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Digital Readiness and Volcanic Disaster Risk Across 55 Nations: OLS Regression and Interactive Visual Analytics

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Abstract
Volcanic disasters disproportionately affect countries with weak institutional capacity to use available technology. However, we have not yet tested this relationship between digital readiness and volcanic disaster risk at a global scale. This study examines whether digital readiness predicts institutional dimensions of volcanic disaster risk across 55 sovereign volcanic nations with complete data. We use the Sendai Framework for Disaster Risk Reduction 2015–2030 as the analytical structure. We integrate seven datasets, including NRI, WRI, INFORM Risk Index, GII, World Bank GDP per capita, GVP records, and EM-DAT data. We apply Pearson correlation and OLS regression to measure relationships between technology capacity and risk components. We present the results in an interactive seven-tab Streamlit dashboard. We find that NRI is strongly and negatively correlated with INFORM Risk ($r = -0.781$, $R^2 = 0.609$, $p < 0.001$). We also find a negative relationship with WRI Lack of Coping Capacities ($r = -0.554$, $R^2 = 0.307$, $p < 0.001$). We find no significant relationship between NRI and composite WRI scores driven by geological exposure. We identify Indonesia as an outlier with an above-median NRI score of 53.84. We also find a positive residual of +27.70 in coping capacity. We conclude that digital infrastructure alone does not improve disaster preparedness without governance and coordination capacity.

Keywords:
Volcanic Disaster, Digital Readiness, NRI, OLS Regression

1. Introduction

Volcanic disasters continue to threaten millions of people worldwide because volcanic activity directly affects human settlements, infrastructure, public health, transportation systems, and economic stability. The Smithsonian Global Volcanism Program records hundreds of active volcanoes distributed across highly populated regions, particularly in the Pacific Ring of Fire, where exposure to eruption hazards remains consistently high [1]. Volcanic eruptions produce multiple cascading hazards such as lava flows, ashfall, pyroclastic density currents, lahars, toxic gases, and seismic disturbances that often disrupt both local and international systems. The increasing frequency of urban expansion near volcanic regions intensifies the complexity of disaster management and risk mitigation. At the same time, governments and disaster agencies attempt to strengthen preparedness strategies through international frameworks such as the Sendai Framework for Disaster Risk Reduction 2015–2030, which emphasizes resilience, risk governance, and technology integration in disaster preparedness systems [2]. However, many countries still struggle to integrate digital readiness into volcanic disaster management despite rapid global technological advancement. This condition creates a major gap between hazard exposure and technological capacity, especially among developing nations with limited digital

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infrastructure and institutional readiness. Therefore, understanding the relationship between digital readiness and volcanic disaster risk becomes increasingly important for improving global disaster resilience strategies. [1], [2]

Digital transformation currently changes how governments and organizations monitor, predict, communicate, and respond to disasters. Information technology enables real-time monitoring, early warning dissemination, geospatial analysis, emergency coordination, and public communication during disaster events [3]. Modern disaster management systems increasingly rely on digital infrastructure such as cloud computing, Internet of Things (IoT), satellite communication, artificial intelligence, and interactive data visualization platforms to improve response efficiency and decision-making quality. Countries with strong digital ecosystems often demonstrate better disaster preparedness because they can process large-scale risk information rapidly and distribute warnings effectively to vulnerable communities [5]. Nevertheless, the global digital divide remains a critical issue because unequal access to digital infrastructure, connectivity, education, and innovation capability limits the ability of many countries to implement advanced disaster technologies [4]. This imbalance becomes more problematic in volcanic regions where rapid evacuation and accurate information dissemination determine survival outcomes. Consequently, digital readiness no longer represents only a technological indicator but also becomes a critical component of disaster resilience and national adaptive capacity. [3], [4], [5]

Several studies emphasize that disaster risk assessment increasingly requires multidimensional approaches that combine environmental, socioeconomic, and technological indicators. Garschagen et al. analyze global disaster and climate risk patterns and show that countries with weak institutional and technological capacities experience higher vulnerability levels despite similar exposure conditions [6]. Birkmann et al. further explain that vulnerability assessment frameworks must include adaptive capacity and technological readiness to support sustainable disaster planning [7]. However, many global risk studies still focus heavily on physical hazards while underestimating the contribution of digital infrastructure and technological preparedness in reducing disaster impacts. Existing disaster indices such as the INFORM Risk Index and the World Risk Report provide broad measurements of risk and resilience but often lack detailed integration of digital transformation variables [14], [18]. As a result, policymakers face difficulties when attempting to evaluate how digital ecosystems influence disaster preparedness and recovery performance across nations. This limitation highlights the need for new analytical frameworks that integrate volcanic risk indicators with digital readiness variables using quantitative statistical methods and visual analytics approaches. [6], [7], [14], [18]

Volcanic disasters create particularly severe challenges because eruptions often occur with short warning periods and affect multiple sectors simultaneously. Indonesia represents one of the clearest examples because the country hosts more active volcanoes than most nations while also facing high population exposure near volcanic zones [9]. Research on volcano-prone communities shows that disaster literacy, preparedness awareness, and risk perception strongly influence community resilience during eruption events [10]. However, these social preparedness factors increasingly depend on digital access and communication systems that support early warning distribution and emergency coordination. Recent volcanic events such as the Reykjanes Peninsula eruptions in Iceland demonstrate how real-time digital monitoring systems, online hazard maps, and public alert platforms significantly improve public safety and evacuation efficiency [13]. Similarly, Japan's MOWLAS monitoring system integrates seismic, geodetic, and tsunami observation technologies into a centralized disaster monitoring infrastructure capable of delivering rapid hazard assessments [12]. Although these systems show the effectiveness of digital disaster management, many countries still lack comparable technological capacity, creating major disparities in volcanic risk preparedness at the global level. [9], [10], [12], [13]

Recent advancements in digital innovation also introduce new opportunities for disaster risk management through smart analytics, digital twins, machine learning, and interactive visualization technologies. Macatulad and Biljecki explain that urban digital twins can enhance disaster preparedness by simulating hazards, monitoring infrastructure vulnerability, and supporting real-time decision-making processes [8]. Izumi et al. further state that innovation-driven disaster risk reduction strategies improve coordination efficiency and strengthen resilience across multiple governance levels [11]. In parallel, machine learning and data-driven analytics increasingly support classification, prediction, and pattern recognition tasks in disaster-related studies [20]–[22]. These technologies allow researchers to analyze large-scale disaster datasets more efficiently and identify hidden relationships among risk indicators. Despite these advancements, cross-national studies that specifically examine the statistical relationship between digital readiness and volcanic disaster risk remain very limited. Most existing research focuses either on technological innovation or hazard assessment independently, without integrating both perspectives into a unified analytical framework. Therefore, a comprehensive study that combines regression modeling and interactive visual analytics becomes highly relevant for filling this research gap. [8], [11], [20]–[22]

The rapid growth of global digital readiness indicators provides an important opportunity for quantitative analysis of disaster resilience. The Network Readiness Index evaluates countries based on technology adoption, governance, people, and digital impact dimensions, offering comprehensive insight into national digital capability [15]. Meanwhile, the Global Innovation Index measures innovation performance and technological development capacity across economies [16]. Economic indicators such as GDP per capita also remain essential because financial capacity significantly influences technological investment and disaster preparedness quality [17]. When combined with disaster databases such as EM-DAT and global volcanic activity records from the Smithsonian Institution, these indicators provide a rich foundation for comparative international analysis [1], [19]. However, previous studies rarely integrate these datasets into a unified model that explains how digital readiness correlates with volcanic disaster exposure and vulnerability across countries. This limitation motivates the development of a more integrated analytical approach capable of identifying significant patterns and relationships between technological readiness and volcanic disaster risk at the global scale. [1], [15]–[19]

Statistical modeling approaches such as Ordinary Least Squares (OLS) regression remain widely used in social science, disaster research, and policy analysis because they provide interpretable relationships between dependent and independent variables. OLS regression enables researchers to quantify how digital readiness indicators influence disaster risk levels while controlling for socioeconomic and environmental variables. In addition, interactive visual analytics offers substantial advantages for communicating complex global datasets because visualization platforms help policymakers and researchers identify trends, anomalies, and geographic patterns more effectively. Interactive dashboards and geospatial visualizations increasingly become essential tools in disaster risk communication because they simplify complex analytical outputs into understandable formats for decision-makers and the public. Nevertheless, many global disaster studies still present static analytical outputs without incorporating interactive visualization mechanisms that support exploratory analysis and policy interpretation. This gap demonstrates the importance of integrating statistical modeling with visual analytics to improve accessibility, interpretability, and practical application of global disaster risk studies. [3], [8], [11]

Based on these challenges, this study investigates the relationship between digital readiness and volcanic disaster risk across 55 nations using OLS regression and interactive visual analytics. This paper utilizes volcanic activity records, disaster risk indicators, digital readiness measurements, innovation indices, and socioeconomic variables obtained from internationally recognized databases to construct a comparative global analysis framework. The study aims to identify whether countries with stronger digital ecosystems demonstrate lower disaster vulnerability and better adaptive capacity in volcanic risk contexts. In addition, this research applies interactive visual analytics to improve the interpretation and communication of cross-national disaster data patterns. Unlike previous studies that separately examine disaster risk or technological readiness, this research integrates both dimensions into a unified quantitative and visual analytical framework. Therefore, this study contributes to disaster informatics, digital resilience research, and evidence-based policymaking by providing a broader understanding of how digital transformation influences volcanic disaster preparedness and resilience at the international level. [1]–[19].

2. Related Works

Previous studies on the digital divide primarily focused on infrastructure availability and internet access disparities between developed and developing countries. However, more recent research expanded this perspective by examining institutional, social, and technological readiness dimensions simultaneously. Lythreatis et al. reviewed the evolution of digital divide research and found that digital inequality extends beyond connectivity limitations because institutional readiness, digital literacy, and technological utilization strongly influence the effectiveness of digital transformation [4]. Their study emphasized that countries with similar infrastructure levels may still experience different digital outcomes due to governance quality and policy implementation differences. AlHinai further investigated digital transformation in disaster management and demonstrated that organizational readiness and environmental governance significantly determine whether technology investments can improve disaster preparedness performance [5]. These findings highlighted that disaster resilience depends not only on technological infrastructure but also on the institutional capacity to operationalize digital systems effectively. Nevertheless, these studies did not specifically analyze volcanic disaster contexts or compare digital readiness against volcanic disaster risk indicators across multiple nations. [4], [5]

Several studies developed the theoretical and methodological foundations for global disaster risk assessment using institutional and vulnerability indices. Garschagen et al. analyzed multiple international disaster risk indices and reported that vulnerability and coping capacity variables produced more consistent results than physical hazard exposure indicators [6]. Their findings suggested that institutional preparedness plays a stronger role in determining disaster outcomes than exposure alone. Birkmann et al. validated global vulnerability indices and confirmed that countries with higher institutional vulnerability experienced greater disaster mortality rates and lower adaptive capacity [7]. These studies provided strong evidence that institutional strength and governance quality directly affect disaster resilience. However, both studies concentrated on broad climate and disaster risks rather than volcanic hazards specifically. In addition, they did not examine whether digital readiness contributes significantly to the institutional dimensions of disaster risk. This limitation created an important research gap regarding the relationship between digital ecosystems and volcanic disaster preparedness at the international scale. [6], [7]

Research related to volcanic disaster management consistently emphasized the importance of preparedness, monitoring systems, and institutional coordination. Malawani et al. reviewed volcanic disaster management practices in Indonesia and found that technological systems support mitigation, preparedness, emergency response, and post-disaster recovery processes [9]. Their study also revealed that many volcanic disaster programs still underutilize monitoring data and digital communication systems in practical operational activities. Saifudin et al. examined communities living near Mount Merapi and reported that preparedness significantly influenced resilience levels among volcano-prone populations [10]. The study showed that disaster literacy and effective communication systems strongly determine how communities respond during volcanic emergencies. Although these studies highlighted the importance of preparedness and technology, they mainly focused on local-scale disaster management without conducting cross-national quantitative comparisons. Furthermore, they did not integrate digital readiness indicators into broader volcanic disaster risk analysis frameworks. [9], [10]

Several studies investigated the role of technological innovation and digital systems in disaster risk reduction frameworks. Izumi et al. analyzed disaster risk reduction innovations under the Sendai Framework and identified digital communication systems, community-based preparedness platforms, and data-sharing technologies as major contributors to disaster resilience improvement [11]. Macatulad and Biljecki later examined the role of urban digital twins in disaster management and concluded that interactive digital platforms improve real-time decision-making, infrastructure monitoring, and hazard simulation capabilities [8]. These studies demonstrated that advanced digital technologies enhance the effectiveness of disaster risk governance and emergency response coordination. However, they also noted that many countries still struggle to integrate scientific information systems into practical policy implementation. Most importantly, the reviewed studies focused on technological opportunities without quantitatively measuring how national digital readiness levels correlate with disaster risk performance across countries. [8], [11]

Country-level evidence from Japan and Iceland illustrated successful implementations of digital disaster management systems in volcanic environments. Japan's MOWLAS system integrated thousands of seismic, geodetic, and ocean-bottom sensors into a centralized monitoring network capable of providing real-time hazard assessments and rapid warning dissemination [12]. Similarly, Iceland utilized integrated volcanic monitoring systems during the Reykjanes Peninsula eruptions to coordinate evacuations and public communication effectively [13]. These systems demonstrated how digital infrastructure, monitoring integration, and institutional coordination reduce disaster impacts and improve response efficiency. Both countries maintained strong digital readiness and institutional capacity, which supported successful operationalization of technological systems. Nevertheless, these studies focused primarily on operational disaster management practices rather than examining the statistical relationship between digital readiness and volcanic disaster risk. Consequently, existing literature lacked comparative global analysis that quantitatively evaluates how digital capability influences volcanic disaster resilience across multiple nations. [12], [13]

Global indices and international datasets increasingly supported comparative studies on risk, resilience, innovation, and digital transformation. The World Risk Report and INFORM Risk Index provided comprehensive assessments of exposure, vulnerability, coping capacity, and adaptive capacity across countries [14], [18]. Meanwhile, the Network Readiness Index and Global Innovation Index measured digital infrastructure, governance, technological adoption, and innovation performance at the national level [15], [16]. Researchers widely used these indices to evaluate technological competitiveness and institutional readiness. Economic indicators such as GDP per capita also frequently appeared in resilience and development studies because financial capacity strongly influenced technological investment and disaster preparedness quality [17]. Although these datasets offered rich analytical opportunities, previous studies rarely integrated them into a unified framework for volcanic disaster analysis. Most research used these indicators independently rather than exploring the interconnected relationship between digital readiness, innovation, socioeconomic conditions, and volcanic disaster risk. [14]–[18]

Machine learning and data-driven approaches also contributed to disaster-related research, particularly in classification and predictive analysis tasks. Wijaya et al. applied Naive Bayes and Chi-Square methods for occupancy house classification and demonstrated that statistical classification techniques can support disaster-related decision-making processes efficiently [20]. Subsequent studies utilized K-Nearest Neighbor and Random Forest algorithms to classify post-eruption housing occupancy conditions and rehabilitation priorities after volcanic events [21], [22]. These studies confirmed that computational intelligence methods improve disaster data analysis and support evidence-based recovery planning. However, the scope of these studies remained focused on local post-disaster classification problems rather than large-scale national or international disaster risk analysis. In addition, they did not utilize regression-based approaches or visual analytics platforms to examine cross-national patterns in disaster preparedness and technological readiness. Therefore, further research remained necessary to bridge local computational disaster analysis with global comparative disaster risk modeling. [20]–[22]

Despite substantial advancements in disaster informatics, digital governance, and volcanic risk management research, significant gaps still remain in the literature. Existing studies separately investigated disaster vulnerability, digital transformation, technological innovation, or volcanic preparedness, but very few integrated these dimensions into a single analytical framework. No previous study comprehensively analyzed volcanic nations as a unified population while simultaneously examining how digital readiness indicators influence institutional disaster risk components using Ordinary Least Squares (OLS) regression and interactive visual analytics. Moreover, most disaster studies still relied on static statistical outputs without incorporating interactive visualization approaches capable of supporting dynamic policy exploration and comparative interpretation. Therefore, this study extends previous research by combining volcanic disaster datasets, global digital readiness indicators, innovation metrics, and socioeconomic variables into an integrated analytical framework across 55 nations. This approach contributes a broader understanding of how digital transformation and institutional readiness influence volcanic disaster resilience and adaptive capacity at the global scale.

3. Proposed Method

A. Research Design

The unit of analysis is the sovereign nation-state. The study population comprises all countries with at least one active volcano documented in the Smithsonian Global Volcanism Program (GVP) database [1], which identifies 77 such territories globally. Two territories were excluded before any indicator-based analysis: Antarctica, which is non-sovereign and has no permanent population, and Taiwan, which is absent from all institutional indicator datasets used in this study due to its political recognition status at major international data-producing bodies. This yields 75 sovereign volcanic nations as the working dataset. The spatial distribution of active volcanoes across the 75-country study population is shown in Fig. 1.

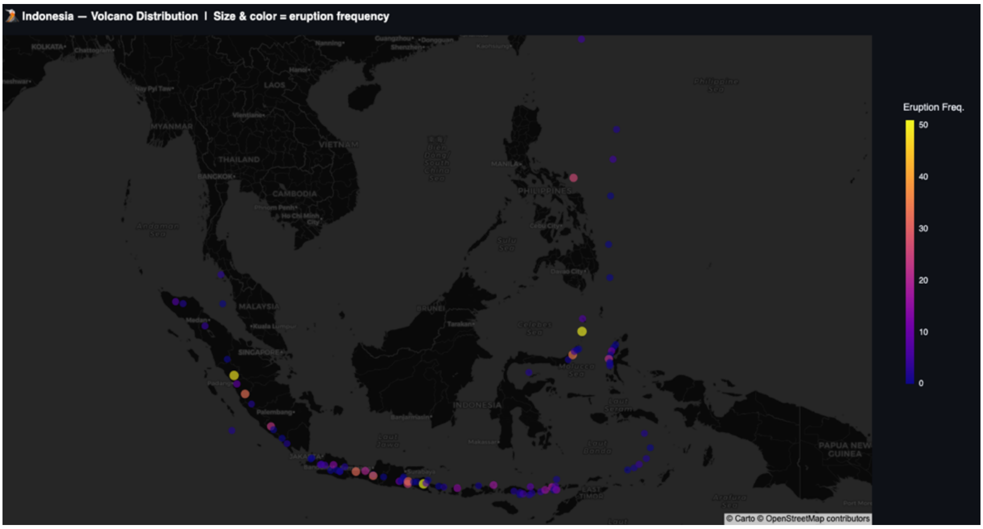

Fig. 1. Active volcano counts per country across the 75-country study population (Smithsonian GVP data).

This study applied listwise deletion to four primary indicators, namely the WRI Score, NRI Score, GDP per capita, and INFORM Risk Index, to ensure statistical consistency in the regression and quadrant analyses. Through this process, this paper produced a complete analytical dataset consisting of 55 countries. The excluded countries were primarily Small Island Developing States (SIDS) and fragile nations with incomplete digital readiness information because the Portulans Institute did not publish NRI scores for these regions due to limited data availability. This study found that the excluded countries had a mean eruption frequency of 0.0, while the selected analytical sample recorded an average eruption frequency of 64.2, indicating that the exclusion mainly affected countries with relatively low volcanic activity and did not significantly influence the overall analytical findings.

Furthermore, we organized the research workflow into four integrated stages. First, this paper collected and integrated data from seven global datasets and indices, including GVP, WRI, NRI, GII, World Bank GDP, INFORM, and EM-DAT, into a unified database structure. Second, we conducted preprocessing by harmonizing country identifiers, transforming higher-is-worse indicators, and applying listwise deletion to obtain the final analytical sample. Third, this study utilized descriptive statistics, Pearson correlation analysis, Ordinary Least Squares (OLS) regression, quadrant classification, and Sendai Framework phase mapping using Python libraries such as Pandas and SciPy. Finally, this paper implemented an interactive seven-tab Streamlit dashboard to visualize the analytical results and support dynamic cross-national exploration for disaster risk policy evaluation, as illustrated in Fig. 2.

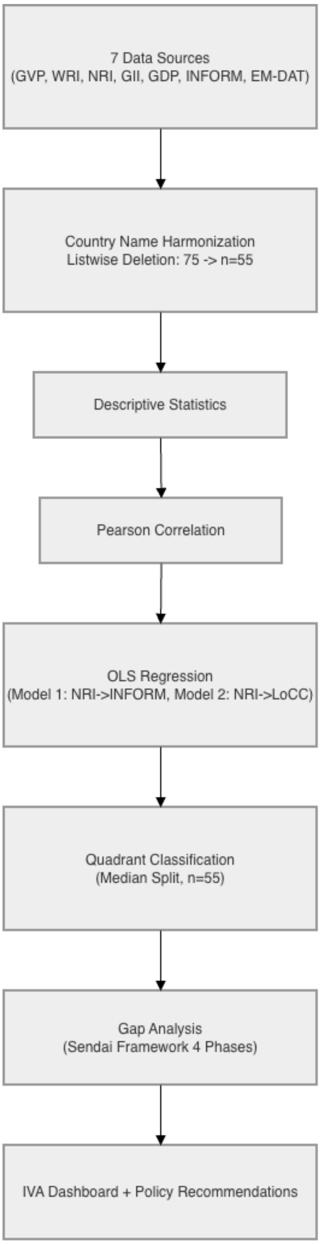

Fig. 2. Research design and data integration pipeline.

B. Data Sources and Variables

This study integrated seven global data sources across the 75-country dataset. Table 1 summarizes the data sources, selected variables, country coverage within the volcanic nation population, publishing institutions, and scale directions. This paper considered scale direction as an important factor in the analytical interpretation because the WRI and INFORM Risk indices apply higher-is-worse scales, whereas the NRI and GII apply higher-is-better scales. We addressed these scale differences through the normalization procedures described in subsection E. Furthermore, this study utilized the 2024 editions of several global indices and databases, including the World Risk Index [14], Network Readiness Index [15], Global Innovation Index [16], World Bank GDP per capita [17], INFORM Risk Index [18], and EM-DAT database [19].

Table 1 Data Sources, Variables, and Coverage

Source	Variables Used	Coverage (Volcanic Nations)	Institution	Scale Direction
Smithsonian GVP	Active volcanoes, eruption frequency (1900–2025), VEI	75/75 (100%)	Smithsonian Institution, USA	N/A (categorical)
WRI 2024	WRI Score, Susceptibility, Lack of Coping Capacities, Lack of Adaptive Capacities	75/75 (100%)	Bündnis Entwicklung Hilft & IFHV	Higher = worse risk ↑
NRI 2024	NRI Score, Technology Pillar, People Pillar, Governance Pillar, Impact Pillar	56/75 (75%)	Portulans Institute, Washington D.C.	Higher = better ↑
GII 2024	GII Score, Human Capital & Research, Infrastructure, Knowledge Outputs	52/75 (69%)	WIPO & Cornell University	Higher = better ↑
World Bank GDP 2024	GDP per Capita (current USD)	70/75 (93%)	World Bank Open Data	Higher = richer ↑
INFORM Risk 2024	INFORM Risk, LoCC, DRR, Physical Infrastructure, Institutional, Communication	75/75 (100%)	EU Joint Research Centre & OCHA	Higher = worse risk ↑
EM-DAT	Total Deaths, Total Affected, Events (1900–2025)	75/75 (100%)	CRED, UCLouvain, Belgium	N/A (counts)

C. OLS Regression Specification

NRI Score was selected as the independent variable because it is the most comprehensive measure of national digital ecosystem readiness, covering technology infrastructure, human capital, governance, and societal impact dimensions simultaneously. Two dependent variables were chosen for complementary analytical reasons. INFORM Risk is the broadest composite humanitarian crisis predictor, aggregating hazard, vulnerability, and coping capacity into a single 0–10 scale. WRI Lack of Coping Capacities captures the institutional sub-component most directly linked to policy intervention, representing the dimension that governments can address through governance investment rather than waiting for economic development. Both models follow the standard OLS specification:

$$\hat{Y} = \beta_0 + \beta_1 \times (\text{NRI Score}) + \varepsilon \tag{1}$$

OLS estimates the coefficients β_0 and β_1 by minimizing the sum of squared residuals (SSR) between observed and predicted values:

$$SSR = \sum_i \left(Y_i - \hat{Y}_i\right)^2 = \sum_i (Y_i - \beta_0 - \beta_1 X_i)^2 \tag{2}$$

Taking the partial derivatives of SSR with respect to β_0 and β_1 and setting them to zero yields the normal equations:

$$\beta_1 = \frac{\sum_i (X_i - \bar{X})\,(Y_i - \bar{Y})}{\sum_i (X_i - \bar{X})^2} \tag{3}$$

$$\beta_0 = \bar{Y} - \beta_1 \bar{X} \tag{4}$$

where $\bar{X}$ and $\bar{Y}$ are the sample means of the NRI Score and the risk outcome, respectively. OLS was selected over more complex regression approaches because the research question requires a single interpretable slope coefficient that directly quantifies the marginal association between digital readiness and disaster risk across a 55-country population, where interpretability and reproducibility are methodological priorities in cross-national policy research. $\hat{Y}$ is the predicted value of the risk outcome, β_0 is the intercept (the expected risk value when NRI equals zero), β_1 is the slope coefficient (the change in predicted risk per one-unit increase in NRI Score), and ε is the residual term capturing variance not explained by the model. Statistical significance is assessed at $p < 0.05$.

Model 1 regresses INFORM Risk on NRI Score ($n = 55$). Model 2 regresses WRI Lack of Coping Capacities on NRI Score ($n = 55$). The Pearson correlation coefficient r, ranging from −1 to +1, measures the strength and direction of the linear relationship between two variables. The coefficient of determination R^2 measures the proportion of variance in the outcome variable explained by the predictor, ranging from 0 to 1, where higher values indicate stronger predictive power.

D. Quadrant Classification

We apply a two-dimensional quadrant classification to group volcanic nations into preparedness profiles based on their relative positions on the NRI Score and WRI Score. We compute dynamic median thresholds from the listwise-deleted sample for each variable pairing; for the primary NRI–WRI pairing ($n = 55$), the median NRI Score is 49.93 and the median WRI Score is 11.40. We define four profiles: Preventive (high NRI, low WRI), where technological capacity translates into reduced disaster risk; Alert (high NRI, high WRI), where technological capacity coexists with elevated volcanic risk, indicating incomplete institutional conversion; Reactive (low NRI, high WRI), which represents the most concerning configuration due to limited technological capacity combined with high risk; and Passive (low NRI, low WRI), which reflects limited capacity alongside below-median composite risk but still indicates latent vulnerability. The dynamic threshold approach recalculates medians from the available complete-case sample whenever users change variable pairings in the dashboard, ensuring that fixed thresholds do not distort country comparisons when the analytical scope shifts.

E. Sendai Framework Variable Mapping

Available index variables were mapped to the four phases of the Sendai Framework for Disaster Risk Reduction 2015–2030 based on each phase's operational definition. Mitigation, corresponding to Sendai Priority 1 (Understanding Disaster Risk), is proxied by INFORM DRR, INFORM Physical Infrastructure, INFORM Infrastructure, and GII Infrastructure. Preparedness, corresponding to Sendai Priority 4 (Enhancing Disaster Preparedness), is proxied by INFORM Communication, NRI Technology Pillar, NRI Score, and NRI People Pillar. Response, corresponding to Sendai Priority 2 (Strengthening Governance), is proxied by INFORM Institutional, INFORM Lack of Coping Capacity, and NRI Governance Pillar. Recovery, corresponding to Sendai Priority 3 (Investing in DRR for Resilience), is proxied by GDP per capita, GII Human Capital and Research, GII Score, and GII Knowledge and Technology Outputs

INFORM indicators that use a higher-is-worse scale were inverted before normalization using the formula: inverted value = maximum sample value − observed value. All indicators were then normalized using min-max scaling across the 55-country sample.

$$normalized = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{5}$$

This produces scores from 0 (lowest resilience in the sample) to 1 (highest resilience). Phase scores are computed as the mean of their constituent normalized indicators.

4. Experimental Setup

A. Data Collection

This study collects all data from publicly accessible portals of seven international institutions. We retrieve GVP data from the Smithsonian Institution’s online database and filter eruption records to events from 1900 onward, while we extract per-volcano attributes such as coordinates, type, elevation, and VEI and merge them with country-level aggregates. We obtain WRI 2024 data from the World Risk Report 2024 supplementary dataset published by Bündnis Entwicklung Hilft, NRI 2024 data from the Portulans Institute annual report, GII 2024 data from the WIPO publication portal, GDP per capita (2024) from the World Bank Open Data platform using the NY.GDP.PCAP.CD indicator, INFORM Risk Index 2024 data from the European Commission Joint Research Centre portal, and EM-DAT volcanic event records from the CRED public query interface filtered for volcanic activity between 1900 and 2025. We store all seven datasets in a single Microsoft Excel workbook with separate sheets per source, and we apply a harmonization pipeline that standardizes country names, resolves conflicts in the “Infrastructure” variable appearing across WRI, GII, and INFORM datasets, and removes regional aggregates from World Bank GDP data before merging. This study constructs a final master dataset containing 75 volcanic countries, from which we derive a 55-country analytical sample through listwise deletion on WRI score, NRI score, GDP per capita, and INFORM Risk Index.

This study follows a four-stage analytical procedure aligned with Section 3. We first compute descriptive statistics for all variables in the 55-country sample and classify countries using WRI 2024 risk thresholds and NRI capacity tiers. We then calculate Pearson correlations between technology capacity indicators (NRI, GII, GDP per capita, and sub-pillars) and risk–resilience indicators (WRI, LoCC, and INFORM sub-indicators), testing all relationships at the 95% confidence level. In the third stage, we estimate OLS regressions with NRI as the independent variable in two models (INFORM Risk and LoCC as dependent variables), report standard model statistics (slope, intercept, R^2, p-value), and compute residuals to identify performance gaps, including explicit predictions for Indonesia. In the fourth stage, we conduct a Sendai Framework gap analysis by inverting higher-is-worse indicators, applying min-max normalization, and averaging indicators into phase scores; we define gaps as differences between Indonesia and a benchmark of Japan, New Zealand, and Iceland. We implement the full pipeline in Python and integrate it into a Streamlit–Plotly dashboard that enables dynamic re-computation under different configurations.

This study finds substantial heterogeneity across the sample in both risk and capacity dimensions. We observe that WRI scores range from 1.17 to 46.91 with a mean of 14.35 and a median of 11.40, indicating a right-skewed distribution where most countries exhibit moderate risk while a smaller subset faces very high risk. We also find that NRI scores range from 21.49 to 78.96 with a mean of 51.76 and a median of 49.93, reflecting an approximately symmetric distribution across technological capacity. In addition, we observe wide disparities in coping capacity, with LoCC scores ranging from 3.24 to 73.82 and a mean of 25.08, highlighting uneven resilience among volcanic countries.

Table 2 Descriptive Statistics n = 55 Volcano Countries

Variable	Mean	Median	Std Dev	Min	Max
WRI Score	14.35	11.40	11.27	1.17	46.91
NRI Score	51.76	49.93	14.07	21.49	78.96
GII Score*	33.74	30.05	14.71	12.3	62.4
GDP per Capita (USD)	20772.45	8452.37	24089.34	649.38	86785.43
INFORM Risk	3.94	3.6	1.64	1.4	7.8
Lack of Coping Capacities	25.08	13.51	21.57	3.24	73.82
Eruption Frequency (1900–2025)	64.2	5	137.54	0	763
No. of Volcanoes	20.89	8	33.48	1	101

This study finds that volcanic burden is highly concentrated across the sample. We observe a mean eruption frequency of 64.2 events per country since 1900, compared to a median of 5, driven upward by Indonesia as a strong outlier with 763 recorded eruptions. We also find that the mean number of volcanoes per country is 20.89, while the median is only 8, again reflecting Indonesia’s extreme value of 101 active volcanoes. In addition, we classify WRI distribution across the 55-country sample and find that 17 countries fall in the Very High category (>20.00), 16 in High (10.01–20.00), 10 in Medium (5.01–10.00), 10 in Low (2.01–5.00), and 2 in Very Low (0.00–2.00), confirming that volcanic countries as a group skew toward higher risk levels consistent with their geological exposure.

5. Result and Analysis

This study places Indonesia in the Alert quadrant (NRI = 53.84, WRI = 41.13) alongside 14 other countries, including Japan, the Philippines, Mexico, and the United States, with the overall distribution showing 13 Preventive, 15 Alert, 14 Passive, and 13 Reactive countries. We find that Indonesia's NRI exceeds the sample median of 49.93, indicating above-median technological capacity, yet its WRI is far above the median of 11.40 and falls within the Very High-Risk category under World Risk Report 2024 thresholds. We estimate that reaching the Preventive quadrant median would require an increase of 11.31 NRI points and a reduction of 33.59 WRI points, highlighting a substantial mismatch between capacity and risk reduction outcomes. This result indicates that current technology capacity alone does not sufficiently suppress disaster risk to Preventive-level performance. We further interpret Alert status as a dynamic condition in which countries already possess a digital foundation that can support institutional and infrastructural improvements, suggesting that targeted governance coordination and disaster infrastructure investment offer a more efficient pathway than broad-based technology expansion. The full spatial distribution of volcanic countries across quadrants is presented in Fig. 3.

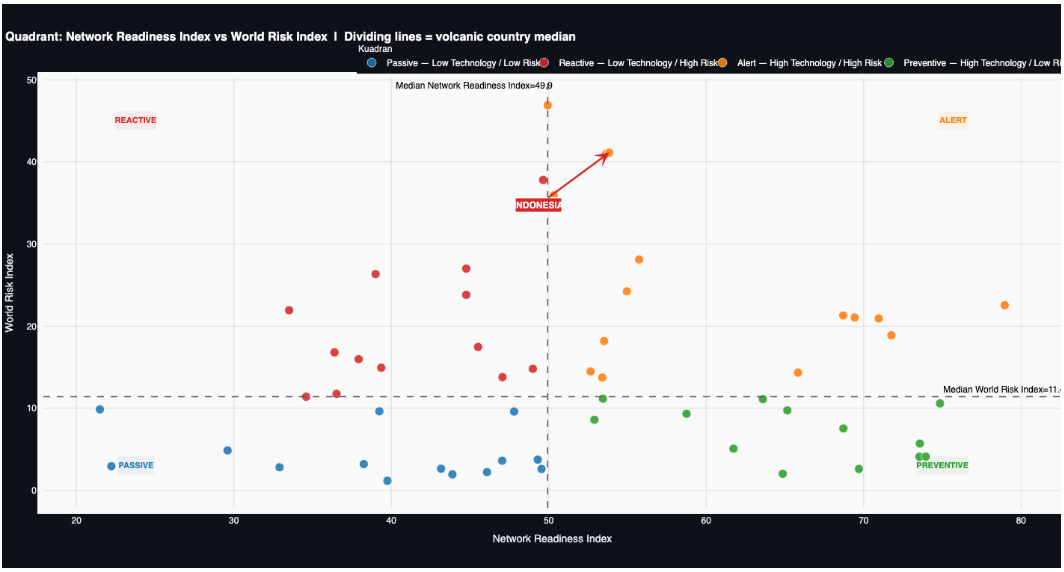

Fig. 3. Quadrant classification of 55 volcanic nations by NRI Score and WRI Score. Dashed lines indicate median thresholds.

Pearson correlation analysis confirmed a consistent pattern of negative associations between technology readiness indicators and disaster vulnerability sub-components. The correlation between NRI and LoCC was r=−0.554 ($p<0.001$), indicating that countries with higher digital readiness tended to have lower coping capacity deficits. Stronger negative correlations were observed between NRI and Vulnerability (r=−0.755, $p<0.001$) and between NRI and INFORM Risk (r=−0.781, $p<0.001$). In contrast, the correlation between NRI and WRI overall score was near zero and not statistically significant, which reflects the fact that WRI's exposure component is driven by geological and geographic factors that technology capacity does not influence. The relevant associations are therefore concentrated in the vulnerability and coping capacity dimensions, where institutional and infrastructural factors play a larger role.

Two OLS regression models were estimated with NRI as the independent variable. Model 1, with INFORM Risk as the dependent variable, produced the equation: INFORM Risk = 8.640 − 0.091 × NRI (R^2=0.609, p<0.001). This indicates that NRI alone explained 60.9 percent of the variance in INFORM Risk scores across the 55-country sample, a substantial explanatory contribution for a single-predictor cross-national model. Model 2, with LoCC as the dependent variable, produced: LoCC = 69.014 − 0.849 × NRI (R^2=0.307, p<0.001). Each one-point increase in NRI was associated with a 0.849-point reduction in LoCC on average. The lower R^2 in Model 2 reflects the broader set of factors that determine coping capacity beyond technology readiness alone, including economic strength and governance quality.

Comparing the two models directly, Model 1 (INFORM Risk, R^2 = 0.609) explains nearly twice the variance of Model 2 (WRI Lack of Coping Capacities, R^2 = 0.307). This difference is analytically expected rather than a limitation. INFORM Risk is a composite index that aggregates hazard, vulnerability, and coping capacity into a single score, meaning NRI captures a broader share of its variance because digital readiness influences multiple component dimensions simultaneously. WRI Lack of Coping Capacities, by contrast, isolates the institutional sub-component most directly shaped by governance and coordination structures, which technology readiness alone cannot fully determine. The lower R^2 in Model 2, therefore, reflects greater analytical precision, not weaker findings: it confirms that institutional coping capacity is a more demanding outcome to predict, and that the governance and coordination gap identified in Indonesia's residual represents a genuine structural deficit beyond what digital infrastructure can resolve independently.

Fig. 4. OLS regression of NRI Score on WRI Lack of Coping Capacities (n=55).

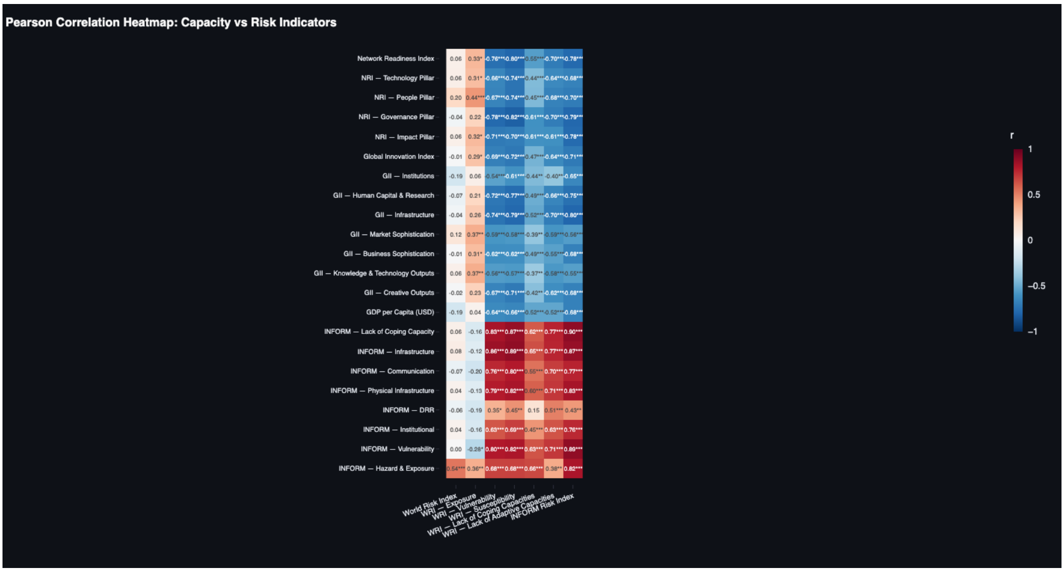

Fig. 5. Pearson correlation heatmap between technology capacity and disaster risk indicators.

Residual analysis in Model 2 revealed Indonesia's paradox in quantitative terms. With NRI=53.84, the model predicted a LoCC of 23.31 for Indonesia. The actual LoCC was 51.01, producing a positive residual of +27.70 points. This means Indonesia's coping capacity deficit was substantially worse than expected, given its technology capacity. All three benchmark countries showed negative residuals: Japan (NRI=70.96, actual LoCC=6.89, residual=−1.89), New Zealand (NRI=65.83, actual LoCC=6.19, residual=−6.94), and Iceland (NRI=64.86, actual LoCC=3.34, residual=−10.62). These countries not only possessed higher technology capacity but also converted that capacity into disaster management systems that outperformed model predictions. Indonesia's large positive residual indicates the presence of a systematic implementation gap between available technology and actual disaster outcomes.

This implementation gap has concrete policy implications. The three benchmark countries demonstrate that negative residuals are achievable at NRI score levels not dramatically higher than Indonesia's: Japan's NRI of 70.96 is 17 points above Indonesia's 53.84, yet its residual improvement relative to the model prediction is −1.89 points, a modest outperformance. Iceland's residual of −10.62 at NRI 64.86 suggests that the conversion of digital capacity into disaster preparedness outcomes is driven less by raw technology scores and more by the institutional architecture built around them. For Indonesia, this means that closing the +27.70 residual gap does not require reaching Iceland’s or Japan's NRI level first. It requires building the governance coordination systems, inter-agency command structures, and physical disaster infrastructure that allow existing digital capacity to translate into effective coping outcomes, a pathway that is institutionally demanding but does not depend on prior economic development reaching developed-nation levels.

Table 3: OLS Model 2 Residuals - Indonesia vs Benchmark Countries

Country	NRI Score	LoCC (Actual)	LoCC (Predicted)	Residual	Interpretation
Indonesia	53.84	51.01	23.31	+27.70	Underperforms model by 27.70 pts
Japan	70.96	6.89	8.78	−1.89	Outperforms model
New Zealand	65.83	6.19	13.13	−6.94	Outperforms model
Iceland	64.86	3.34	13.96	−10.62	Outperforms model significantly

Gap analysis across the four Sendai Framework phases revealed that Indonesia's underperformance was consistent across the entire disaster management cycle. After inverting higher-is-worse INFORM indicators and applying min-max normalization across the 55-country sample, the recovery phase showed the largest gap between Indonesia and the benchmark average. This reflects Indonesia's GDP per capita of USD 4,925 and GII scores that fall substantially below those of Japan, New Zealand, and Iceland, limiting the fiscal and innovative capacity available for post-disaster reconstruction. The response phase showed the second-largest gap, pointing to institutional coordination deficits and weak inter-agency command structures under emergency conditions, as evidenced by Indonesia's low INFORM institutional and coping capacity sub-scores. The mitigation phase showed the third gap, reflecting limited investment in physical protection infrastructure, such as lahar diversion channels and DRR program implementation. The preparedness phase showed the smallest gap among the four, consistent with Indonesia's above-median NRI, suggesting that its general digital capacity has contributed somewhat to monitoring and communication systems, though coverage and integration across remote volcanic zones remain incomplete.

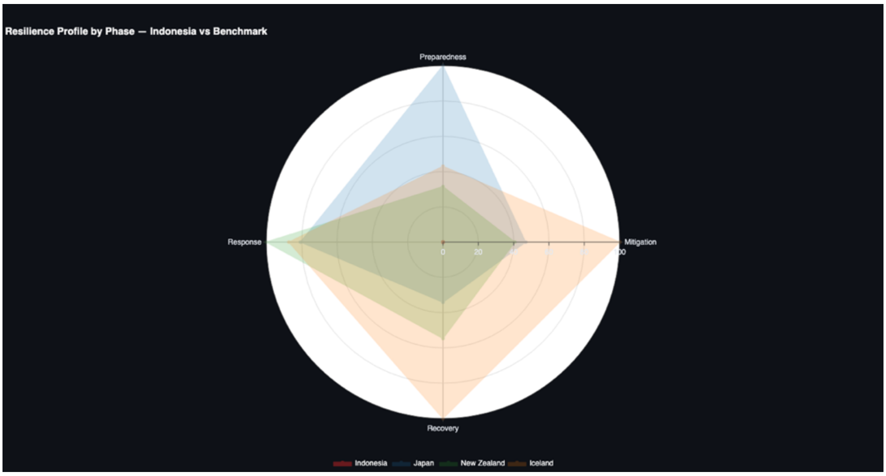

Fig. 6. Normalized resilience scores across four Sendai Framework phases for Indonesia and benchmark countries.

Table 4: Quadrant Distribution 55 Volcanic Nations

Quadrant	Label	Condition	Count	% of Sample	Notable Countries
Preventive	Preventive	High NRI (≥49.93) + Low WRI (≤11.40)	13	23.6%	Iceland, Portugal, Germany, Netherlands
Alert	Alert	High NRI (≥49.93) + High WRI (>11.40)	15	27.3%	Indonesia, Japan, Philippines, USA, Mexico
Passive	Passive	Low NRI (<49.93) + Low WRI (≤11.40)	14	25.5%	Bolivia, Guatemala, South Africa, Mongolia
Reactive	Reactive	Low NRI (<49.93) + High WRI (>11.40)	13	23.6%	Peru, Ecuador, Papua New Guinea

These findings together confirm the technology-resilience paradox framed in the introduction. Indonesia is not a technologically deficient country by the standards of volcanic nations: its NRI places it above the majority of the sample. The deficit lies in the translation of that capacity into effective disaster governance, physical infrastructure, and economic resilience. The IVA dashboard enabled dynamic verification of these findings across variable combinations and confirmed that the patterns reported here were robust to alternative indicator selections within each analytical category.

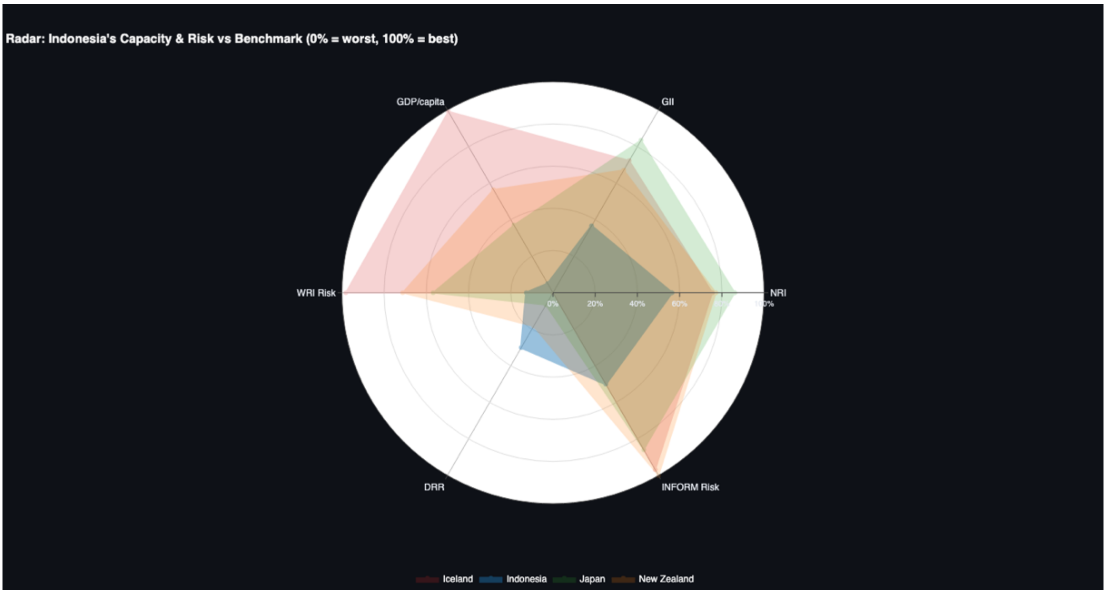

Fig. 7. Multi-dimensional resilience profile comparing Indonesia against benchmark countries across six indicators.

6. Conclusion

This study examines the relationship between national digital readiness and volcanic disaster coping capacity across 55 sovereign volcanic nations using 2024 global indicators and identifies three main findings. First, quadrant analysis places Indonesia in the Alert quadrant (NRI = 53.84), showing that above-median technological capacity has not translated into Preventive-level risk reduction; while Iceland occupies the Preventive quadrant and Japan and New Zealand also sit in the Alert quadrant, both achieve substantially lower Lack of Coping Capacities, confirming a persistent institutional conversion gap beyond quadrant position alone. Second, we find a statistically significant negative relationship between NRI and disaster vulnerability, where NRI explains 60.9% of the variance in INFORM Risk ($r = -0.781$, $R^2 = 0.609$, $p < 0.001$) and 30.7% of the variance in LoCC ($r = -0.554$, $R^2 = 0.307$, $p < 0.001$); Indonesia shows a large positive residual (+27.70), with an observed LoCC of 51.01 compared to a predicted 23.31, indicating a systematic coping capacity deficit beyond what digital infrastructure predicts. Third, phase-based gap analysis across the Sendai Framework shows underperformance across all stages, with the largest gap in recovery, followed by response, mitigation, and preparedness, suggesting that resilience deficits span the full disaster management cycle.

We conclude that closing the technology–resilience gap requires combined investment in digital infrastructure, economic recovery capacity, emergency coordination, and physical mitigation systems. We further identify future research directions, including subnational analysis in Indonesia, longitudinal panel studies to test causal mechanisms, extension of the framework to other hazards such as seismic and tsunami risks, and targeted investigation of the 20 volcanic countries excluded due to missing NRI data, which may represent the most severe cases of the digital divide.

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