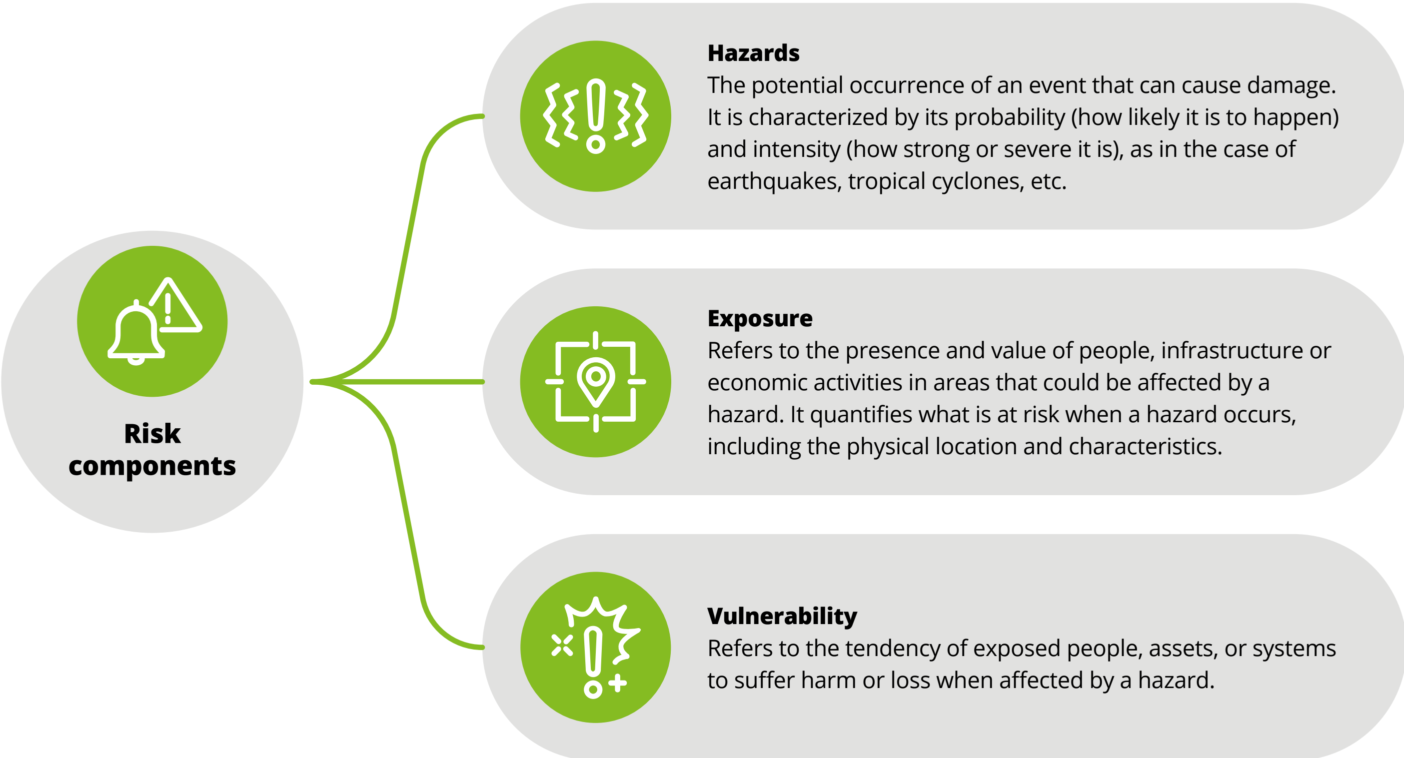
Infrastructure comprises the assets and networks that help deliver the essential services supporting modern life—from water, food, and energy to health care, education, and communications.[20] These assets include physical systems such as energy generation and distribution, roads, railways, bridges, ports, airports, water treatment and supply, and waste management, as well as the digital platforms that control, monitor, and optimize their operation.[21,22] In many economies, infrastructure investment makes up a substantial share of GDP—for example, over six percent in China in 2020—and its value continues to grow.[23]

Recognizing the role of infrastructure systems in underpinning economic growth is important, especially when confronted with disasters. Such events can profoundly disrupt systems, which can result in economic consequences. The complex interconnections between infrastructure and the broader economy reveal how indirect effects—such as supply chain interruptions, service disruptions, and community displacements—can decelerate economic activity. Furthermore, the long-term impacts on productivity, access to education, and health emphasize the necessity for resilient infrastructure to help alleviate these challenges.

Infrastructure systems are subject to disaster risks that can entail both physical damage costs and service disruptions. Risk to infrastructure emerges from the interaction of three dimensions[22]—hazard, exposure, and vulnerability (Figure 1)—which together help determine the risk of damage when a disruptive event occurs. Hazards are the potentially damaging physical events themselves—storms, floods, heatwaves, or earthquakes—whose frequency and intensity are increasing. Exposure refers to the presence and value of assets within a hazard zone, from power stations and pipelines to digital control networks. Exposure can increase as societies invest more heavily in infrastructure. Vulnerability describes how susceptible those assets can be to harm—driven by factors like design standards, material types, maintenance regimes and system interdependencies. By analyzing how a given hazard interacts with exposed, vulnerable infrastructure, decision-makers can help quantify risk and prioritize investments that can reduce exposure (for example, by relocating assets), strengthen design and maintenance to lower vulnerability, and build adaptive capacity— helping to ensure that new and existing systems remain resilient in the face of evolving risks.

Engineers and planners can embed resilience in infrastructure by designing and managing systems to help withstand shocks—absorbing impacts, responding swiftly during an event, and adapting afterward to help restore service with minimal disruption. This can bring significant economic benefits. The benefit-to-cost ratio (BCR) estimates for investments in resilience exceed three, and in some cases can even reach as high as 50.[24] This means for US$1 invested in a resilience solution, US$3 to US$50 worth of damages and losses can be avoided. According to the National Institute of Building Sciences, each dollar invested in resilience saves between US$4 and US$11 in disaster response and recovery costs.[25] Locating infrastructure in places less likely to experience hazards, and reducing its vulnerability to hazards through better design or building redundant systems, can help develop infrastructure resilience.

Figure 1. Understanding infrastructure risks for disaster management



Source: Deloitte Global based on the assessments carried by CDRI,[22] United Nations,[26] and IPCC.[27]

In its broader definition as a branch of computer science that enables machines to perform tasks requiring human intelligence,[28] AI is transforming our societies. It is also revolutionizing industries such as healthcare, transportation, manufacturing, and retail, by optimizing supply chains and providing predictive diagnostics, real-time decision-making, personalized recommendations, and different types of automation.[29] Beyond these transformations, AI is positioned to help strengthen infrastructure resilience: it can help predict equipment degradation and schedule maintenance before failures occur,[30] use high-resolution weather and sensor data to forecast floods or heatwaves days in advance,[31] and deploy computer-vision drones to inspect bridges and pipelines after an event.[32] By layering these capabilities atop traditional resilience measures—such as hazard-based land-use planning, robust engineering standards, and emergency response drills[33]—organizations can gain earlier warning, more precise risk assessments, and automated decision support that together help reduce downtime, limit damage, and accelerate recovery.

While AI has demonstrated its value in optimizing operations,[34] and strengthening industrial systems,[29] there is still a lack of focused, concise assessment of its role in infrastructure resilience—especially as asset exposure and frequency and intensity of extreme weather events grow. This report aims to help fill this gap by first, identifying the risks threatening the infrastructure and potential damages, and second, assessing the key applications of AI to help enhance the resilience of infrastructure and the resultant economic benefits.

Using a data-driven, model-based approach, this analysis estimates both the current and future value of infrastructure systems, as well as the average losses caused by major natural disasters. Using examples and case studies based on empirical findings and modeled applications, AI's resilience improvement potential is assessed and calculated. The findings are then compiled and interpreted from a decision-maker lens, to identify not only the answer to the question "what", but also to "how" to harness AI to enhance infrastructure resilience.

2. Investing in stability: Why infrastructure resilience matters

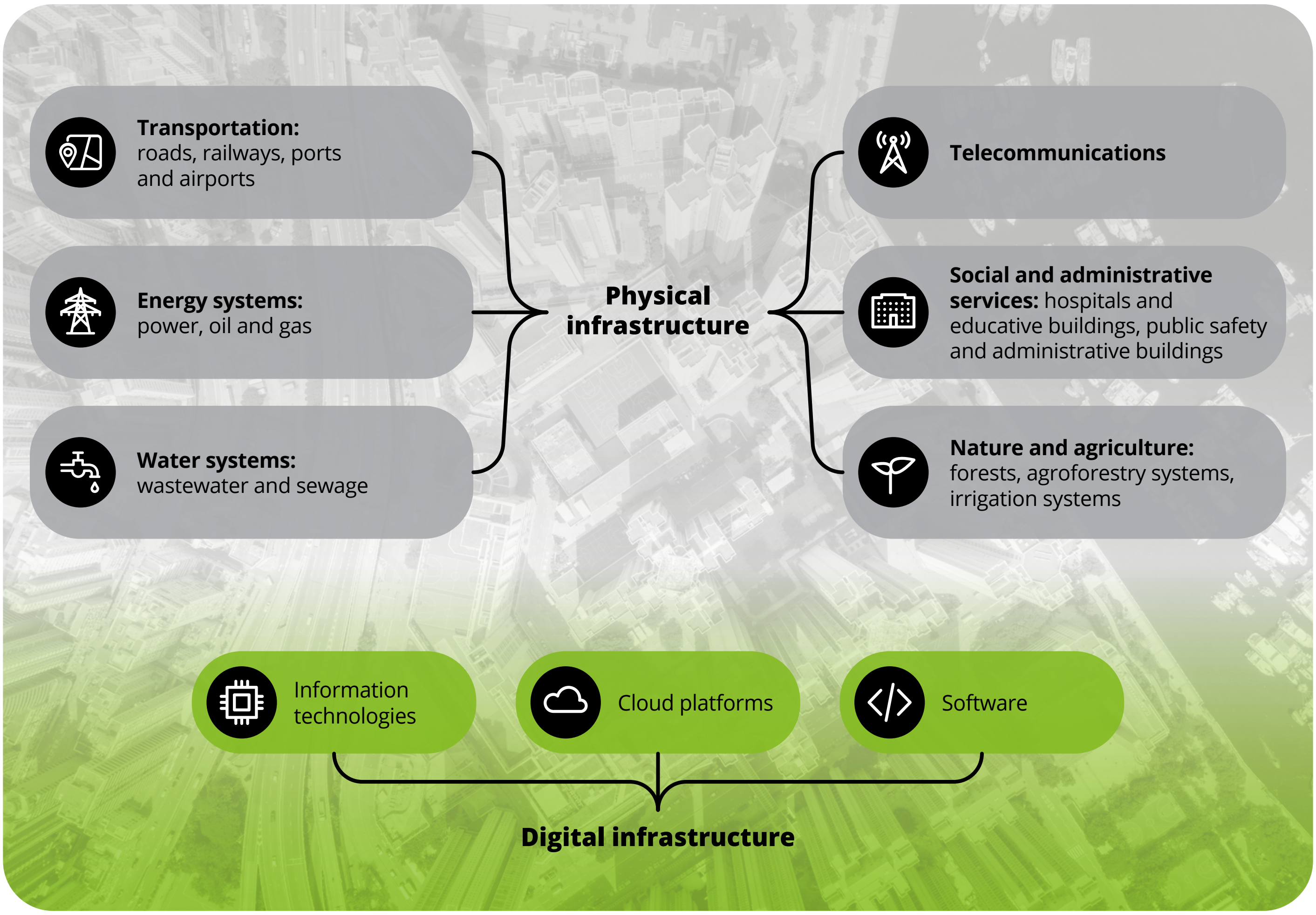
Infrastructure serves as a backbone of communities and society. Deloitte Global's analysis shows the economic value of infrastructure could reach US$390 trillion by 2050, an 85% increase compared to 2022, while the annual average losses to infrastructure caused by natural hazards could more than double by 2050, reaching approximately US$460 billion. Resilience can create impact in each of its implementation phases against a hazard—planning and prevention, detection and response as it happens, and recovery afterwards—becoming increasingly important to help minimize these losses.[35]

Infrastructure refers to the fundamental facilities and systems serving a country, city, or other area, including the services and facilities necessary for its economy to function.[36] Infrastructure can be divided into two main categories: physical infrastructure and digital infrastructure.

Physical infrastructure encompasses the built environment, serving communities: transportation infrastructure, utilities, telecommunications, and social (administrative and public) service buildings, including schools, hospitals, social housing, and public safety infrastructure.[37] Digital infrastructure refers to the digital side of physical and social infrastructure, supporting and enhancing its functionality. It includes information technologies, cloud platforms, software, etc.[38] (Figure 2).

Physical and digital infrastructure systems are among some of the key investments that help support economic growth and social development.[6]

Figure 2. Physical and digital infrastructure systems



Source: Deloitte Global analysis based on The World Bank[37,38,39]

2.1. Growing infrastructure exposure

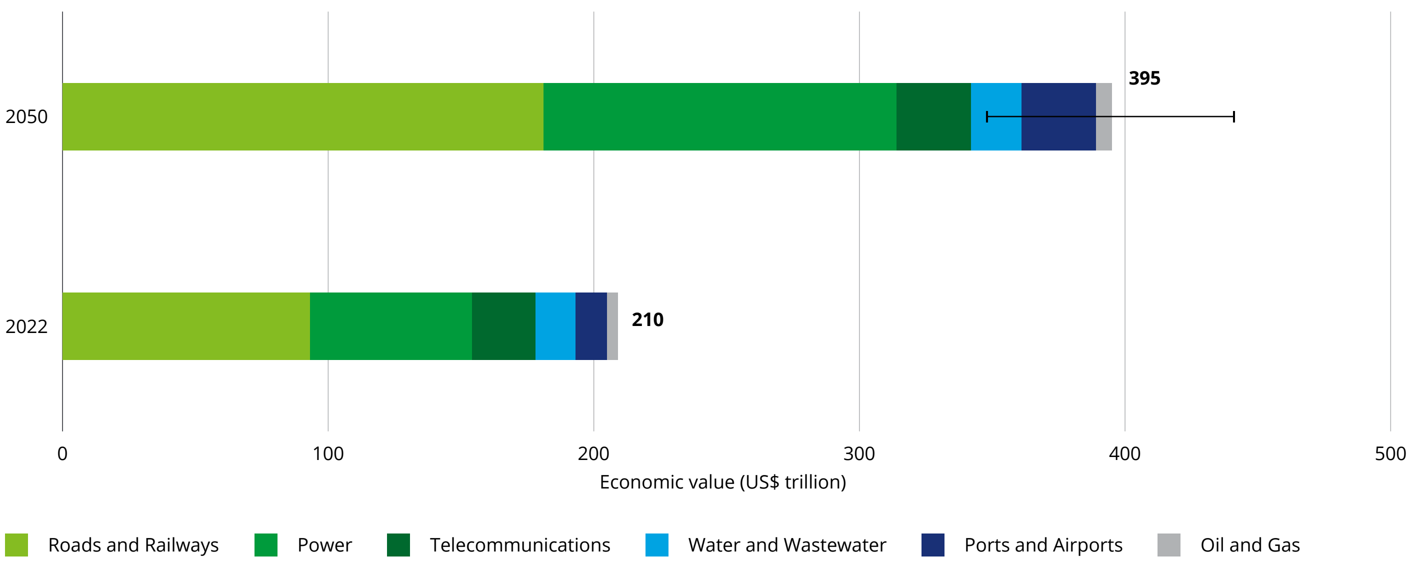
Infrastructure development is an important pillar for the global economy. Every year countries spend between 0.2% and 6% of their GDP in transportation infrastructure development alone, representing more than US$200 billion of annual investments.[40,41] Infrastructure investments are expected to reach trillions of dollars in the coming decades to help support future economic development and population growth.[42] The total estimated infrastructure value for 2050 is expected to grow by approximately 85%, from more than US$200 trillion in 2022 to approximately US$390 trillion in 2050, driven by these investments (Figure 3).

2.2. Risks impacting infrastructure systems

Infrastructure systems can be subject to a wide range of risks that can be caused by different types of hazards and incidents, including natural disasters, technical failures, cyber threats, and social instability (Figure 4). Acute natural shocks such as earthquakes, floods, and hurricanes can cause sudden, severe, and extensive damage to infrastructure.[43] Chronic stresses amplify the frequency and severity of extreme events, intensifying natural hazards.[44] Concerns related to the health and state of physical assets, such as corrosion, aging components, or material degradation, can gradually undermine performance, causing technical incidents and failures. As infrastructure systems become increasingly digital, intelligent, and data-heavy, cyberattacks represent a growing risk, with the potential to disrupt operations and compromise safety.[45] Finally, war/conflicts, geopolitical tensions, and social movements can also impact infrastructure systems and cause damages. For instance, the latest report of the Rapid Damage and Needs Assessment (RDNA4) commissioned by the Ukrainian Government, the World Bank Group, the European Commission, and the UN found that that the Russia-Ukraine war caused more than US$520 billion of damages by the end of December 2024, primarily in housing, transport, and energy infrastructure.[46]

As different types of infrastructure and economic sectors become more interconnected, the potential impact of risks across multiple domains becomes more severe.[47] A disruption in one sector can quickly cascade into others, such as power outages affecting communications, or water supply interruptions hindering energy production. These cross-sector interdependencies can complicate planning and response to crises, especially as threats grow in scale and frequency, from cyberattacks to extreme weather events.

Figure 3. Infrastructure and its economic value



Source: Deloitte Global analysis based on CDRI[22] for historical values and the methodology described in Appendix 1 for future projections using population growth data from the World Bank estimations[48] and economic growth from the Economist Intelligence Unit projections.[49]
Notes: 1. Other types of infrastructure (health, education, buildings) are not considered in this modeling exercise.
2. The uncertainty bar represents the uncertainty on the linear regression. See Appendix 1 for more information.

Figure 4. Risks threatening the infrastructure systems

	Natural disasters (acute shocks)	Natural disasters (chronic stresses)	Technological hazards	Cyberattacks and targeted physical attacks	Social and political instability
Energy systems	Wildfires, storms, floods and earthquakes: • Destroy transmission lines and transformers • Cause generation outages	Temperature trends: • Cause power demand levels exceeding grid capacity Less water availability: • Limits cooling for thermal and nuclear plants and affects hydropower output	Mechanical failures: • Cause repair cost and downtime Transmission network or generation failure: • Cause outages and disruption across sectors	Cyberattacks targeting power grids: • Entail blackouts and disruption of services State-sponsored attacks: • Can disrupt critical energy infrastructure operation Military attacks on power plants • Cause widespread blackouts	Opposition to new energy projects/fossil fuel phase-out: • Impacts energy supply and operation Regional conflicts • Disrupt energy trade
Water systems	Floods and storms: • Overwhelm treatment and drainage systems • Contaminate freshwater reservoirs Wildfires, storms, floods and earthquakes: • Destroy water pipelines, pumping stations, etc.	Shifting rainfall patterns: • Cause water scarcity or flooding Temperature trends: • Entail high evaporation, straining water resources	Poorly maintained infrastructure: • Cause failures in dam infrastructure (outdated or poorly maintained) • Cause pipe bursts or breakdowns in water treatment and filtration systems	Targeting water treatment and distribution systems: • Contaminate freshwater sources • Block access to freshwater for sanitation and drinking	Mass migration: • Strains existing water systems Social instability: • Causes conflicts over water resources, with protests or violence over actual and perceived shortages
Transport	Wildfires, storms, floods and earthquakes: • Damage transport infrastructure and destroy railways, bridges and ports • Disrupt supply chains	Temperature trends: • Increase derailment risk due to track expansion • Cause pavement buckling and asphalt rutting due to heat stress	Aging transportation: • Entail structural failures Poorly maintained infrastructure: • Cause failures in bridges, tunnels, roads and rail transport infrastructure • Delay mobility	Hacking smart transport systems (e.g., connected vehicle networks, toll systems) • Compromises traffic management systems (traffic lights, rail signaling, airport control)	Social instability and strikes: • Limit the availability of public transportation • Block transport infrastructure, reducing its use
Buildings	Wildfires, storms, floods and earthquakes: • Cause structural collapse • Damage non-structural elements (e.g., windows, ceilings, utilities)	Temperature trends: • Create urban heat islands and worsen living conditions • Increase air pollution • Raise cooling demand and bills	Industrial accidents (corrosion, fire, etc.): • Cause structural damages and destroy buildings Mechanical failures: • Destroy assets	Cyberattacks on urban systems (e.g., smart city infrastructure) • Cause service outages • Delay administrative processes Targeted demolition in urban conflict zones • Destroy buildings (schools, hospitals, etc.)	High population density and inequalities • Can strain public services (healthcare, emergency services)
Nature and agriculture	Floods, storms, and wildfires: • Destroy crops • Damage irrigation systems • Cause landslides and soil erosion	Temperature trends: • Reduce crop yields due to heat stress and shifting growing seasons • Degrade soils and reduce arable land availability • Increase wildfires due to drier conditions	Industrial accidents of nearby industries: • Contaminate soil and water • Cause crop loss and damage	Disruption of automated processes: • Lead to inability to monitor soil, weather, or livestock health sensors, reducing efficiency of operations	Increased population density and armed conflicts: • Damage rural areas, forests and natural ecosystems
Telecommunications	Wildfires, storms, floods and earthquakes: • Destroy equipment, damage towers and snap cables	Temperature trends: • Overheat network equipment, causing degradation	Mechanical failures, software bugs, hardware malfunction: • Lead to network outages, data loss, or degraded performance • Entail downtime	Cyber or physical attacks to telecommunication systems • Cause service outages • Delay administrative processes	High population density • Increase network congestion and overwhelm local systems

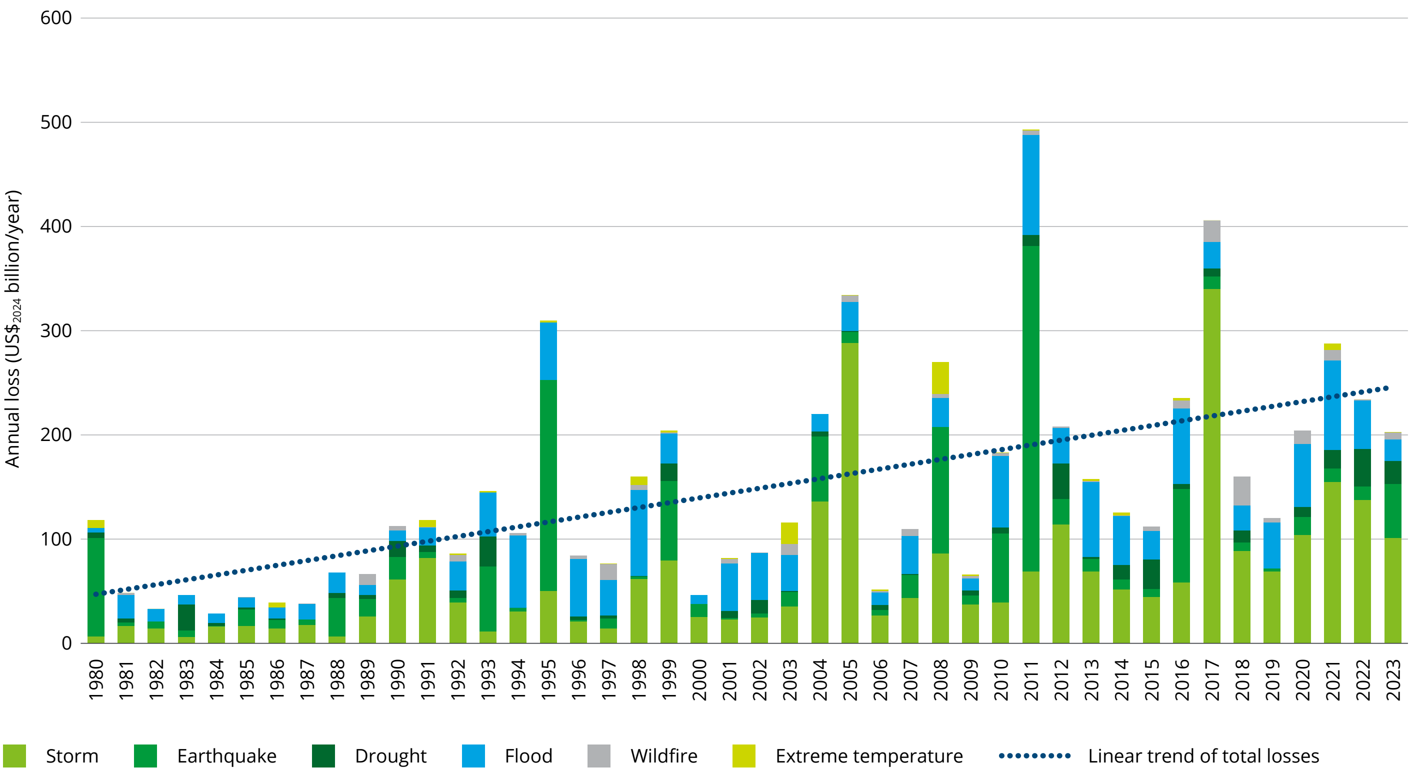
Source: Deloitte Global analysis based on EIB,[50] CDRI,[22] CISC,[51] Lam,[52] Leal Fiho et al.,[53] International Decade for Natural Disaster Reduction,[54] IMF,[55] CISA.[56]

Among natural disasters, acute shocks such as earthquakes, hurricanes, and tsunamis can strike suddenly, causing widespread physical damage to important systems. Chronic stresses can evolve over longer timeframes and can cause equally severe damage to infrastructure systems,[53] requiring sustained adaptation and retrofitting efforts. Concerning technical hazards, risks may arise from a range of causes, including human error, design flaws, aging infrastructure, inadequate maintenance, software bugs, and mechanical breakdowns. Since the beginning of this millennium, cyberthreats are increasingly sophisticated and harmful, and as infrastructure systems become more digitized and interconnected, their vulnerability to these attacks also grows. These events can challenge infrastructure resilience due to their scale and speed, and can lead to economic losses and poor performance due to breakdown, destruction, or malfunction.

As seen in Figure 4, natural disasters are not the only forces threatening infrastructure systems. Technical failures can also cause property damage, where equipment malfunction or failure can lead to asset destruction, production downtime resulting from halted operations, and the associated costs of repair or replacement. In this context, the main economic impact often stems from business interruption rather than the direct physical damage costs. In industrial sectors, downtime alone can reduce annual revenues by up to 11%.[57] This underscores the importance of technical reliability and timely maintenance in infrastructure systems. However, when focusing solely on the infrastructure itself, natural disasters can represent much greater risks than technical failures.[58] The relative damage caused by cyberattacks, mainly from disruption of operations and downtime, is much less than natural disasters.[59] As such, the modeling focus in this analysis remains on natural hazards (both acute shocks and chronic stresses), which represent the bulk of the direct economic risks to infrastructure systems.

Over the past four decades, natural disasters have become both more frequent and more intense (Figure 5). Rapid urbanization, denser asset concentrations, and broader economic development have expanded infrastructure's footprint—and with it, its exposure to storm surges, floods, wildfires, and other events.[60] As infrastructure systems expand in size and complexity, their exposure also increases based on several factors, which may include geography, age, and quality of infrastructure. At the same time, hazards are intensifying: cyclones are growing stronger, heatwaves are lasting longer, and flood events are becoming deeper and more widespread, while chronic stressors like observed sea-level trends and shifting precipitation patterns steadily impact system performance. The Intergovernmental Panel on Climate Change (IPCC) report warns that these trends will only accelerate, putting ever-greater pressure on the resilience of both existing networks and new infrastructure yet to be built.[3]

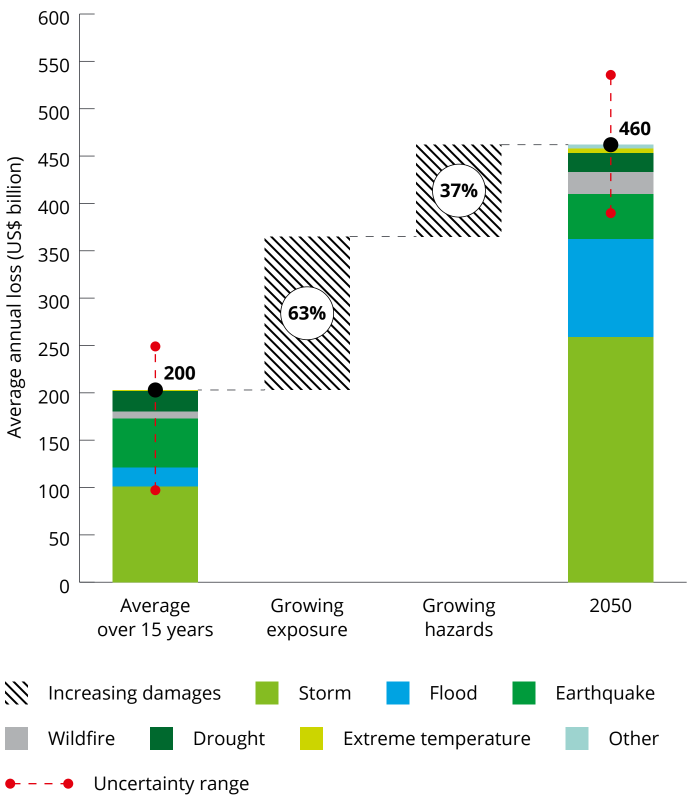
Figure 5. Historical losses due to natural disasters (including acute shocks and chronic stresses)



Source: Deloitte Global analysis based on CRED[2]

Among the losses incurred in the last 10 years, only about 25% were insured. For lower middle-income and low-income economies, the figure is starker, with less than 5% of total damages insured in the last 10 years.[2] This is a concern because uninsured losses tend to place a much heavier financial burden on individuals, businesses, and governments, slowing recovery and development efforts as they materialize as direct costs, driving macroeconomic impact.[61] Moreover, uninsured losses are growing much faster than insured losses, especially in low- and middle-income countries, where a small proportion of infrastructure assets are covered by insurance.[62]

Figure 6. The evolution of average damages caused by natural hazards by type (including acute shocks and chronic stresses)[63]



Source: Deloitte Global analysis based on IPCC[3] and CRED[2]

Notes:

1. These values correspond to the direct economic impact of hazards on infrastructure, and excludes externalities and indirect impacts, which can represent several times the direct physical costs (Box 1).
2. Uncertainty range corresponds to the annual variability of hazards concerning the historical variability, and corresponds to a 50% probability that total annual damages fall within this range for future projections.
3. Average Annual Loss (AAL) represents the expected economic loss per year due to specific hazards based on probabilistic modeling. This metric provides a long-term average of potential damages rather than implying the exact annual damage level.

By 2050, average annual losses from natural hazards are projected to rise to approximately US$460 billion—and they could even exceed US$500 billion (Figure 6). That marks an increase of approximately US$260 billion compared to the past 15-year average. Nearly two-thirds of this jump (63%) stems from greater economic exposure—that is, more and higher-value assets placed in harm's way—while the remaining 37% reflects the intensifying frequency and severity of hazards.

According to Figure 6, storms—including tropical cyclones, tornados, thunderstorms, hailstorms, and blizzards—drive the largest share of infrastructure losses, due to their high frequency, wide geographic reach, and increasing intensity. Though extreme temperatures and wildfires currently account for a smaller portion of total losses, both are projected to rise by 2050, as observed temperature trends continue. By contrast, geophysical hazards such as earthquakes are not projected to change in frequency or intensity; any rise in their economic losses stems largely from higher infrastructure asset values that are exposed to hazards in vulnerable areas. It is important to note that these numbers represent a potential average in the modeled year and can vary greatly from one year to another. In any given year, the actual values may be significantly higher or lower depending on specific events or unforeseen circumstances.

By 2050, average annual losses from natural hazards are projected to rise to approximately US$460 billion. These losses are more than double the annual average compared to the last 15 years.

Box 1. The downstream impacts of natural disasters

A well-functioning infrastructure system is important for maintaining economic stability. When disasters impact these systems, the consequences often ripple through the economy causing further indirect damages.[64] The scale of the loss is closely tied to the degree of interdependence between the affected infrastructure system and the broader economy. Indirect impacts can have wider and extended consequences, such as disruptions to supply chains, lower productivity due to service outages, economic slowdowns from displaced communities or damaged businesses, and longer-term social and economic effects on education or health.[65] Indirect impacts can also cause long-term health and social problems, such as respiratory issues from wildfire smoke.[66] Businesses are often required to shut down, which can result in lost productivity, unemployment, and declining regional GDP. Transportation networks may be severely damaged or closed, which can impede the movement of goods and workforce, potentially leading to shortages and increased prices of essential goods.

According to the Minderoo Foundation's *Fire and Flood Resilience Blueprint*, between 2000 and 2020, natural hazards caused 350 deaths and millions of hectares of forest burned. In economic terms, they resulted in more than AU$25 billion in direct damage (US$15.9 billion), but the total economic costs reached over AU$100 billion (US$63.6 billion).[67] Similarly, California's 2018 wildfire season caused economic damages of US$148.5 billion with US$27.7 billion in monetary losses, US$32.2 billion in health costs, and US$88.6 billion in indirect losses.[68] These two examples help underscore the vast scope of total societal impact, including both unquantifiable and indirect cascading effects.

This report's focus is limited to the direct impacts of natural hazards on infrastructure as immediate physical damage, excluding externalities such as degradation in health, biodiversity loss, and so forth.

2.3. Incorporating resilience into infrastructure

As the world continues to experience hazardous events such as the 2025 wildfires in Southern California and 2024 floods in Spain's Valencia, infrastructure resilience has gained significant attention in recent years.[5] Resilience refers to the ability of a system to help anticipate, absorb, adapt to, and recover from disruptive events.[4] Key themes of resilience can encompass adaptation, which refers to modifying structures to help withstand future risks; absorption as the ability to withstand shocks without complete failure; and recovery, restoring functionality efficiently.[69] These processes unfold across three timeframes: planning before the hazard or incident (prevent), response during the event (detect and react), and recovery after the event, which together help shape a system's capacity to endure and bounce back from hazardous events and incidents (Figure 7).[70,71]

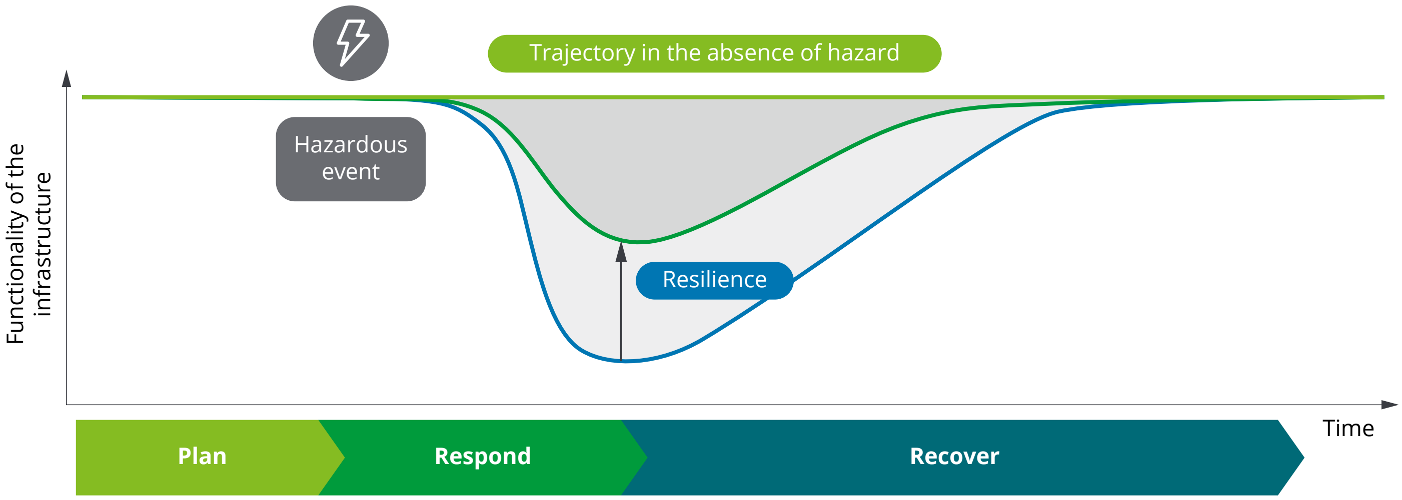
Conventionally, resilience in infrastructure has been achieved through robust engineering design,[33] regular maintenance, and the use of resistant materials.[62,72] Strategies such as redundancy (e.g., backup systems), decentralization of critical services, risk assessments, and pre-disaster planning[73] have been key to preparing for disruptions like natural disasters, system failures, or cyberattacks. Regular maintenance and manual response protocols can play a vital role in helping to ensure that systems can recover or continue operating under stress. These conventional methods, while effective, rely on pre-defined problems and fixed responses, when designing for resilience requires a holistic approach.[74] In the context of rapidly evolving threats,[75] using today's technologies to envisage tomorrow's potential threats can lead to significant resilience gains.[76]

Integrating resilience into infrastructure systems involves a comprehensive approach spanning three critical phases: 1) planning and prevention; 2) response through detection and reaction during a hazard; and 3) recovery afterwards, leading not only to a return to normal operations but also to enhanced system resilience, helping to ensure that future disruptions are less severe or can be mitigated.[77,78]

2.3.1. Plan: the prevention phase

Long-term planning is important for resilience. This phase involves identifying potential risks and vulnerabilities and implementing strategies to help mitigate them. For instance, urban planners and policymakers can design infrastructure to withstand natural disasters, such as earthquakes and floods, by adhering to building codes and investing in high-quality materials.[79] Additionally, communities can be educated on disaster preparedness, and emergency response plans can be developed and regularly updated. These proactive measures can help to minimize infrastructure damage and ensure that systems remain functional even under stress.[80]

Figure 7. Performance curve of infrastructure resilience



Source: Deloitte Global analysis based on United Nations Office for Disaster Risk Reduction's resilience definition[69]

2.3.2. Respond: detection and reaction during the hazardous event

During a hazardous event, the ability to detect and react swiftly is important. Advanced monitoring systems, such as early warning systems for natural disasters, can play a central role in this phase.[81] Real-time observation, data collection, and analysis help enable quick decision-making, allowing authorities to deploy resources effectively and evacuate affected areas promptly. For example, weather radar systems can track the path of a storm, providing valuable information and greater time for preparations.[82] Timely detection can also enable timely reaction, eliminating or minimizing infrastructure damage. For instance, real-time surveillance of forests with IoT sensors and satellites can help detect wildfires early enough to suppress them before they are uncontrollable (Box 5).[83] Such immediate responses help limit the extent of infrastructure damage and protect lives.

2.3.3. Recover: after the incident

The recovery phase focuses on helping to minimize economic disruption and related losses. Post-event, the priority is to help restore essential services quickly. This includes repairing damaged roads, bridges, and other physical assets, as well as providing support to affected businesses and communities. Financial aid and insurance payouts can assist in this phase, helping individuals and businesses to rebuild and resume operations. Effective recovery helps ensure that the economic impact of the event is mitigated, allowing the community to return to normal quickly.[84,85]

Recovery after the incident does not end here. A second but even more critical step of this third phase is to strengthen infrastructure systems against future hazards. This forward-looking approach focuses on reducing vulnerability and increasing adaptability, aiming to help minimize or avoid future disruptions.[2]

3. Leveraging AI for infrastructure resilience

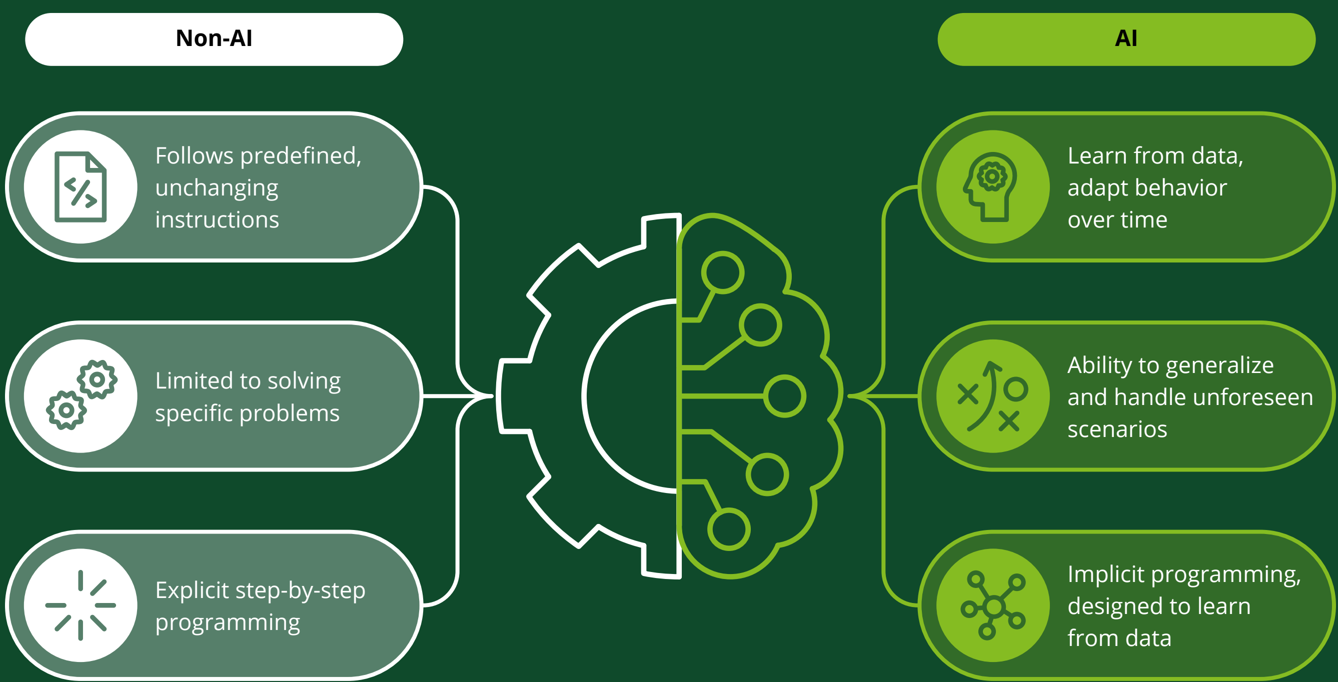
Implementation of AI solutions for broad planning and timely response through real-time hazard detection and reaction can help complement conventional approaches to resilience. This can help reduce the vulnerability of infrastructure systems, reducing the average losses caused by hazards by approximately US$70 billion per year in 2050[16] equivalent to approximately 15% of annual direct damage costs estimated (Figure 10).

AI (Box 2) offers significant opportunities to help enhance efficiency and optimize processes.[86,87] Its transformative potential can also bolster resilience to different types of disasters, complementing conventional resilience options.[88,89] AI can play an important role in anticipating failures, minimizing disruptions, and accelerating recovery. However, realizing its full potential requires a clear understanding of where it adds value and how to measure its effectiveness.[90]

Box 2. What is Artificial Intelligence?

Defining AI is a challenging task. The Organisation for Economic Co-operation and Development (OECD) defines it as "a transformative technology capable of tasks that typically require human-like intelligence, such as understanding language, recognizing patterns, and making decisions."[91] The following key characteristics of AI distinguish it from a non-AI system: learning from data and adapting over time, generalization and handling new scenarios, and implicit programming (see figure below). Machine learning (ML) and deep learning, including neural networks, are different AI modeling techniques that can be used for regression, clustering, or Generative AI.[92,93]

The distinction between AI and non-AI based methods is becoming more fluid as non-AI systems such as digital twins[94] or IoT[95] devices are progressively integrating AI features for enhanced performance. For the sake of this analysis, such technologies are considered to be AI systems as the exact distinction between AI and non-AI is not at the core of the topic.



Source: Deloitte Global analysis

3.1. Measuring the effectiveness of AI for infrastructure resilience

The effectiveness of AI solutions in enhancing infrastructure resilience can be evaluated across four key dimensions: economic, technological and performance, environmental, and social impacts (Figure 8). Assessment of the impact of AI requires defining metrics and providing a framework for determining whether AI helps enhance infrastructure resilience in a cost-effective and efficient manner. These metrics can then enable decision-makers to track progress, compare alternatives, justify investments, and identify areas for improvement.

The economic impact of AI in infrastructure resilience can be quantified in financial gains such as cost savings from optimized operations, reduced asset damage, and the avoidance of repairs or replacements. AI also helps enhance return on investment (ROI) by enabling more strategic allocation of resources and improving overall budget efficiency in infrastructure planning, maintenance, and emergency response. The total cost associated with AI deployment depends on the complexity of the analysis, the performance requirements of the system, and the use of generative AI.[96] While the cost of basic AI solutions such as chatbots can range between US$20,000 and US$80,000, advanced custom solutions such as predictive maintenance systems can cost over US$500,000.[97]

Technological and performance metrics provide clarity on how the reliability, efficiency, and responsiveness of infrastructure systems can be measured. Key aspects include reduced downtime, fewer failures, faster recovery times, and better operational decision-making through real-time data analysis. AI-powered early warning systems can analyze seismic patterns and enhance earthquake forecasts. The implementation of such a system in California has shown more than 90% accuracy in the detection of the maximal magnitude of seismic activities 30 days in advance, outperforming logistic regression models with 32% accuracy.[98] This helps enable timely interventions to maximize the effectiveness of emergency response and minimize losses.[99]

AI can help optimize resource use and monitor and reduce the environmental footprint of infrastructure operations. This includes lower energy and water consumption, reduced waste, and decreased emissions through smarter system planning and

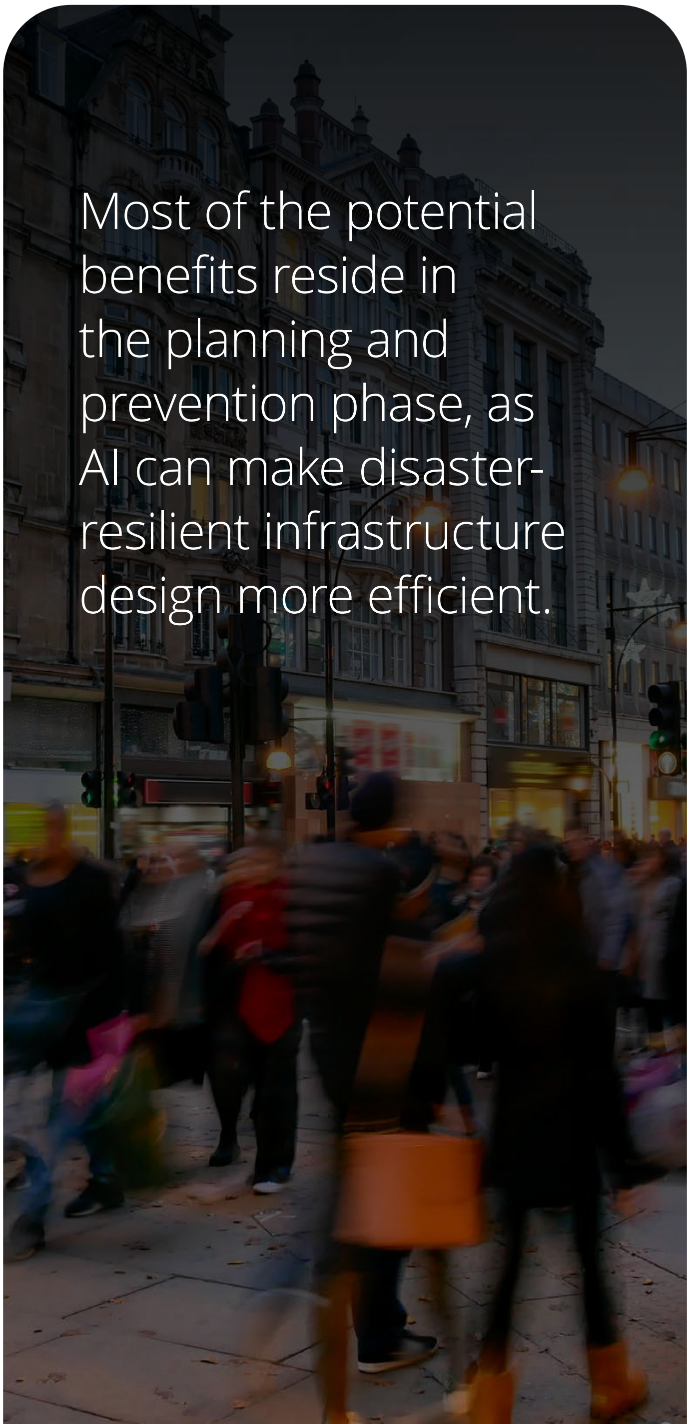
Figure 8. Metrics to measure the effectiveness of AI solutions

Economic impact	Technological and performance metrics	Environmental impact	Social impact
Cost savings ($)	Failure rate reduction (%)	Energy consumption and carbon footprint reduction (tCO_2/unit)	Change in number and types of jobs
Avoided cost ($)	Downtime reduction (%)	Material consumption reduction (t/unit)	AI score perception
Revenue growth (%)	Prediction accuracy (%)	Resource efficiency	Reduction in incident/ accident rates
Profitability increase (%)	Anomalies detected		Number of avoided deaths
Productivity gains (%)	Resolution time/runtime		
Return on Investment	Efficiency (%)		

Source: Deloitte Global analysis

renewable integration. However, the environmental benefits should be weighed against the energy demand of AI itself, which can cause further environmental burden. As a previous Deloitte Global analysis, *Powering Artificial Intelligence*, has shown, energy demand for data centers and machine learning computation equipment could reach as high as 1,000 TWh in 2030 and almost 2,000 TWh in 2050.[100]

Finally, the social dimension of AI consists of the number of jobs created in the development, deployment, and maintenance of AI systems, as well as changes in workplace accident rates before and after AI implementation. AI adoption will likely impact skill requirements; therefore, it should be carefully managed.



3.2. Potential economic benefits of AI-powered resilient infrastructure

The benefits of AI-enabled resilient infrastructure and the ability to help mitigate potential damage can be assessed across four factors to help evaluate the relative opportunities for economic impact: phase, type of hazard, magnitude of potential losses by hazard, and potential effectiveness of AI to mitigate risks.

All three phases of infrastructure resilience can benefit from being AI-enabled, with the first two phases—planning to reduce vulnerability (prevention) and responding to mitigate hazards (detection and reaction)—having immediate direct economic impact. The planning phase to reduce vulnerability consists of integrating resilience across each stage of infrastructure operation: in the design to create a more resilient infrastructure, notably by using digital twins (Box 3), as well as during operation, using tools such as predictive maintenance systems (Box 4). Most of the potential benefits reside in the planning and prevention phase, as AI can make disaster-resilient infrastructure design more efficient.

The response phase aimed at mitigating hazards includes early warning systems to help allow for better preparedness, which can reduce overall damages and potentially save lives. For example, AI can help to efficiently detect and suppress wildfires (Box 5). AI can also help mitigate the damage caused by floods with AI-enhanced flood forecasts, real-time flood mapping, and smart operations of flood-management systems (Figure 9).

The savings of AI-enabled resilience depends on two key factors: the magnitude of the damage caused by hazard type and AI's effectiveness potential for each hazard. For instance, losses caused by storms are estimated to exceed US$250 billion annually by 2050, while the estimated damage to infrastructure systems by wildfires remains an order of magnitude lower (US$23 billion annually). Therefore, although AI can avoid a higher share of damage in the face of wildfires, due to its limited overall direct economic damage to the infrastructure systems, the absolute savings due to AI (approximately US$7 billion) remain smaller than those associated with planning for and responding to storms and floods (approximately US$30 billion and US$20 billion respectively).

Figure 9. Benefits of AI-enabled infrastructure resilience per type of hazard and resilience strategy in 2050

Hazard	Plan (prevent)	Respond (detect and react)	Infrastructure damage – 2050 (US$ billion)
Storm	Storm-resistant infrastructure design using digital twins.	Better preparedness with AI-enhanced storm forecasts can help reduce damages to a limited extent.	260 / 230
Flood	Flood-resilient urban planning under current and future extreme weather conditions with AI-powered weather models and digital twins.	Better preparedness with AI-enhanced flood forecasts can help reduce damages.	100 / 80
Earthquake	Earthquake-resilient design, identifying risky terrain and suggesting additional mitigations.	Ongoing research aimed at forecasting earthquakes before they occur, but impact on mitigating infrastructure damages remains low.	50 / 40
Wildfire	Wildfire prevention due to efficient vegetation management and asset inspection.	Wildfire detection with IoT sensors, drones, and satellite images for quick fire suppression, helping to reduce its impact.	23 / 16
Drought	Optimal water use, identification of water leakage, drought forecasts for early implementation of scarcity measures.	AI-powered drought predictions can be made up to a year in advance, allowing for better preparedness. However, direct economic damage reduction remains limited.	21 / 20
Extreme temperatures	Understanding resilience of infrastructure in extreme temperatures (low or high) for more temperature-resilient infrastructure design.	AI-enhanced extreme temperature forecasts; however, not sufficient for reducing direct economic damage to infrastructure.	5 / 4

0 100 200 300

AI's effectiveness level: 2.5% Low, 10% Medium, 20% High

Without AI / With AI

Source: Deloitte Global analysis based on the methodology described in Appendix 3
Note: Only the six most important hazards are investigated as they represent over 99% of average damage costs predicted in 2050.

3.3. AI-enabled infrastructure resilience in action

There are many examples where AI-enabled infrastructure resilience can create positive benefits across the three phases of hazards—before, during and after—from resilient design and preventive measures by leveraging digital twins and predictive maintenance, to reactive measures such as wildfire detection and mitigation, as well as optimal recovery measures such as AI-enabled post-hazard damage assessment.

3.3.1. Reducing vulnerability: robust planning and preventive measures

Incorporating resilience into infrastructure design helps reduce vulnerability to hazards. Using AI tools in the planning phase, such as digital twins (Box 3), can help leverage more robust infrastructure design by analyzing, for example, the impacts of potential floods on the infrastructure. AI tools can also be leveraged for preventive and predictive measures, as in predictive maintenance systems (Box 4), which are designed to efficiently anticipate and address maintenance needs before incidents or structural failures occur. AI-based simulations are being used for numerous purposes including to help simulate potential cyclones in the US, allowing for better awareness and preparedness,[101] or for helping city planners in Japan identify areas vulnerable to soil liquefaction during an earthquake.[102]

Box 3. Digital twins for resilient urban planning

Digital twins are virtual replicas of physical systems designed to simulate the behavior of their real-world counterparts. They offer a transformative approach to urban planning by integrating real-time data, AI, and simulation technologies.[103] Digital twins are powerful tools that can be used for real-time infrastructure monitoring, predictive analytics and stress-testing, therefore improving infrastructure resilience. Moreover, they are economically viable solutions with a typical payback period of four to nine years.[104] Numerous municipalities are using digital twins for resilient urban planning, such as:

Flood resilience in Lisbon, Portugal: To help increase flood resilience, the city of Lisbon used a digital twin to simulate flood occurrences under current and future scenarios, enabling a more holistic assessment of the impacts of flood-induced events. This led to the development of an appropriate drainage plan, which was stress-tested against potential floods via simulations. Its implementation could help to mitigate up to 20 floods over the next century, which can be translated into savings of more than US$100 million in damage over this period.[105]

Smart solid waste management in India: Solid waste can become a major sanitary concern if not collected in time. Deloitte India developed a digital twin for an Indian municipality, helping forecast solid waste collection needs and optimizing collection routes. Leveraging the AI-based simulation and optimization platform and a better overall understanding of the resilience of the waste collection service, this solution helped mitigate sanitary risks by helping to ensure quick collection of solid waste, resulting in more than 20% cost savings on fuel consumption and 36 tCO_2 emission reduction annually by optimizing the waste collection route.

Urban extreme weather adaptation in Florida, USA: The Broward Metropolitan Planning Organization (BMPO) in the Miami area is addressing risks from observed sea-level trends and extreme weather events, with over 35 organizations coordinating infrastructure investments and resilience efforts. Facing challenges from siloed information and limited analytics, BMPO sought a unified scenario planning platform. Deloitte Consulting LLP is providing a solution using Google Cloud Platform, Google Earth Engine, and Vertex AI, offering data visualization, analytics, simulation, and modeling. This platform can help policymakers, planners, researchers, and community leaders collaborate and assess the impacts of extreme weather events, resilience measures, and infrastructure projects. The need for such platforms is common among regional planning organizations, highlighting the opportunity for these AI-enabled solutions to help enhance engagement, geospatial planning, and mission insights for state and local agencies.[106,107]

Urban heat island mitigation in Singapore: An urban heat island (UHI) is an urban area that experiences higher temperatures than the surrounding areas. UHI can reduce economic productivity and daytime work efficiency by up to 10%,[108] and increase cooling electricity demand[109] and heat-induced mortalities.[110] To help mitigate the UHI effect, Singapore is developing a digital twin to help identify potential future UHIs and investigate the impacts of additional green spaces, water bodies, or new buildings, helping Singapore develop appropriate adaptation strategies to increasing heat waves.[111]

Box 4. Predictive maintenance for enhanced infrastructure reliability

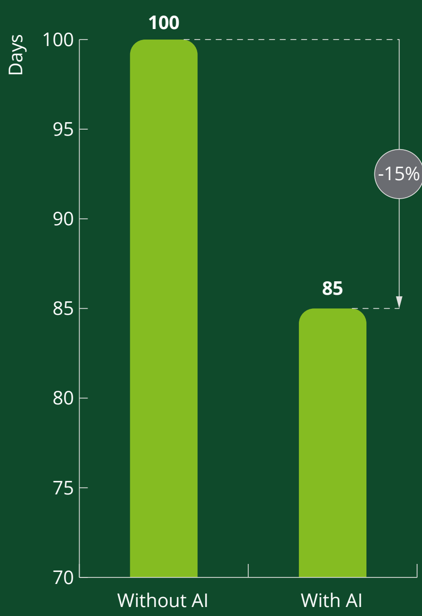
Predictive maintenance (PdM) is a maintenance strategy that uses the continuous or periodic monitoring and diagnosis of systems and equipment to predict failures. AI/ML[112]-enabled PdM identifies the how, why, and when a machine will fail before it occurs, reducing downtime and emergency maintenance as well as increasing capacity and productivity.[113,114] A main component of PdM is the ability to integrate AI with data captured from IoT sensors, which help provide visibility into the state of the assets. IoT[95] sensors capture operational signals, such as vibration, temperature, ultrasonic, and image data, which are then used by the AI/ML model.[115] The AI/ML model continuously monitors asset health, forecasting failures, and optimizing maintenance schedules. These systems can help detect subtle signs of wear long before they escalate into costly repairs or unplanned downtime.

Predictive maintenance of a 10-MW offshore wind turbine in the UK

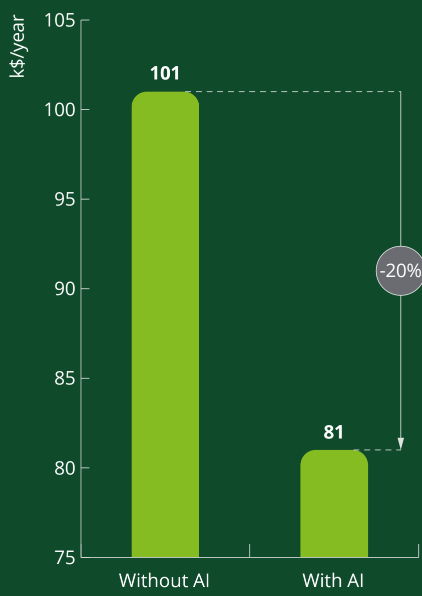
PdM is especially valuable for logistically challenging assets, such as offshore wind operations, where maintenance is not only costly—accounting for 25–30% of total lifecycle costs[116]—but also logistically challenging and potentially hazardous. Offshore wind turbines are often far from land and difficult to access, making reactive repairs costly, time-consuming, and risky. Predictive maintenance can help minimize unplanned interventions, reduce downtime, and significantly lower operational costs while helping to ensure safer and more reliable turbine performance.[117]

For a turbine, key parameters to monitor include vibration frequency, temperature, and operational load.[118] By extracting these features, the AI/ML model can focus on the most important data, improving its predictive accuracy.[119] Artificial Neural Networks (ANNs) and their variants are the most versatile AI techniques for wind turbine maintenance,[120] as they can be applied to monitoring, optimization, data prediction, and decision-making tasks. The implementation of the PdM system can help reduce downtime (Figure A below) and create significant savings in repair costs (Figure B). By minimizing unplanned downtime, wind turbines can remain operational for longer periods, which can enable increased electricity generation and, in turn, higher revenues (Figure C).

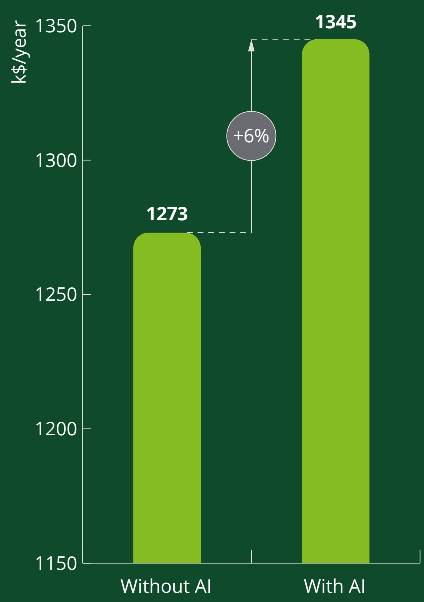
a) Annual turbine downtime reduction through PdM



b) Average repair costs avoided via PdM



c) Yearly revenue increase due to downtime reduction via PdM

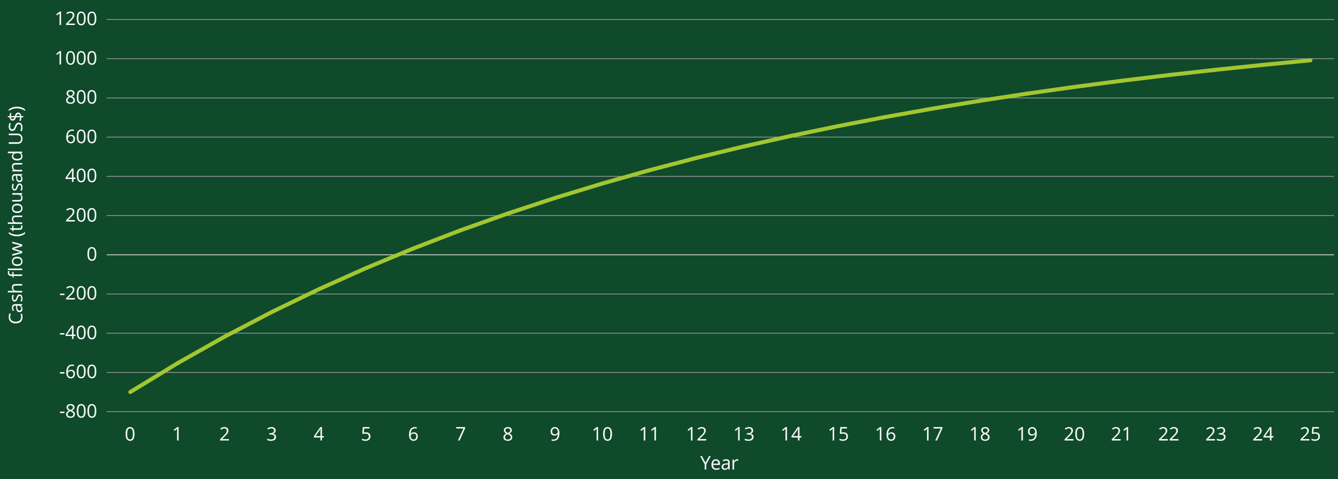


Source: Deloitte Global analysis based on the research by Adeiza Ahmed and Boadu Asamoah[118]

Box 4. Predictive maintenance for enhanced infrastructure reliability (continued)

Adopting AI technologies in offshore wind power systems can require upfront investment, but it can also lead to substantial long-term savings. Initial costs typically include the installation of additional sensors—such as vibration, temperature, and acoustic sensors—on wind turbines, the acquisition or development of AI software platforms, and the training of personnel in data science and turbine-specific analytics.[97] These investments can pay off over time: the payback period for implementing an AI-driven predictive maintenance solution is approximately six years, after which the system begins to deliver net financial benefits (see figure below).

Total cumulative cash flows from AI investments over time



Source: Deloitte Global analysis based on Rinaldi et al.[116] and Adeiza Ahmed and Boadu Asamoah[118]

Vegetation management
AI-powered predictive maintenance can also be a useful vegetation management tool by enabling proactive planning, monitoring, and control of plant growth around critical field assets, such as electrical power lines. If vegetation growth near power lines is not checked and managed, it can lead to electrical arcing, equipment damage, wildfires, and power outages (the largest cause of power outages in the US).[121] Rather than relying on manual inspections by humans, which can be time-consuming, expensive, and prone to error, AI systems can analyze satellite and field imagery, drone footage, and historical growth patterns to help identify high-risk areas. This shift from reactive to predictive/preventive maintenance helps enhance the safety, reliability, and resilience of the grid infrastructure.

A Deloitte Consulting LLP field-validated analysis shows that leveraging AI-driven inspections over a 50,000 circuit mile span of power lines can help reduce inspection costs as well as reduce human errors in trimming. The AI models can identify vegetation clearances with a geospatial accuracy of up to 6 inches using Light Detection and Ranging (LiDAR) and/or 15 cm ortho-photogrammetry, enabling up to a 40% near-term vegetation inspection automation potential.

AI models can also help prioritize inspections and trimming based on both the likelihood and potential impact of vegetation-related outages. This helps reduce unnecessary fieldwork while minimizing the risk of missing important trimming needs.

Water supply systems
Predictive maintenance can be a powerful tool for enhancing power infrastructure reliability and can also play an important role in safeguarding other essential infrastructure such as water supply systems. AI-powered PdM offers a highly effective solution for cities dealing with aging water supply and sewage infrastructure. Water networks are often decades old with materials subject to deterioration, which can lead to water losses, service disruption and costly repairs. To address this, the municipal water supply and sewerage company of Wroclaw collaborated with Deloitte Poland to help implement an AI-driven system analyzing pipe age, material type, environmental conditions, and other external stress factors such as the proximity to tram tracks.[122] The solution can help predict potential failures with up to 90% accuracy. Given budget constraints and an extensive water supply network, AI can enable effective planning for modernization and rehabilitation.

3.3.2. Mitigating hazard: real-time detection and reactive measures

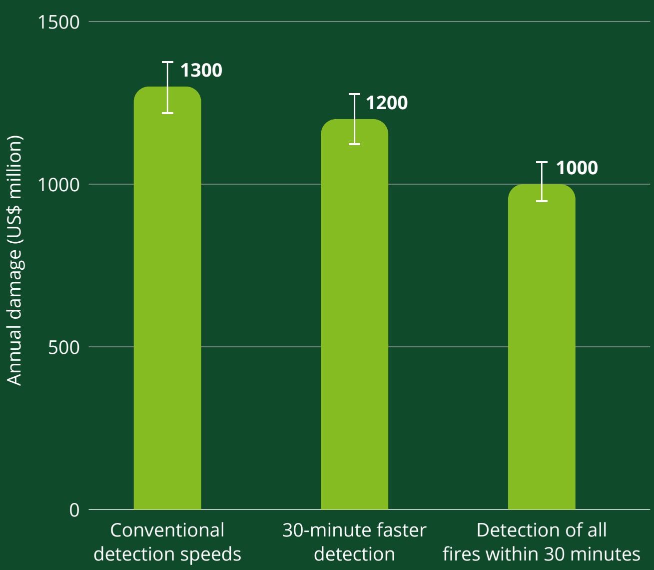
AI also plays an increasingly important role in hazard mitigation by helping enable faster response, with more accurate detection and reaction to disasters and incidents. AI-powered early warning systems can process vast amounts of real-time data, such as seismic activity, weather patterns, or satellite imagery, to help provide timely alerts for events like earthquakes, floods, wildfires or hurricanes.[123] Although for a large majority of hazards, early warning systems provide only limited benefits in terms of mitigating infrastructure damage, they can allow for better preparedness, saving lives and reducing losses to movable assets, such as vehicles and personal belongings.[124]

AI's use goes beyond timely detection and reaction, also assessing the potential spread of a hazard. Wildfire management is an example, where AI models are used to help predict fire spread dynamics, identify high-risk zones, and guide the strategic deployment of firefighting resources. For instance, deep learning algorithms have been used to detect wildfire outbreaks from satellite data and forecast their progression under various weather conditions which can lead to cost avoidance (Box 5).[125]

Box 5. Bushfire detection and early action in Australia

AI-powered early warning systems (EWS) are powerful tools for early detection of potential hazards, enabling timely response to hazards such as floods and wildfires. According to a study by the Australian National University, faster bushfire detection can help avoid direct losses of between US$100 million and US$300 million each year, depending on the detection and reaction time (see figure below).[15]

Annual direct damages due to bushfires in Australia in different detection scenarios



Source: Deloitte Global analysis based on the findings of the ANU study[15]

The cost is estimated based on the implementation of such a system in California. An EWS system with over 1000 IoT sensors across the state of California, including the AI system to detect potential fires in real-time, accounted for a total investment of approximately US$24 million.[126] Assuming that investing in a similar system for covering Australia's forests (around 12 times the surface covered in California) would cost proportionally to the surface area, this system would cost around US$288 million. Thus, investing in such a system for wildfire detection in Australia that can avoid between US$100 million and US$300 million annually, can result in a payback period of just a few years, with the potential to save billions of dollars (US$) in the long term.

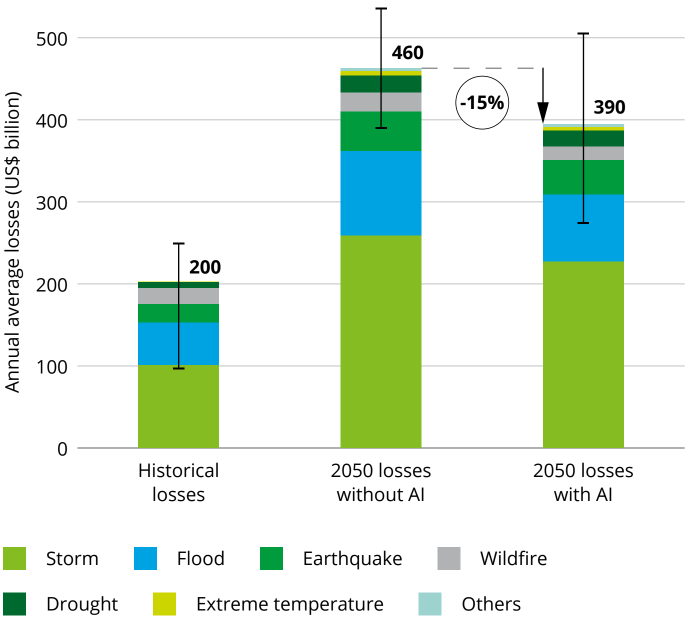
Combining IoT with other technologies, such as real-time satellite imagery and analysis or wildfire risk forecasting, could help further improve early wildfire detection and suppression, reducing fire-related damage even more than using them alone.[127]

3.3.3. Timely optimal recovery

Improved infrastructure resilience also includes the capacity to recover swiftly and effectively following a disaster.[128] While quick recovery does not reduce direct infrastructure damage, it can help restore public services, sustain quality of life, and ensure the continuity of economic activity, reducing indirect economic losses. AI-driven technologies can support this process by facilitating post-disaster damage assessment (Box 6), and helping with data-driven decision-making, such as smart resource allocation and prioritization.[129] AI algorithms can, for instance, help identify optimal routes for emergency services in case of damaged or non-usable roads.[10]

By improving risk assessment, optimizing operations, and enabling data-driven decision-making, AI can help improve infrastructure resilience in all three phases of disruptive events: before, during, and after a hazard, saving approximately US$70 billion (15%) from direct damages by 2050 (Figure 10). The remaining losses (approximately US$390 billion) can also be partially avoided using other resilience options, notably by earlier planning, better building practices, redundancy, decentralization of assets, using durable materials, or other mitigation strategies.[73,130]

Figure 10. Future losses with and without AI



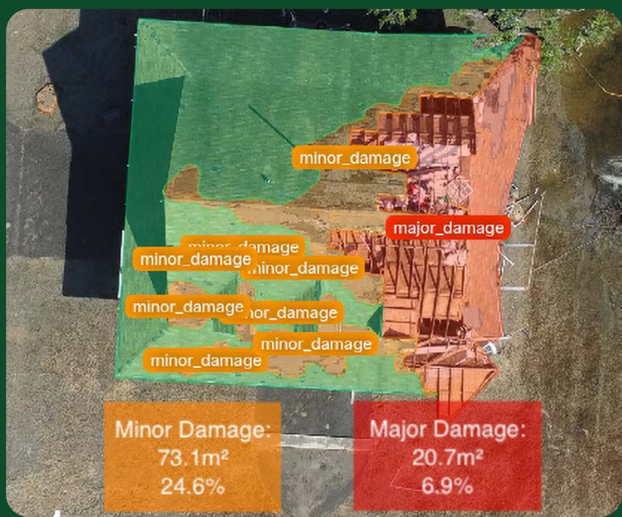
Source: Deloitte Global analysis based on the methodology described in Appendices 2 and 3
Note: Uncertainty bars represent the natural variations of hazards, showing the range of the first and third quartile. The uncertainty bar of "2050 losses with AI" also includes uncertainties on the benefits of AI.

Box 6. Post-disaster damage assessment

After a disaster, a timely and accurate damage assessment is important for effective emergency response and recovery planning. It can enable authorities and rescuers to identify the most affected areas, allocate resources efficiently, and prioritize rescue and rebuilding efforts. Overall, AI technologies can significantly accelerate decision-making time during critical moments of post-disaster damage assessment.

By reducing the time needed to assess damage and identify priorities, AI can help recovery efforts be both timely and efficient. Real-time data from satellite imagery and drones is important to help assess the extent of damage with precision. AI models can detect rare anomalies and structural defects, improving the speed and accuracy of assessments (see figure below). Additionally, by analyzing historical disaster recovery patterns, AI can help optimize future responses,[131] making infrastructure systems more adaptive and resilient.

Example of a post-disaster damage detection by AI



Source: Deloitte's OptoAI tool[132] for post-disaster damage assessment

The use of Deloitte Consulting LLP's OptoAI, an advanced AI tool for post-disaster inspections, has helped to demonstrate the ability to reduce roof repair timelines from up to seven days to just three, while cutting material overages by 15% to 30%. The OptoAI tool uses 2D to 3D photogrammetry to create digital twins of damaged areas and helps train AI models on both real and synthetic data. These models are then deployed on drones to help detect damage in near real-time, significantly improving disaster response.

4. Unlocking the resilience potential of AI for infrastructure

This analysis shows that the economic value of infrastructure could reach US$390 trillion by 2050, an 85% increase compared to 2022 (Appendix 1). This anticipated increase in the economic value of infrastructure can lead to greater economic exposure to risks. In parallel, the amplitude and frequency of natural hazards are also increasing. According to these findings, the annual average losses to infrastructure systems caused by natural hazards could more than double by 2050, reaching approximately US$460 billion (Appendix 2). The increased economic value at risk is the primary driver, accounting for 63% of the growth in potential losses, with the remaining 37% of the increase in losses due to the increasing hazard profile.

Resilience can be enabled by several types of solutions: robust design and construction mainly by using high-quality and resistant materials, regular maintenance, emergency preparedness through holistic community resilience, and infrastructure development that accounts for natural hazards.[133,134] These solutions can help avoid a large share of the estimated losses. Many of them can incorporate AI solutions for higher efficiency and robustness, such as digital twins for robust and smart design, predictive maintenance tools for targeted and timely maintenance, and early-warning systems for timely reaction to hazards.

Implementation of AI solutions alone for robust planning and response through real-time hazard detection and reaction can help reduce the vulnerability of infrastructure, decreasing the average losses caused by natural hazards by approximately US$70 billion per year in 2050, accounting for approximately 15% of annual direct damage costs (Figure 11). They complement the conventional resilience solutions, that can help mitigate and avoid a proportion of the remaining US$390 billion of losses.

4.1. Barriers to the implementation of AI

Despite its potential to enhance infrastructure resilience, the successful deployment of AI in infrastructure is often hindered by technological limitations. A primary concern is data quality and the availability of sufficiently large, varying, and accurate datasets necessary for effective AI training and decision-making. Poor or biased data can lead to unreliable outputs, undermining trust in AI systems.[135] An AI algorithm is only as good as the data source it learns from.[17] Moreover, integrating AI into existing infrastructure is complex, as many government agencies that manage infrastructure rely on legacy systems that were not designed to support modern AI technologies. These systems can be incompatible with modern technologies, requiring redesigns or upgrades. Thus, AI implementation often encounters technical obstacles such as interoperability problems.[136]

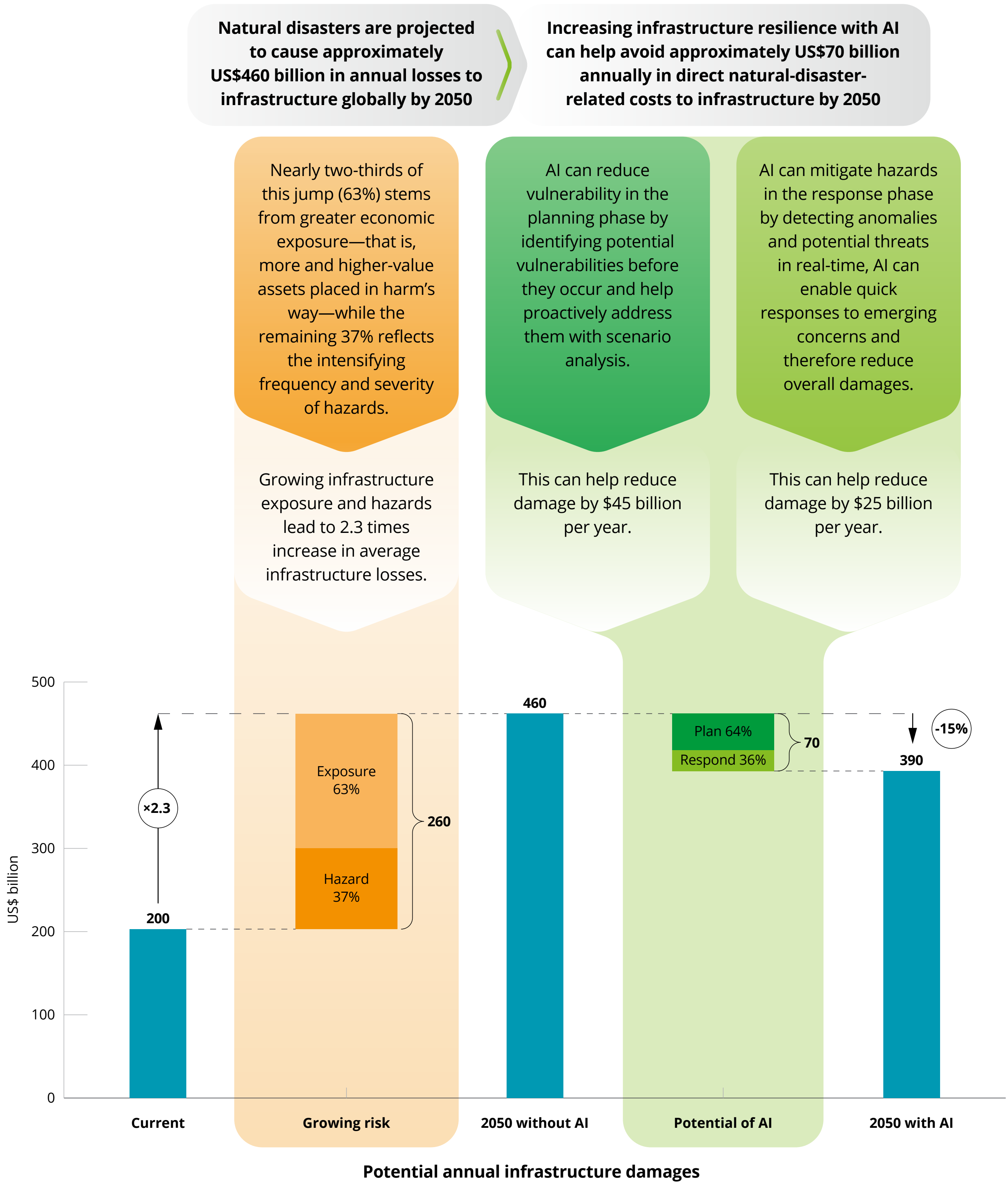
AI adoption often faces significant financial hurdles. The high upfront cost of developing, testing, and deploying AI solutions can be an important obstacle.[19,137] In a recent survey about data and AI in the UK, a majority of respondents (170 civil servants across all major government departments) underscored financial burden as the primary roadblock to adopting AI.[18] This cost hurdle includes not only the cost of technology, but also investments in data acquisition, storage, computing power, and skilled personnel. Additionally, given that the technology is relatively new, there is a more limited track record demonstrating its effectiveness. This uncertainty in return on investment can make decision-makers hesitant to commit financial resources.

In addition, the regulatory landscape surrounding AI remains in flux, which can impact its safe and secure adoption. Coupled with limited consistent, AI-specific regulations, concerns over privacy, security, and ethics can create mistrust of AI technologies.[135] It is still difficult for AI to provide transparent, auditable decision-making. Regulatory frameworks often require detailed documentation, while most AI systems cannot clearly articulate or justify their actions in a traceable format.[138]

Lastly, organizational and institutional factors can impact AI deployment. One of the most pressing challenges is the lack of a skilled workforce with experience in AI.[19,139] This talent gap can make it difficult to design, implement, and maintain AI systems effectively. Additionally, organizational resistance to change, ambiguous leadership on AI initiatives, and lack of clear governance frameworks can impede adoption and integration of AI.[140] These challenges are particularly true in environments that lack digital maturity or are slow to adopt innovation.

To conclude, a potential user of an AI solution, especially for infrastructure resilience applications, may opt not to deploy such technology due to a lack of transparency and demonstrated track record. This apprehension is rooted in lack of trust in the effectiveness of the solution. Without standardized regulations and norms, users may find it challenging to gauge the reliability and robustness of AI technologies. High upfront costs associated with AI technology, data acquisition, and skilled personnel can further complicate its adoption.

Figure 11. Growing risks and the utility of AI to enhance infrastructure resilience



Source: Deloitte Global analysis based on Appendices 1, 2 and 3

4.2. A way forward

Despite these challenges, the integration of AI into infrastructure resilience strategies offers a transformative opportunity to help reduce exposure and strengthen systems and assets against the increasing frequency and intensity of hazards, reducing overall risks and potential losses. Yet, harnessing this potential requires coordinated effort across the infrastructure ecosystem involving both public and private sectors. In particular, governments, infrastructure operators, technology companies, the finance ecosystem, and engineering and architecture firms have important roles to play.

Policymakers are pivotal to lay the foundations and to create an enabling environment for the widespread adoption of AI across infrastructure systems through regulatory frameworks, economic support schemes, a flexible regulatory environment and continuous investments in upgrading and extending legacy infrastructure. However, this role goes beyond setting regulations and economic incentives, and encompasses coordination among the key actors across the value chain of infrastructure systems:

- Governments can play a role in standard setting, informing definitions, and creating the enabling governance architecture for AI transparency, accountability, and risk assessment in infrastructure projects. AI principles, such as the OECD's that call for AI actors to help promote a general understanding of AI systems, including their capabilities, limitations, and the nature of human-AI interactions, to enhance transparency and accountability, are largely voluntary.[141]
- Harmonized approaches for secure, cross-sector, and cross-border data sharing can help promote collaboration to train robust AI models by facilitating secure data sharing. Several countries and regions have established regulations that safeguard personal data anonymity—for instance, the European Union has introduced the General Data Protection Regulation (GDPR) "the toughest privacy and security law in the world" in 2016, that has been put into effect on May 2018.[142] This type of secure and standardized data use and sharing could help regional AI cooperation for disaster prediction systems that rely on cross-border environmental data (e.g., floods, wildfires, or earthquakes), helping to ensure that AI models can be trained on diverse datasets.
- Policies should consider the need for flexibility and adaptability as technology and its application is changing, often faster than governments can keep up.[143] The rapid evolution of AI technology can further complicate standardization.[144] Flexible AI policy can be more sustainable, less risky and can allow for a calibrated evolution of AI governance.
- Economic support mechanisms to help the deployment of AI across different infrastructure systems play an important role in reducing the financial burden and accelerating technology adoption. Some countries have used tax credit schemes to support innovation, such as the Dutch Wet Bevordering Speur- en Ontwikkelingswerk (WBSO), which can provide tax credits for research and development (R&D) efforts.[145] The tax credit partially compensates R&D-related investments in AI-based predictive maintenance, intelligent transport systems, energy optimization, or disaster management tools. Economic support mechanisms can go beyond R&D to include subsidies for pilot projects that help demonstrate the societal and economic benefits of AI-enhanced infrastructure.

Infrastructure owners and operators can integrate AI solutions into their planning and operational processes to enable the benefits of AI-enabled resilience:

- Based on the findings of this study, integrating AI-powered solutions for hazard mitigation and vulnerability reduction could generate approximately US$70 billion in annual savings from direct disaster costs by 2050, representing approximately 15% of estimated average losses. These investments should cover the entire infrastructure lifecycle, including upfront planning and construction. Hazards occur throughout the infrastructure's operational phase, and AI-embedded detection and reaction can help bring significant levels of cost reduction. More significantly, as shown in Chapter 3, leveraging AI for robust design and construction accounts for about two-thirds of the cost reductions, underlining the importance of AI-embedded planning and construction.[25]
- Infrastructure owners and operators should prioritize pinpointing specific AI applications with significant potential for positive change rather than embarking on expansive, broad-based AI projects. Beginning with smaller initiatives helps provide opportunities for learning, adjustment, and gradually expanding successful efforts, supporting more sustainable and organized adoption of AI technologies.
- Upgrading legacy infrastructure is important for enabling compatibility with modern AI technologies. Those managing infrastructure should emphasize developing adaptable and expandable IT frameworks that can incorporate AI smoothly, facilitating efficient data processing and system interoperability.
- The cost of deploying advanced AI solutions is decreasing rapidly. At the hardware level, costs have declined by 30% annually, while energy efficiency has improved by 40% each year.[146] Maintaining this momentum through strategic investments, pilot projects, and scaled adoption can help make AI-enhanced resilience solutions increasingly accessible, cost-effective, and reliable. To help overcome barriers associated with trust and resistance to change, infrastructure owners and operators should raise awareness among employees and stakeholders on the utility of AI solutions in enhancing their operations. This includes awareness campaigns and training programs that can help the workforce leverage these solutions in their daily operations.[147,148]

- Finally, to leverage the full potential of what AI can offer, a key priority is the sharing of high-quality and high-precision data for longer and more effective training of context-specific AI models, which could improve the performance of these models.

Within the finance ecosystem, **financial institutions and commercial and investment banks** can help play an important role in supporting AI adoption for infrastructure resilience, while also using AI to better assess project risk:

- Financial institutions can act as catalysts for AI-embedded resilience deployment by designing and promoting financing tools, such as resilience bonds[149] or targeted credit lines that include AI. While several financial mechanisms can be used to fund infrastructure resilience,[150] these institutions could prioritize AI-driven infrastructure projects. Such multi-year projects often face financing challenges due to delayed returns, despite their long-term value in reducing risks and enhancing societal well-being.
- Financial institutions can also integrate AI into their own decision-making processes to help improve risk analysis in areas such as credit underwriting and asset evaluation.[151]
- These institutions can co-invest in AI-powered resilience solutions through public-private partnerships, together with governments, technology providers, and multilateral organizations to help fund and reduce investment risks in cutting-edge AI infrastructure. Recent announcements such as the EU's AI investment agenda[152] demonstrate how strategic financing can help strengthen AI ecosystems.

Insurance providers, within the financial services sector, are particularly well-placed to help integrate AI into their operations and make it a core component of their business, both to enhance their services, and to extend them to the new needs of infrastructure systems. This is driven by AI adoption and increasing losses due to the increasing value of infrastructure and extreme weather events:

- AI-powered resilience solutions can involve trust in the effectiveness of the solution. Insuring AI solutions is a key enabler to help build trust in their value. In collaboration with technology providers, insurers can develop insurance products for new AI solutions that have limited commercial track record but can enhance resilience.[153]
- The growing use of AI systems can include new vulnerabilities. AI usage and larger data centers bring the need for extension of insurance to new AI systems, as well as potential AI-related liabilities (self-driving cars, AI-powered manufacturing plant malfunctions, etc.).[153] By developing new insurance products, insurers can help support both infrastructure owners and developers with adoption and technology providers with further development of AI solutions.
- Insurers can also play an important role in incentivizing adoption of AI solutions for infrastructure resilience. This would require insurers to assess the risk-reduction potential of AI for infrastructure and reflect these improvements in their pricing models. By offering preferential terms, insurers can promote the adoption of resilient technologies in infrastructure projects.[154] This can enable them to encourage AI adoption through price signals with lower rates.
- Furthermore, insurance providers can integrate AI into their risk assessment processes to help enhance the accuracy of their pricing and damage estimations. AI can provide benefits to the insurance value chain, from AI-powered risk assessment processes to more efficient claims management.[155]

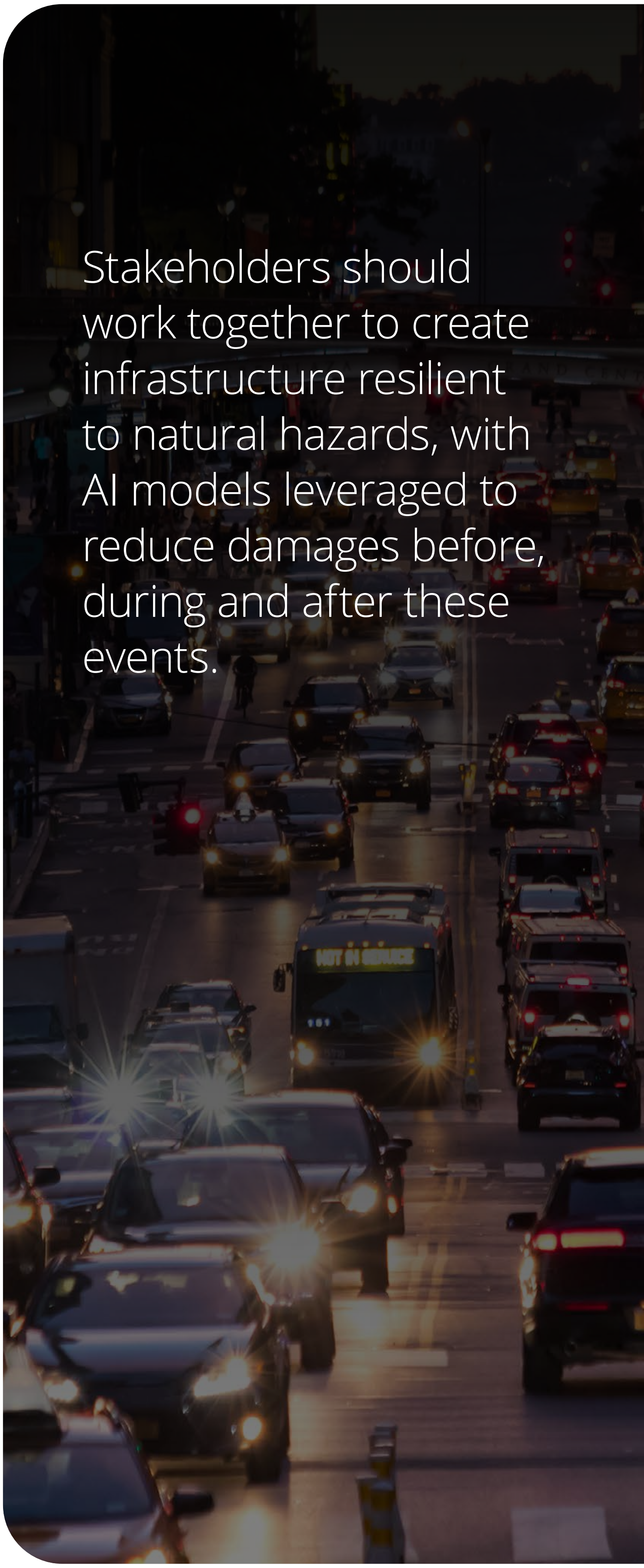
Technology companies are the technological backbone enabling the development and progress of AI solutions. They play an integral role in fueling innovation, integrating AI with other digital solutions for added value, while ensuring their growing energy demand is met by alternative energy sources:[100]

- Technology leaders should identify and evaluate the growing need for resilience to develop innovative and efficient AI-powered resilience solutions. Continued investment in research, especially at the intersection of AI and complementary technologies such as IoT, digital twins, and cloud computing, can be important for enhancing and improving AI solutions. For instance, the combined use of IoT sensors and AI models enables high-quality predictive maintenance systems that can deliver significant economic, safety and reliability benefits (Box 4).
- It is important to demonstrate the benefits of a technological solution in economic terms. This could help build trust and motivate infrastructure operators to implement AI-enhanced resilience solutions. Clear economic and financial benefits, such as avoiding damage, reducing insurance premiums, and operational savings, should be demonstrated for infrastructure operators to adopt these solutions.
- AI's energy consumption could reach as high as 1,000 TWh by 2030 and even up to 3,500 TWh by 2050, representing an increasing share of global power consumption.[100] Companies providing AI-based solutions can face growing energy demand for their operations. Technology providers should strive to maximize energy efficiency in their operations to mitigate increased energy costs due to higher electricity demand and reduce their environmental impact. As data centers consume more energy, many economies strive to expand electrification efforts to help achieve energy transition goals. In such contexts, technology providers are encouraged to enter into Power Purchase Agreements with renewable energy developers to ensure a reliable and cost-effective energy supply.

Finally, **architecture and engineering firms** designing and constructing the infrastructure systems should help ensure they not only leverage AI, but also help prepare for infrastructure operators to embed AI-powered resilience solutions in their operating environment:

- Architecture and engineering firms play a central role in embedding AI tools into the planning and design phases of infrastructure systems early to help enhance their resilience. This includes leveraging AI-powered digital twins, as illustrated in Box 3, to simulate system behavior under different stress scenarios (e.g., extreme weather, heavy usage, or cyber threats), enabling better-informed decisions and proactive risk mitigation.
- New infrastructure should be compatible with AI applications, such as predictive maintenance, automated system diagnostics, and real-time performance monitoring. This involves incorporating smart sensors, data platforms, and connectivity infrastructure from the outset to enable seamless integration of AI tools throughout the lifecycle of assets. Doing so would help ensure that operational teams could adopt AI solutions in the future, avoiding costly retrofits or redesigns.
- These firms are ideally placed to collaborate with technology and service providers, such as AI developers or data platform providers, to co-develop solutions tailored to infrastructure needs, serving as a bridge between infrastructure operators and these companies. These relationships can help ensure that new technologies and AI solutions developed are in line with the sector's needs, and that these AI solutions can be integrated into their design.

Coordinated and decisive effort across stakeholders is important to help create resilient infrastructure. Stakeholders should work together to create infrastructure resilient to natural hazards, with AI models leveraged to reduce damages before, during and after these events, reinforced with AI models in each key resilience phase: planning, response, and recovery.



Stakeholders should work together to create infrastructure resilient to natural hazards, with AI models leveraged to reduce damages before, during and after these events.

Appendices

Appendix 1. Estimation of the economic value of infrastructure

The 2022 infrastructure value is calculated based on the values from the Coalition for Disaster Resilient Infrastructure (CDRI)[22] which is then used as a baseline for estimating future infrastructure value. The correlation between each infrastructure type and key economic indicators, notably GDP, population, and country income categories[156] is analyzed and a linear regression function is developed for each infrastructure and each country economic category as a function of population and GDP using the World Bank data.[48] The key considered infrastructure systems are roads and railways, power, telecommunications, water and waste water, ports and airports, and oil and gas, as defined by CDRI.

Using the GDP and population growth values estimated by the Economist Intelligence Unit[49] through 2025, the future values of infrastructure systems are estimated. Using uncertainty propagation theory, based on the underlying uncertainty on the linear regression coefficients, an uncertainty range is assigned to the estimations.

Appendix 2. Assessment of the average direct costs of different hazards

The average losses occurred by hazards analysis is grounded in the Emergency Events Database (EM-DAT),[2] which includes economic damages resulting from both types of natural disasters: acute shows and chronic stresses. The risk categories examined in this analysis include storms, floods, earthquakes, wildfires, droughts, and extreme temperatures. Disasters that do not fall into these categories are grouped into a residual “other” category. The EM-DAT database offers global coverage and includes reported economic losses where such data is available, with a country level precision for each year until 2024. However, it is important to note that economic damages are often underreported, particularly in countries with limited insurance or reinsurance coverage, and where disaster events are less severe.[2]

To project the average annual loss to 2050 (in direct economic-loss terms), trend functions—exponential, linear, and logarithmic—were fitted to the available historical economic loss data for each hazard type. The function that exhibited the strongest correlation with the data was selected to project future losses. To incorporate variability in historical data and uncertainty of future evolution, a probability distribution function was applied around the selected trend line. This approach allowed for a representation of the potential volatility in future average annual losses. The projected values for the year 2050 should therefore be interpreted as the average annual loss expected, and actual annual figures can vary considerably depending on the frequency and intensity of disaster events in any given year.

To account for the increase in sustainability-related risks, the projections were adjusted using findings from IPCC projections in AR6 (2023).[3] These adjustments were applied to relevant risk categories, specifically storms, floods, droughts, and extreme temperatures, where the scientific consensus suggests an increasing trend due to changing climate conditions.

It is worth mentioning that these projections should be considered as conservative average estimates, as underreported hazard and underlying damage data are not considered. Actual future losses, therefore, will likely exceed those presented here due to underreporting and data gaps.

Appendix 3. Calculation of the resilience enabled by implementation of AI

Estimating the benefits of AI for infrastructure resilience is a complex task. In this study, the potential of AI for infrastructure resilience is assessed only in terms of avoided direct infrastructure damages. Indirect costs, such as induced economic disruptions due downtime or externalities (fatalities, cultural heritage, etc.) are not considered.

Benefits of AI vary depending on the hazard. While it can mitigate wildfires thanks to monitoring images 24/7, the impact of AI for earthquake mitigation remains limited. This is why the benefits of AI are assessed by the type of hazard.

Only the six largest hazards in terms of annual average damages are investigated (storm, flood, earthquake, wildfire, drought, extreme temperatures), which represent over 99% of annual average damages (Figure 9).

For each hazard, the potential benefit of AI is considered for each of the most impactful two phases: planning and prevention, and response through detection and reaction. Benefits are assumed to be cumulative over resilience phases as both prevention and detection measures can be implemented. Potential of AI per type of hazard ranges from nearly 0% for earthquakes[157] to up to 30% for wildfires[158] (Figure 9).

By attributing a percentage multiplied to the projections of average annual infrastructure damages by 2050 (Appendix 2) by type of hazard, based on a qualitative estimation of the effectiveness of AI (low, medium, and high), a quantitative value is extrapolated as the avoided damages caused by it. The high value corresponds to 20% based on the case study on early bushfire detection in Australia (Box 5), while the low value is estimated at 2.5%, central between 0 % and 5% to account for a reasonable low potential of AI for disaster risk reduction for very rare and extreme events that are hard to predict.[159] Uncertainties are also estimated by adding a reasonable range around the central value, based on the different case studies of this report and the literature in Figure 13. Figure 12 summarizes the attributed values for effectiveness of AI solutions for each qualitative tag.

Figure 12. Effectiveness of AI solutions for different qualitative mapping tags

Mapping	Central	Uncertainty
high	20%	± 5%
medium	10%	± 5%
low	2.5%	± 2.5%

Source: Deloitte Global analysis based on the case studies and the existing quantifications

The qualitative tags of high, medium, and low are then defined based on the existing qualitative evaluations of different AI solutions, summarized in Figure 13 below.

Figure 13. Sources for levels of potential of AI for infrastructure resilience

Type of hazard	Plan / Prevent		Respond / Detect and React	
	Level	Source	Level	Source
Storm	Medium	United Nations for Disaster Risk Reduction, "USA: AI for designing hurricane-resistant buildings", 2023.	Low	US government Accountability Office, "Artificial Intelligence in Natural Hazard Modelling: Severe Storms, Hurricanes, Floods, and Wildfires", December 2023.
Flood	Medium	K. Feng, N. Lin, et al., "Reinforcement learning–based adaptive strategies for climate change adaptation: An application for coastal flood risk management", Proc. Natl. Acad. Sci. U.S.A. 2025.	Medium	US government Accountability Office, "Artificial Intelligence in Natural Hazard Modelling: Severe Storms, Hurricanes, Floods, and Wildfires", December 2023.
Earthquake	Medium	Cong Y, Inazumi S. "Artificial Neural Networks and Ensemble Learning for Enhanced Liquefaction Prediction in Smart Cities". *Smart Cities*. 2024.	Low	Cemil Emre Yavas, Lei Chen, Christopher Kadlec et. al, "Improving earthquake prediction accuracy in Los Angeles with machine learning", 2024.
Wildfire	Medium	United Nations for Disaster Risk Reduction, "What sparks a wildfire? The answer often remains a mystery", 2025.	High	US government Accountability Office, "Artificial Intelligence in Natural Hazard Modelling: Severe Storms, Hurricanes, Floods, and Wildfires", December 2023.
Drought	Low	Miao Zhang, Hajra Arshad, et al. 2025. "Quantifying Greenspace with Satellite Images in Karachi, Pakistan." ACM J. Comput. Sustain. Soc. 3, 1, Article 6 (2025), https://doi.org/10.1145/3716370	Low	Alexander Marusov, Vsevolod Grabar, et al. "Long-term drought prediction using deep neural networks based on geospatial weather data", Environmental Modelling & Software, 2024.
Extreme temperatures	Low	Camps-Valls, et al. "Artificial intelligence for modeling and understanding extreme weather and climate events". *Nat Commun* 16, 1919 (2025).	Low	Vonich, P. T., & Hakim, G. J. "Predictability Limit of the 2021 Pacific Northwest Heatwave From Deep-Learning Sensitivity Analysis", Geophysical Research Letters. 2024.

The multiplication of the identified qualitative tags in Figure 13 by the values in Figure 12 results in the following avoided economic damage values for each of the resilience phases against each type of natural hazard in Figure 14.

Figure 14. The final avoided damage values due to AI-powered resilience against each hazard in 2050 (US$ billion per year)

	Central	Uncertainty
Storm	32	±19
Flood	21	±10
Earthquake	6	±4
Wildfire	7	±2
Drought	1	±1
Extreme temperature	1	±1

Source: Deloitte Global analysis based on the values in Figure 12 and Figure 13 and the methodology described above

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