



Monitoring-Informed Scenario Forecasting of Spatial Seismic Demand for Proactive Resilience in the İzmir Basin

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Abstract

Recorded seismic observations from monitoring networks provide a direct empirical basis for updating regional representations of earthquake demand, yet their use in scenario forecasting and proactive resilience planning remains limited. This study proposes a monitoring-informed sense–forecast–adapt workflow for forecasting spatial seismic demand in the İzmir Basin, western Türkiye. The framework transforms accumulated strong-motion records into a regional residual correction layer, embeds this layer within active-fault-based earthquake scenarios, and translates the resulting demand fields into adaptation-oriented spatial indicators.

A transparent reference ground-motion representation is first fitted using event magnitude, source-to-site distance, and site-condition information. Event–station residuals are then aggregated at the station level and interpolated to construct monitoring-informed residual and residual-variability fields. These updating layers are embedded within five representative active-fault scenarios around the İzmir Basin to generate baseline and monitoring-updated PGA fields. The resulting demand fields are evaluated through persistence, scenario sensitivity, monitoring/inspection priority, rank variability, and spatial concentration of high-demand domains.

The workflow is evaluated through residual-field validation, Gaussian-process benchmarking, robustness analyses, cumulative model-version tracking, and Monte Carlo uncertainty propagation. The results identify the Tuzla Fault scenario as the dominant demand case and the Yenifoça Fault scenario as the main secondary case. High-demand zones organize into spatially coherent regions, several locations remain repeatedly critical across multiple source scenarios, and the virtual regional demand representation stabilizes as the monitoring archive expands from 1977–2010 to 1977–2025.

The main contribution is an updateable forecasting workflow that integrates monitoring-derived residual updating, scenario-based spatial demand simulation, uncertainty-aware exceedance mapping, and resilience-oriented decision indicators. By transforming accumulated strong-motion observations into an evolving regional demand representation, the proposed framework moves beyond pointwise ground-motion estimation and provides a digital-twin-oriented basis for proactive seismic resilience planning in monitored basin environments.

Keywords: monitoring-informed forecasting; spatial seismic demand; residual updating; scenario-based forecasting; digital-twin-oriented workflow; proactive resilience.



37 1. Introduction

38 Earthquake effects are commonly interpreted through pointwise ground-motion estimates,
39 although seismic demand is inherently spatial and is influenced by geological heterogeneity, basin
40 structure, source-to-site configuration, and local site conditions. In sedimentary basins, these
41 factors produce spatially coherent shaking patterns that cannot be fully represented by isolated
42 station-level estimates. Consequently, regional resilience planning requires not only the prediction
43 of shaking intensity at individual locations but also the identification of how elevated demand is
44 organized across space, how it changes under alternative earthquake scenarios, and which areas
45 remain consistently critical. Strong-motion monitoring networks provide an empirical basis for
46 constructing and progressively refining such regional representations of spatial seismic demand.

47 Observation-conditioned estimation of spatial ground-motion fields has a long history.
48 Foundational studies established the probabilistic framework for conditional simulation of ground-
49 motion fields at uninstrumented locations using correlation-consistent prediction and Kriging-
50 based estimators (Vanmarcke and Fenton, 1991; Vanmarcke et al., 1993). Subsequent
51 developments incorporated filtering techniques for adaptive field updating (Sato and Imabayashi,
52 1999), while more recent studies employed Gaussian-process regression to estimate ground-motion
53 fields at locations without observations (Tamhidi et al., 2022). Operational systems such as
54 ShakeMap further demonstrated the practical value of combining recorded motions, empirical
55 prediction models, and spatially correlated residuals to produce event-specific shaking maps
56 (Worden et al., 2010). Collectively, these studies established the importance of monitoring
57 observations as constraints on spatial ground-motion fields.

58 A related body of work has focused on the spatial correlation of ground-motion residuals and its
59 implications for regional hazard and risk assessment. Previous studies showed that intra-event
60 residuals exhibit strong spatial dependence and that neglecting this dependence may bias regional
61 hazard and portfolio-loss estimates (Park et al., 2007; Goda and Atkinson, 2009; Loth and Baker,
62 2013). Region-specific correlation models (Huang and Wang, 2015) and basin-oriented
63 investigations (Mizutani et al., 2019) further demonstrated that sedimentary environments may
64 generate characteristic spatial demand patterns that differ from generic regional assumptions.
65 However, these studies have primarily addressed event-specific conditioning, correlation
66 modelling, or post-event field reconstruction rather than repeatedly updating a regional demand
67 representation for future scenario forecasting.

68 Bayesian updating studies provide another important foundation. Instrumental observations have
69 been incorporated into regional probabilistic seismic hazard assessment (Viallet et al., 2019), while
70 post-event regional analyses have shown that recorded motions reduce uncertainty in spatial hazard
71 representations (Du and Padgett, 2021). Similar updating concepts have also been applied to
72 regional liquefaction modelling and intensity-map refinement using newly available observations
73 (Engler et al., 2025; Kwak and Ahn, 2026). These developments demonstrate the value of
74 observation-informed updating but remain largely focused on post-event estimation rather than
75 scenario-based forecasting.

76 A complementary perspective originates from structural health monitoring and digital twins.
77 Recent predictive digital-twin frameworks emphasize continuous sensing, model updating,
78 uncertainty quantification, forecasting, and decision support as components of a unified



79 information loop (Torzoni et al., 2024). Broader reviews similarly identify physical-to-virtual
80 information transfer, uncertainty propagation, and adaptive decision-making as defining
81 characteristics of digital-twin systems (Thelen et al., 2022; Thelen et al., 2023). Although these
82 concepts have primarily been developed for individual structures, the same information flow can
83 be extended to regional seismic monitoring by treating accumulated observations as a continuously
84 updated representation of spatial seismic demand.

85 Accordingly, this study develops a monitoring-informed sense–forecast–adapt framework for
86 basin-scale seismic-demand forecasting in the İzmir Basin, western Türkiye. Accumulated strong-
87 motion observations are first converted into residual information relative to a transparent reference
88 ground-motion representation. Station-level residual statistics are then transformed into spatial
89 correction layers and combined with five representative active-fault scenarios—the İzmir Fault,
90 Seferihisar Fault, Tuzla Fault, Gülbahçe Fault Zone, and Yenifoça Fault—to generate baseline and
91 monitoring-updated PGA fields. Beyond deterministic demand mapping, the framework derives
92 persistence, scenario sensitivity, monitoring priority, rank variability, and spatial concentration
93 indicators. The residual field is evaluated using leave-one-station-out validation and Gaussian-
94 process benchmarking, while the robustness of the proposed indicators is examined through
95 threshold sensitivity, weighting sensitivity, and Monte Carlo uncertainty propagation.

96 To investigate the updateability of the framework, a digital-twin-oriented model-version
97 experiment is further introduced. Cumulative monitoring archives covering 1977–2010, 1977–
98 2015, 1977–2020, and 1977–2025 are used to regenerate the reference model, spatial residual field,
99 scenario forecasts, and adaptation indicators. This enables the evolution of the regional virtual
100 demand representation to be quantified as new monitoring records become available.

101 The study addresses four principal questions:

- 102 1. How can accumulated strong-motion observations be transformed into a monitoring-
103 informed regional residual correction layer?
- 104 2. How do monitoring-updated spatial demand fields differ under alternative active-fault
105 scenarios?
- 106 3. How stable and informative are persistence, scenario sensitivity, monitoring priority, and
107 spatial concentration indicators for resilience planning?
- 108 4. How does the regional virtual demand representation evolve as the monitoring archive
109 expands over time?

110 The resulting workflow transforms regional strong-motion observations from retrospective
111 measurements into an updateable forecasting layer capable of supporting scenario comparison,
112 uncertainty-aware interpretation, and adaptation-oriented decision making. In doing so, the study
113 provides a field-based and digital-twin-oriented framework for proactive seismic resilience
114 planning in monitored basin environments.

115 2. Study Area, Monitoring Dataset and Scenario Sources

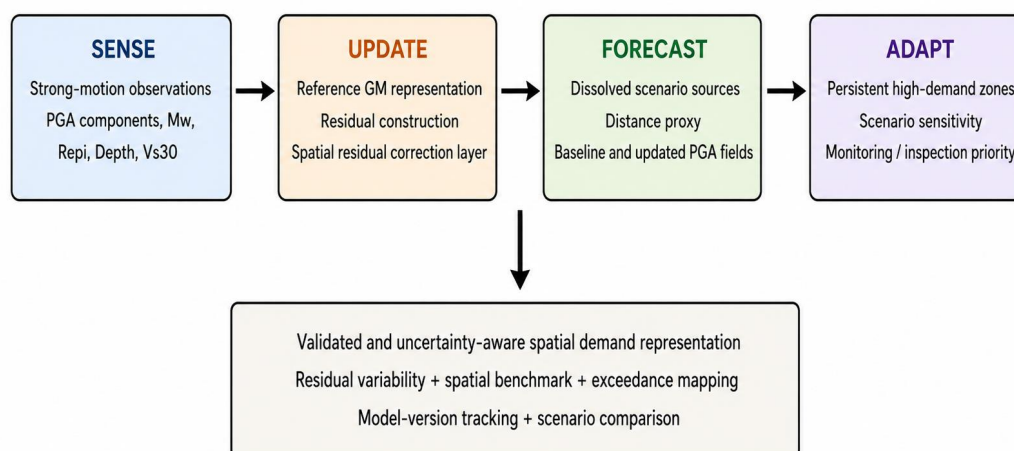
116 The study focuses on the İzmir Basin and its surrounding seismotectonic region in western Türkiye.
117 İzmir is located within an active extensional tectonic setting and is influenced by several mapped
118 active fault systems in and around the metropolitan area. At the broader Eastern Mediterranean



scale, western Türkiye lies within the western part of a proposed deep quasi-ring mantle structure centred beneath the Cyprus region, whose surface projection is interpreted as exhibiting a predominantly counterclockwise rotational pattern (Eppelbaum et al., 2021). This regional interpretation was subsequently developed using additional magnetic-field, paleobiogeographic, and seismic-tomography evidence (Eppelbaum et al., 2025). The combination of active seismic sources, basin-controlled site conditions, and spatially distributed strong-motion observations makes the region a suitable test case for monitoring-informed forecasting of spatial seismic demand. In this study, the İzmir Basin is treated as a regional spatial domain in which earthquake demand may vary, concentrate, and shift under different source scenarios, rather than as a collection of isolated recording stations.

The overall workflow of the study is illustrated in **Figure 1**. The framework follows a sense–forecast–adapt logic. In the sensing stage, recorded strong-motion observations are used to derive residual information relative to a reference ground-motion representation. In the forecasting stage, this monitoring-informed regional demand representation is combined with active-fault-based earthquake scenarios to generate baseline and updated spatial seismic demand fields. In the adaptation stage, the resulting forecasts are interpreted through resilience-oriented indicators, including persistent high-demand zones, scenario-sensitive demand shifts, spatial concentration of high-demand domains, monitoring or inspection priority, and rank stability of critical areas.

Monitoring-informed sense–forecast–adapt workflow for spatial seismic demand forecasting



137

138 **Figure 1.** Sense–Forecast–Adapt workflow for monitoring-informed scenario forecasting of spatial
139 seismic demand.

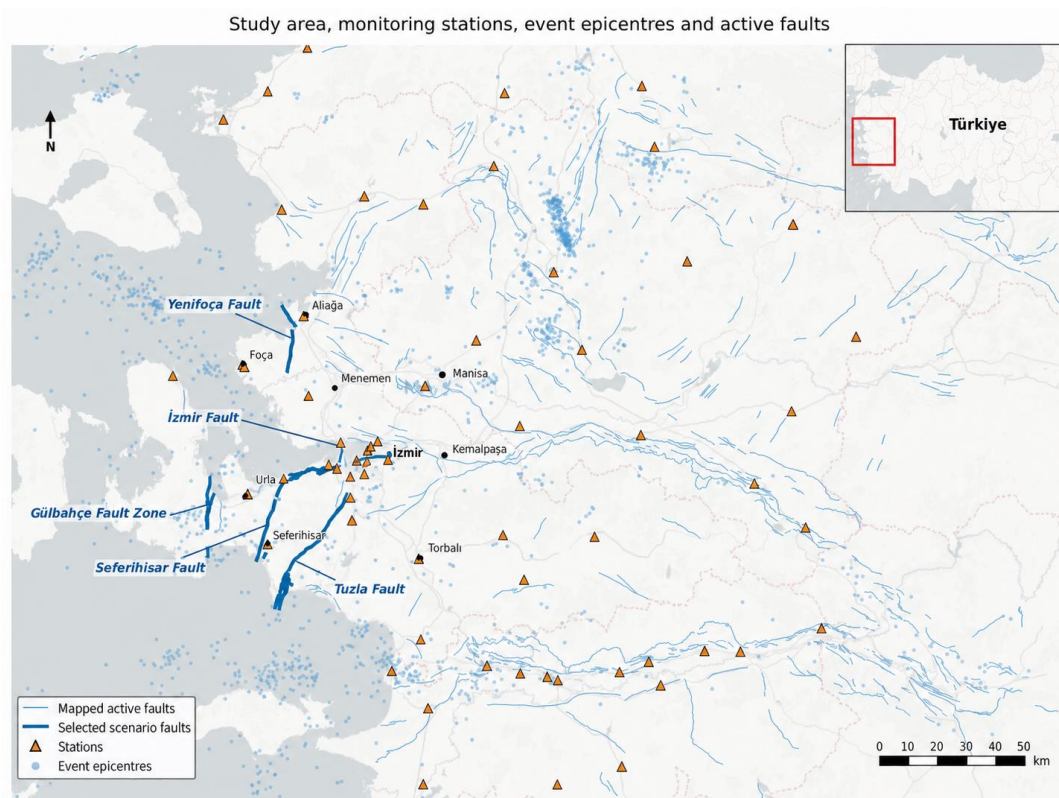
140 The monitoring dataset consists of 37,130 event–station records obtained from 119 strong-motion
141 stations. The records correspond to 2,980 earthquake events spanning the period 1977–2025. The
142 magnitude range of the catalogue is approximately M 2.2–7.6. The full event catalogue extends



beyond the İzmir metropolitan area and provides a broader regional basis for residual construction, whereas the İzmir-focused subset is used to support basin-scale interpretation and scenario forecasting. A practical İzmir subset defined by station identifiers beginning with 35 contains 15,639 event–station records from 39 stations and 1,379 events.

For each event–station record, the two horizontal PGA components are combined using their geometric mean and used as the primary intensity measure in the analysis. Site-condition information is represented by station-level V_{s30} . The event magnitude, epicentral distance, depth, and V_{s30} are used to construct a transparent reference ground-motion representation, while the residuals between observed and predicted logarithmic PGA values provide the empirical basis for monitoring-informed spatial updating.

A regional active fault inventory is used to define the seismotectonic context of the study area and to support the selection of representative earthquake scenarios. The active fault database contains mapped fault traces in geographic coordinates. The spatial distribution of monitoring stations, recorded event epicentres, mapped active faults, and selected scenario sources is shown in Figure 2.



158

Figure 2. Study area, monitoring stations, recorded event epicentres, mapped active faults, and selected scenario faults.

160



For scenario-based forecasting, a subset of active faults located around the İzmir Basin is selected as representative source configurations. These scenarios are not intended to reproduce specific historical earthquakes. Rather, they are used to examine how spatial seismic demand may change under alternative physically interpretable source conditions. The selected scenarios include the İzmir Fault, Seferihisar Fault, Tuzla Fault, Gülbahçe Fault Zone, and Yenifoça Fault. Each scenario is defined by a mapped fault trace, an assigned moment magnitude, and a representative source depth. These scenario sources are summarized in Table 1.

Table 1. Selected earthquake scenarios used for spatial demand forecasting.

Scenario	Source	Mw	Depth (km)	Purpose in the analysis
S1	İzmir Fault	6.5	10	Near-basin source scenario
S2	Seferihisar Fault	6.6	10	Southwestern source scenario
S3	Tuzla Fault	7	10	High-magnitude southern source scenario
S4	Gülbahçe Fault Zone	6.6	10	Western source scenario
S5	Yenifoça Fault	6.8	10	Northwestern source scenario

The monitoring observations and the scenario source definitions are used for complementary purposes in the study. The recorded event–station observations provide the empirical basis for residual construction and regional demand updating, while the selected active-fault scenarios provide the source configurations for forward forecasting of spatial seismic demand. This structure links observed ground-motion data, regional active source conditions, and resilience-oriented interpretation within a single monitoring-informed forecasting framework.

3. Methodological Framework

3.1. Monitoring-Informed Residual Updating

The first stage of the framework converts recorded strong-motion observations into an observation-informed residual representation of regional seismic demand. Peak ground acceleration is used as the primary intensity measure, and the two horizontal components are combined using the geometric mean:

$$PGA_H = \sqrt{PGA_{NS} \times PGA_{EW}}$$

where PGA_{NS} and PGA_{EW} are the two recorded horizontal components. This horizontal intensity measure is used consistently in the residual construction, spatial updating, and scenario forecasting stages. Station-level site effects are represented using V_{s30} , which is available for the monitoring stations and provides a practical site-condition descriptor for regional ground-motion analysis.

The logarithmic form of the horizontal intensity measure is used in the residual analysis:

$$y_{ij}^{obs} = \ln(PGA_{H,ij})$$



188 where i denotes the monitoring station and j denotes the earthquake event. A transparent
189 reference ground-motion representation is then used to estimate the expected logarithmic PGA
190 for each event–station pair:

$$191 \quad y_{ij}^{pred} = f(M_j, R_{ij}, V_{s30,i})$$

192 where M_j is the event magnitude, R_{ij} is the event-to-station distance measure, and $V_{s30,i}$ is the
193 station-level site-condition descriptor. In the present implementation, the reference representation
194 is fitted in logarithmic PGA space using magnitude, effective distance terms, and normalized V_{s30} .
195 The effective distance is defined as:

$$196 \quad R_{eff,ij} = \sqrt{R_{epi,ij}^2 + h_j^2}$$

197 where $R_{epi,ij}$ is the epicentral distance and h_j is the event depth. The reference model is not intended
198 to replace a full ground-motion prediction equation; rather, it provides a consistent and transparent
199 baseline against which monitoring residuals can be constructed.

200 The event–station residual is computed as:

$$201 \quad r_{ij} = y_{ij}^{obs} - y_{ij}^{pred}$$

202 or equivalently,

$$203 \quad r_{ij} = \ln(PGA_{H,ij}^{obs}) - \ln(PGA_{H,ij}^{pred})$$

204 Positive residuals indicate stronger-than-expected shaking relative to the reference representation,
205 whereas negative residuals indicate weaker-than-expected shaking. The residuals are then
206 aggregated at the station level to obtain a monitoring-informed residual tendency:

$$207 \quad \bar{r}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} r_{ij}$$

208

209 where n_i is the number of usable records at station i . The value $\bar{r}_i$ represents the average deviation
210 of recorded motions at a station from the reference prediction and is used as an observation-derived
211 correction term for regional demand updating.

212 The variability of residuals at each station is also evaluated as:

$$213 \quad s_{r,i} = \sqrt{\frac{1}{n_i-1} \sum_{j=1}^{n_i} (r_{ij} - \bar{r}_i)^2}$$

214 where $s_{r,i}$ provides a station-level indicator of residual variability across events. Together, $\bar{r}_i$ and
215 $s_{r,i}$ describe the monitoring-informed correction and its variability at the station scale.



216 To extend the residual information from monitoring stations to the regional prediction grid, the
217 station-level residuals are converted into a spatial residual correction field:

$$218 \quad r_s(x) = I(\tilde{r}_1, \tilde{r}_2, \dots, \tilde{r}_N; x)$$

219 where x denotes a prediction location, N is the number of monitoring stations used for spatial
220 updating, and $I(\cdot)$ is the spatial interpolation operator. In the baseline implementation, inverse-
221 distance weighting is used to construct the residual correction field. The same spatial interpolation
222 logic is also used to generate the residual-variability field and the station-informed V_{S30} field. The
223 resulting residual correction field $r_s(x)$ represents the monitoring-informed regional updating layer
224 used in the scenario forecasting stage.

225 To evaluate whether the spatial residual correction layer provides meaningful out-of-station
226 information, a leave-one-station-out cross-validation procedure is applied. In each validation step,
227 one monitoring station is removed, the residual correction surface is reconstructed using the
228 remaining stations, and the residual at the omitted station is predicted. The observed and predicted
229 station residuals are then compared using the RMSE, MAE and Bias metrics.

230 A Gaussian-process residual surface is also fitted as a benchmark to compare the IDW-based
231 residual correction layer with a covariance-based spatial prediction alternative.
232

233 3.2. Scenario-Based Spatial Demand Forecasting

234 The second stage uses active-fault-based earthquake scenarios to generate spatial seismic demand
235 forecasts. Each scenario is represented by:

$$236 \quad S_k = \{M_{w,k}, Faulttrace_k, h_k\}$$

237 where $M_{w,k}$ is the assigned scenario magnitude, $FaultTrace_k$ is the mapped fault trace, and h_k is the
238 representative source depth.

239 For scenario-based forecasting, source-to-site distance is computed from the mapped scenario fault
240 traces. Distance-to-source measures are fundamental inputs in empirical ground-motion prediction
241 and regional seismic-demand modelling, and alternative definitions may be adopted depending on
242 the source representation and the objective of the analysis (Kaklamanos et al., 2011; Campbell and
243 Bozorgnia, 2014). In this study, the primary horizontal source-distance measure is defined as the
244 shortest distance from a station or prediction location x to the corresponding scenario fault trace:

$$245 \quad R_{trace,k}(x) = \min d_{horizontal}(x, Faulttrace_k)$$

246 To incorporate the representative scenario depth, a depth-adjusted source-distance metric is
247 calculated as

$$248 \quad R_{proxy,k}(x) = \sqrt{R_{trace,k}(x)^2 + h_k^2}$$



249 where $h_k=10$ km for the selected scenarios. This metric is used consistently across all scenario
250 sources to generate comparable spatial seismic demand forecasts.

251 For each scenario k , the baseline logarithmic PGA field is computed as

$$252 \quad y_k^{base}(x) = f(M_{w,k}, R_{proxy,k}(x), V_{s30}(x))$$

253 where $V_{s30}(x)$ is the station-informed spatial site-condition field. The corresponding baseline PGA
254 value is obtained as:

$$255 \quad PGA_k^{base}(x) = \exp(y_k^{base}(x))$$

256 The monitoring-informed updated forecast is obtained by adding the spatial residual field to the
257 baseline scenario demand:

$$258 \quad y_k^{upd}(x) = y_k^{base}(x) + r_s(x) \text{ and } PGA_k^{upd}(x) = \exp(y_k^{upd}(x)).$$

259 This updated field combines the scenario source condition, reference ground-motion
260 representation, site-condition descriptor, and observation-derived residual correction. The
261 difference between the updated and baseline demand fields is expressed as a demand escalation
262 index:

$$263 \quad DEI_k(x) = y_k^{upd}(x) - y_k^{base}(x)$$

264 Because the updating is additive in logarithmic space, $DEI_k(x)$ is equivalent to the spatial residual
265 correction applied to the baseline scenario field. Positive values indicate locations where
266 monitoring-informed updating increases forecasted demand relative to the baseline scenario field.

267 3.3. Adaptation-Oriented Forecast Indicators

268 The third stage translates the forecasted demand fields into indicators that support proactive
269 resilience planning. These indicators are not intended to represent direct damage or loss estimates.
270 Instead, they identify areas where forecasted seismic demand is elevated, persistent, scenario-
271 sensitive, spatially concentrated, or associated with higher updating uncertainty.

272 For a selected demand threshold PGA_c , the high-demand domain under scenario k is defined as:

$$273 \quad H_k(x) = \begin{cases} 1, & PGA_k^{upd}(x) \geq PGA_c \\ 0, & PGA_k^{upd}(x) < PGA_c \end{cases}$$

274 The high-demand threshold, PGA_c , is defined as the 80th percentile of all monitoring-updated PGA
275 values pooled across the five scenario fields and all prediction-grid locations. This percentile-based
276 definition identifies the upper-demand portion of the scenario ensemble and provides a common
277 threshold for persistence, connected-domain, and exceedance-probability analyses.



278 The persistence of high-demand behavior across all scenarios is then quantified as:

279
$$P(x) = \frac{1}{K} \sum_{k=1}^K H_k(x)$$

280 where K is the number of earthquake scenarios. Values of P(x) close to 1 indicate locations that
281 repeatedly fall within high-demand zones across multiple scenarios.

282 Scenario sensitivity is evaluated from the variability of updated logarithmic PGA forecasts across
283 the scenario set:

284
$$SS(x) = std(y_1^{upd}(x), y_2^{upd}(x), \dots, y_K^{upd}(x))$$

285 High values of SS(x) indicate locations where the forecasted demand is strongly controlled by the
286 selected earthquake source.

287 A monitoring / inspection priority indicator is defined by combining normalized forecasted demand
288 and normalized residual variability:

289
$$MPI(x) = w_1 \cdot y^{-upt}(x) + w_2 \cdot \tilde{\sigma}_s(x)$$

290 where $y^{-upt}(x)$ is the normalized mean updated logarithmic demand across scenarios, $\tilde{\sigma}_s(x)$ is the
291 normalized residual-variability field, and w_1 and w_2 are weighting factors. In the baseline
292 implementation, $w_1=0.60$ and $w_2=0.40$, giving greater weight to expected demand while retaining
293 the uncertainty contribution from residual variability. High MPI values identify locations where
294 elevated demand and higher updating variability coincide, making them candidates for intensified
295 monitoring, rapid inspection planning, or further site-specific evaluation.

296 Finally, grid points are ranked according to their updated demand values under each scenario. The
297 variability of these ranks across scenarios is used to evaluate whether a location remains
298 consistently important or whether its relative criticality changes with the assumed source
299 configuration. Rank-stable locations remain high-priority across scenarios, whereas high rank-
300 variability locations are interpreted as source-sensitive.

301 **3.4. Robustness, Uncertainty Propagation and Model-Version Tracking**

302 Beyond the baseline scenario forecasts and adaptation-oriented indicators, three additional analyses
303 are conducted to evaluate the stability, uncertainty and updateability of the proposed workflow.
304 These analyses are designed to test whether the spatial indicators depend strongly on threshold
305 selection or priority-index weighting, whether high-demand domains form coherent spatial
306 structures, how residual variability affects exceedance interpretation, and how the monitoring-
307 informed representation evolves as the strong-motion archive expands.

308 First, threshold sensitivity is evaluated by repeating the high-demand classification using multiple
309 percentile-based and fixed PGA thresholds. The percentile thresholds include the 70th, 75th, 80th,
310 85th and 90th percentiles of all monitoring-updated scenario PGA values. Fixed thresholds of 150,
311 200 and 250 are also tested. For each threshold, the high-demand domains, persistence values and



high-demand grid fractions are recalculated. This provides a robustness check on whether persistent demand patterns are specific to a single threshold or remain visible under alternative demand definitions.

Second, the sensitivity of the monitoring / inspection priority indicator to the weighting scheme is evaluated. The baseline MPI uses a demand-dominant weighting of $w_1=0.60$ and $w_2=0.40$, where w_1 is assigned to normalized updated demand and w_2 to normalized residual variability. To test the stability of the priority structure, the following alternative weight combinations are considered: $(w_1, w_2) \in \{(0.80, 0.20), (0.60, 0.40), (0.50, 0.50), (0.40, 0.60), (0.20, 0.80)\}$.

The resulting MPI rankings are compared with the baseline configuration using Spearman rank correlation and top-10% priority overlap. This test evaluates whether monitoring / inspection priority regions remain stable under alternative planning preferences.

Third, the spatial concentration of high-demand domains is evaluated using connected-component analysis. For each scenario and threshold, the binary high-demand field is converted into connected regions on the prediction grid. The number of connected components, high-demand grid fraction, largest component size, largest component ratio and component fragmentation are computed. These metrics distinguish spatially coherent high-demand domains from fragmented or isolated exceedance patterns.

To incorporate residual variability into uncertainty-aware spatial interpretation, Monte Carlo simulations are performed for each scenario. For each grid point and scenario, the updated logarithmic demand is treated as the mean of a residual-variability-based distribution:

$$Y_k^{mc}(x) = y_k^{base}(x) + r_s(x) + \epsilon(x)$$

where:

$$\epsilon(x) \sim N(0, \sigma_s(x)^2)$$

and $\sigma_s(x)$ is the residual-variability field. When available, the Gaussian-process benchmark uncertainty is combined with the residual-variability field to obtain a conservative uncertainty layer. For each scenario, multiple realizations of $Y_k^{MC}(x)$ are generated and transformed into PGA space:

$$PGA_k^{MC}(x) = \exp(Y_k^{MC}(x))$$

The exceedance probability for the selected threshold PGA_c is then computed as:

$$P_{exc,k}(x) = \frac{1}{N_{MC}} \sum_{m=1}^{N_{MC}} I(PGA_{k,m}^{MC}(x) \geq PGA_c)$$

where N_{MC} is the number of Monte Carlo realizations and $I(\cdot)$ is the indicator function. This produces scenario-specific exceedance-probability maps and summary measures such as mean exceedance probability, maximum exceedance probability, and the fraction of grid points with exceedance probability greater than selected probability levels.



Finally, a cumulative model-version tracking experiment is performed to evaluate how the monitoring-informed regional demand representation evolves as new records become available. The event catalogue is divided into cumulative model versions according to the end years 2010, 2015, 2020 and 2025. Each version includes all usable records up to the corresponding end year:

$$D_v = \{d_j: year_j \leq Y_v\}$$

where D_v is the cumulative dataset for model version v and Y_v is the corresponding end year. For each model version, the reference ground-motion representation is refitted, event–station residuals are recalculated, station-level residual tendencies are reconstructed, and a new spatial residual correction layer is generated. The scenario forecasts and adaptation-oriented indicators are then regenerated for each version.

Sequential update metrics are computed between consecutive model versions. For two consecutive versions $v-1$ and v , the residual-field change is quantified as:

$$\Delta r_s^{RMSE} = \sqrt{\frac{1}{G} \sum_{g=1}^G [r_{s,v}x(g) - r_{s,v-1}x(g)]^2}$$

where G is the number of grid points. Similarly, the change in the monitoring-priority indicator is quantified as:

$$\Delta MPI^{RMSE} = \sqrt{\frac{1}{G} \sum_{g=1}^G [MPI_v x(g) - MPI_{v-1} x(g)]^2}$$

The Spearman rank correlation between consecutive MPI fields and the overlap of the top 10% priority grid points are also computed. These metrics indicate whether updated monitoring records substantially modify the regional priority structure or whether the representation stabilizes as the archive becomes denser. The main methodological quantities used in the workflow are summarized in Table 2.

Table 2. Summary of methodological quantities used in the sense–forecast–adapt framework.

Quantity	Definition	Interpretation
PGA_H	$\sqrt{PGA_{NS}xPGA_{EW}}$	Geometric mean horizontal PGA
(r_{ij})	$(y_{ij}^{\{obs\}} - y_{ij}^{\{pred\}})$	Event–station residual
$(\bar{r}_i)$	station mean residual	Station-level correction
$(r_{s(x)})$	interpolated $(\bar{r}_i)$	Spatial residual correction
$(PGA_k^{\{upd\}(x)})$	$(exp(y_k^{\{base\}(x)} + r_{s(x)}))$	Updated scenario demand
$(P(x))$	$\frac{1}{K} \sum_{k=1}^K H_k(x)$	Persistence
$(SS(x))$	$(std(y_1^{\{upd\}}, \dots, y_K^{\{upd\}}))$	Scenario sensitivity
$(MPI(x))$	$(w_{1\{y\}}^{\{upd\}(x)} + w_{2\{\sigma\}s(x)})$	Monitoring / inspection priority



$(P_{exc,k}(x))$	Monte Carlo exceedance probability	Uncertainty-aware exceedance indicator
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The following section applies this workflow to the İzmir Basin monitoring dataset and the five dissolved scenario sources defined in Section 2. The results are presented in the same sequence as the methodological framework: first, the reference ground-motion representation and residual correction layer are evaluated; second, the spatial residual surface is validated and benchmarked; third, baseline and monitoring-updated scenario forecasts are compared; and finally, the adaptation-oriented indicators, robustness checks, model-version tracking and Monte Carlo exceedance-probability outputs are interpreted in terms of proactive resilience planning.

4. Results

4.1. Reference Model, Residual Correction and Spatial Validation

The reference ground-motion representation was fitted using 37,077 usable event–station records obtained from 119 strong-motion stations and 2,974 earthquake events. The model explains a substantial part of the logarithmic variability in horizontal PGA, with an R^2 value of 0.633. The logarithmic RMSE and MAE are 0.801 and 0.622, respectively. The mean residual is close to zero, indicating that the reference representation provides a balanced baseline at the dataset scale. The residual standard deviation is 0.800, reflecting the expected variability of regional ground-motion observations. The performance metrics are summarized in Table 3.

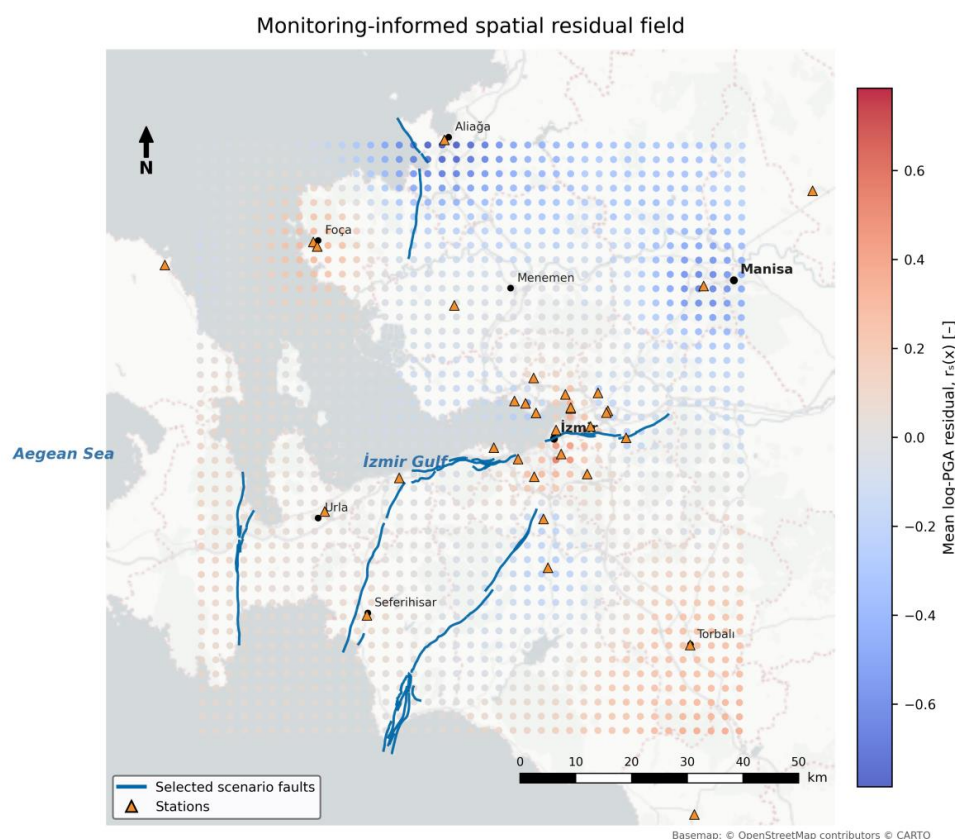
Table 3. Performance of the reference ground-motion representation

Metric	Value
Number of usable records	37,077
Number of stations	119
Number of events	2,974
(R^2) , log scale	0.633
RMSE, log scale	0.801
MAE, log scale	0.622
Mean residual	0.025
Residual standard deviation	0.800

Before using the residuals as monitoring-informed updating quantities, the fitted reference model was examined for physical plausibility. This check is important because the residual correction layer is meaningful only if the reference model captures the main first-order controls on ground-motion intensity in a consistent manner. The scaled coefficients show the expected directional behavior: the magnitude term is positive, indicating larger predicted PGA for larger events, whereas the distance-related terms are negative, reflecting attenuation with increasing source-to-site distance. The V_{S30} -related coefficient is also negative, meaning that, within the fitted log-linear structure, stiffer site conditions are associated with lower predicted PGA. These coefficient signs indicate that the reference model provides a physically reasonable baseline for residual construction, although it is not intended to replace a full ground-motion prediction equation.



400 The event–station residuals were then aggregated at the station level and interpolated over the
401 prediction domain to obtain the monitoring-informed spatial residual correction field. A total of
402 108 stations satisfied the minimum-record requirement and were used for spatial updating. The
403 station-level mean residuals range from -0.790 to 2.867, with an average of 0.163 and a median of
404 0.122. Over the prediction grid, the interpolated residual field ranges from -0.786 to 0.537, with a
405 mean value of -0.036 and a median value close to zero. This indicates that the regional correction
406 field contains both positive and negative deviations relative to the reference ground-motion
407 representation.



408

409 **Figure 3.** Monitoring-informed spatial residual field derived from station-level residuals.

410 In addition to the mean residual correction field, a residual-variability field was constructed by
411 interpolating the station-level residual standard deviations over the same prediction grid. While the
412 mean residual field provides the demand adjustment applied to the baseline scenario forecasts, the
413 residual-variability field represents the spatial distribution of remaining uncertainty in the
414 monitoring-derived correction. This variability field has a mean value of 0.663 and ranges from
415 0.553 to 0.955 over the grid. It is therefore used not as a direct PGA correction, but as an
416 uncertainty-related layer in the monitoring / inspection priority indicator and in the Monte Carlo
417 exceedance-probability analysis.



To evaluate the spatial reliability of the residual correction layer, a leave-one-station-out diagnostic validation was performed. In this test, each station is omitted in turn, the residual surface is reconstructed using the remaining stations, and the residual tendency at the omitted station is predicted. The IDW residual surface was also compared with a Gaussian-process benchmark surface. The validation results are summarized in Table 4.

Table 4. Leave-one-station-out diagnostic validation of the spatial residual correction layer.

Method	RMSE	MAE	Bias	Spearman (ρ)
IDW	0.405	0.319	0.04	0.227
Gaussian process	0.379	0.297	0.002	0.166

The Gaussian-process benchmark slightly reduces RMSE and MAE relative to IDW and produces an almost zero bias. However, both methods show limited rank association with the observed station residuals, indicating that station-level residual tendencies are difficult to predict precisely from spatial position alone. This is expected because residuals represent the remaining unexplained component after accounting for magnitude, distance and site-condition effects. Therefore, the residual surface is not interpreted as a high-precision local residual predictor. Instead, it is used as a low-bias regional correction layer for monitoring-informed scenario forecasting.

4.2. Scenario-Based Spatial Demand Forecasts

The five representative active-fault scenario sources were used to generate baseline and monitoring-updated PGA forecasts over the prediction grid. The scenario sources were selected from mapped active fault systems around the İzmir Basin, consistent with national active-fault inventories and regional tectonic studies of the İzmir Gulf and surrounding fault zones (Emre et al., 2013; Coşkun et al., 2017; Özener et al., 2013; Şengöçmen Geçkin et al., 2021). For each scenario, the baseline field was computed using the assigned magnitude, the depth-adjusted source-distance proxy, and the station-informed V_{S30} field. The monitoring-updated field was then obtained by adding the spatial residual correction layer to the baseline logarithmic PGA field.

The scenario forecast summary is given in Table 5. The results show clear differences among the five source configurations. The Tuzla Fault scenario, S3, produces the highest mean monitoring-updated PGA, with a mean value of 367.10 and a maximum value of 1433.05. The Yenifoça Fault scenario, S5, produces the second highest mean updated PGA, with a mean value of 204.79 and a maximum value of 979.32. The İzmir Fault, Seferihisar Fault, and Gülbahçe Fault Zone scenarios produce lower mean updated PGA values, but still generate localized high-demand areas.



450

451 **Table 5.** Summary of baseline and monitoring-updated PGA forecasts for the five dissolved
452 scenario sources.

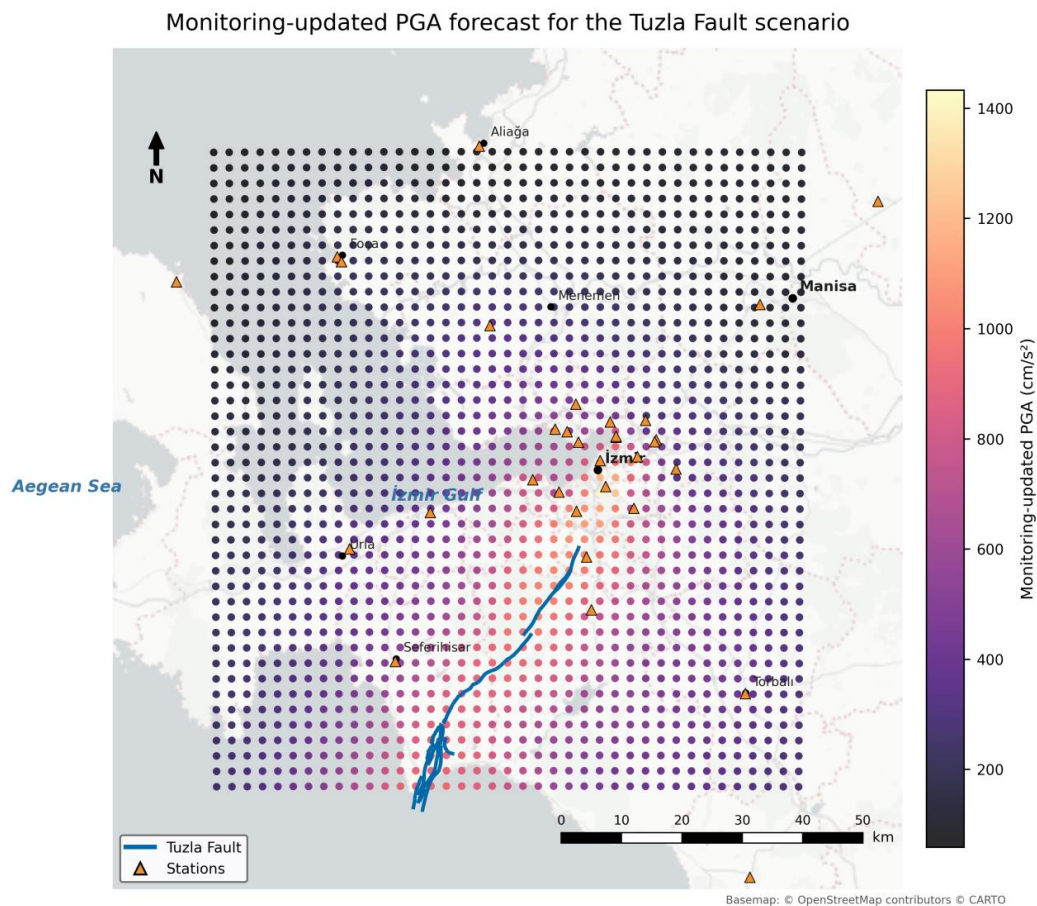
Scenario	Source	Mw	Mean baseline PGA (cm/s ²)	Max baseline PGA (cm/s ²)	Mean updated PGA (cm/s ²)	Max updated PGA (cm/s ²)	High- demand grid (%)
S1	İzmir Fault	6.5	197.13	770.46	188.69	843.83	14.1
S2	Seferihisar Fault	6.6	181.69	544.46	182.87	576.79	13.7
S3	Tuzla Fault	7	368.47	1563.1	367.1	1433.05	42.9
S4	Gülbahçe Fault Zone	6.6	144.62	562.18	146.95	599.78	11.4
S5	Yenifoça Fault	6.8	218.55	1055.47	204.79	979.32	17.9

453 The comparison between baseline and monitoring-updated values in Table 5 demonstrates the
454 hybrid nature of the forecast product. The baseline forecasts reflect the assigned magnitude,
455 dissolved source geometry, depth-adjusted distance structure, and station-informed site
456 representation. The updated forecasts retain this source-controlled structure but modify the spatial
457 demand levels according to the monitoring-derived residual correction layer. The residual update
458 slightly reduces the mean PGA in S1, S3, and S5, while slightly increasing it in S2 and S4. This
459 behavior reflects the spatial interaction between the source-controlled baseline field and the
460 observation-derived correction layer. Overall, S3 remains the dominant scenario in both baseline
461 and updated forms, indicating that the Tuzla Fault source configuration produces the broadest and
462 strongest demand footprint among the selected scenarios.

463 The high-demand grid ratio further distinguishes the scenarios. Using the common p80 high-
464 demand threshold, the Tuzla Fault scenario classifies 42.9% of the grid as high demand, indicating
465 the broadest spatial influence among the selected scenarios. The Yenifoça Fault scenario follows
466 with 17.9%. The İzmir Fault, Seferihisar Fault, and Gülbahçe Fault Zone scenarios produce high-
467 demand grid ratios of 14.1%, 13.7%, and 11.4%, respectively. These results show that the spatial
468 extent of high-demand areas is strongly scenario-dependent.

469 The spatial distribution of the monitoring-updated PGA field for the Tuzla Fault scenario is shown
470 in **Figure 4**. This scenario produces the highest mean and maximum updated PGA values among
471 the five source configurations and therefore provides a representative example of the strongest
472 scenario-controlled demand pattern. The map illustrates how the monitoring-updated demand field
473 is not only controlled by the source geometry, but also shaped by the spatial residual correction
474 layer derived from accumulated strong-motion observations.

475



476

477 **Figure 4.** Monitoring-updated PGA forecast for the Tuzla Fault scenario.

478 **4.3. Adaptation-Oriented Indicators and Robustness Checks**

479 High-demand zones were identified using the 80th percentile of all updated scenario PGA values
480 as the demand threshold. The threshold value and the resulting summary statistics for persistence,
481 scenario sensitivity, and monitoring priority are reported in **Table 6**. For each scenario, grid points
482 exceeding this value were classified as high-demand locations. The persistence indicator was then
483 computed as the fraction of scenarios in which each grid point exceeded the threshold.

484

485

486



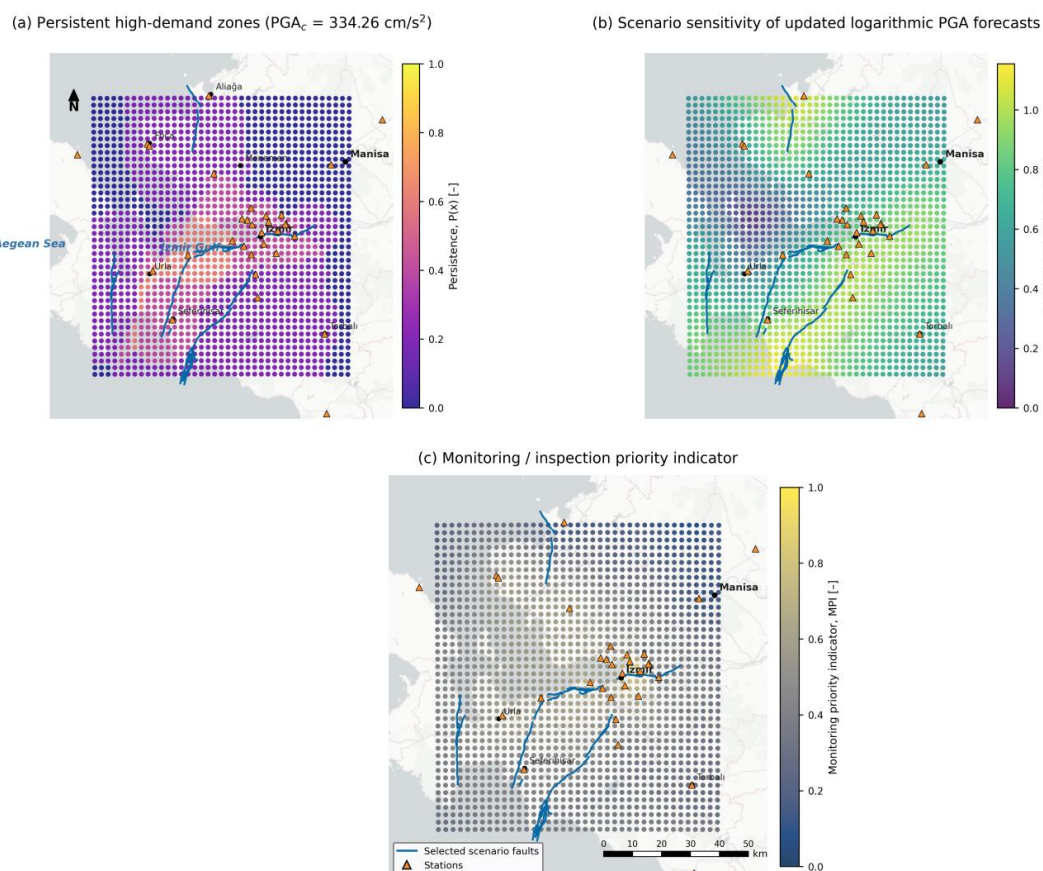
Table 6. Summary of persistence, scenario sensitivity, and priority indicators

Indicator	Value
High-demand threshold, (PGA_c)	334.26
Threshold mode	80th percentile
Number of grid points	1,638
Mean persistence	0.2
Maximum persistence	0.8
Mean scenario sensitivity	0.487
Maximum scenario sensitivity	0.96
Mean monitoring priority indicator, MPI	0.419
Maximum monitoring priority indicator, MPI	0.937

The mean persistence value over the grid is 0.200, while the maximum persistence value is 0.800. Since five scenarios are considered, a maximum persistence of 0.800 indicates that some locations exceed the high-demand threshold in four of the five source scenarios. The spatial pattern of this indicator is shown in **Figure 5a**. Higher persistence values identify locations that repeatedly fall within the upper-demand class across the scenario set, whereas lower values indicate areas that become critical only under fewer source configurations.

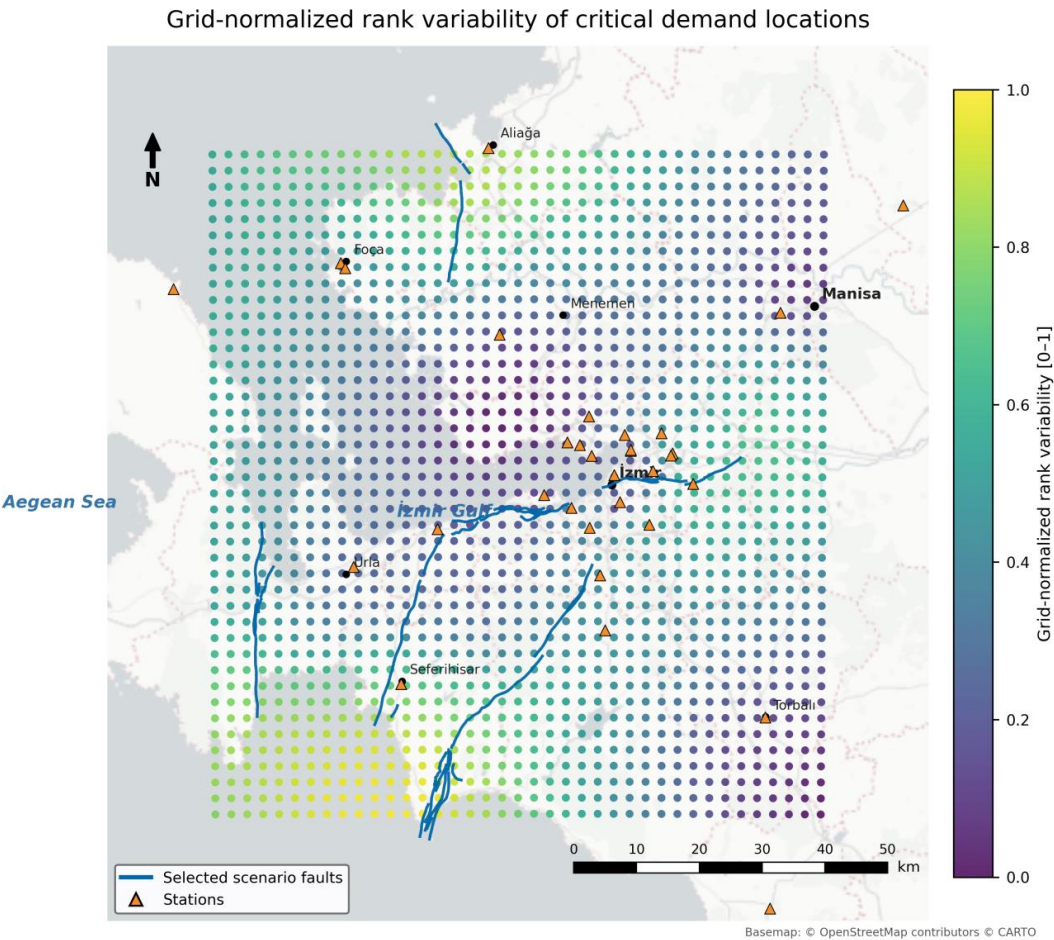
Scenario sensitivity was evaluated using the standard deviation of updated logarithmic PGA forecasts across the five scenarios. The mean scenario sensitivity is 0.487, and the maximum value is 0.960. Its spatial distribution is shown in **Figure 5b**. In contrast to the persistence map, which highlights repeatedly critical zones, the scenario-sensitivity map identifies areas where forecasted demand changes strongly depending on the assumed earthquake source. These areas are important for what-if forecasting because they cannot be represented adequately by a single deterministic demand field.

The monitoring / inspection priority indicator combines normalized mean updated demand and normalized residual variability. In the baseline implementation, the demand component is assigned a weight of 0.60 and the residual-variability component a weight of 0.40. The resulting MPI field is shown in **Figure 5c**. High-MPI zones indicate locations where elevated forecast demand coincides with higher updating variability. The MPI values have a mean of 0.419 and reach a maximum of 0.937, suggesting candidate areas for intensified monitoring, rapid inspection planning, or more detailed site-specific assessment.



508

509 **Figure 5.** Adaptation-oriented spatial indicators derived from the monitoring-updated scenario
 510 forecasts: (a) persistent high-demand zones based on the common p80 threshold, $PGA_c=334.26$
 511 cm/s^2 ; (b) scenario sensitivity of updated logarithmic PGA forecasts; and (c) monitoring /
 512 inspection priority indicator combining normalized updated demand and residual variability.



513

514 **Figure 6.** Rank variability of critical demand locations across the selected earthquake scenarios.

515 Rank variability (**Figure 6**) was also evaluated by ranking grid points according to their updated
516 PGA values under each scenario and measuring the variability of these ranks across the scenario
517 set. This indicator complements persistence and scenario sensitivity by distinguishing locations
518 whose relative demand ranking remains stable from those whose relative importance changes with
519 source configuration. Because rank variability provides a secondary interpretation of scenario
520 dependence, it is retained as a supporting output rather than as a primary adaptation indicator.

521 Robustness checks were then performed for the demand threshold, priority-index weighting, and
522 spatial concentration of high-demand zones. Threshold sensitivity shows that mean persistence
523 decreases as the threshold becomes more restrictive, but maximum persistence remains 0.800 up
524 to the p80 threshold and remains 0.600 at p90. This indicates that a core set of locations remains
525 repeatedly critical even under stricter high-demand definitions.



Table 7. Robustness summary for threshold selection and MPI weighting

Test	Main result
Threshold sensitivity	Maximum persistence remains 0.800 up to p80 and 0.600 at p90
Fixed PGA thresholds	Maximum persistence reaches 1.000 at fixed thresholds of 150 and 200 cm/s ²
MPI 0.80/0.20	Spearman = 0.985; top-10% overlap = 0.908
MPI 0.50/0.50	Spearman = 0.977; top-10% overlap = 0.865
MPI 0.40/0.60	Spearman = 0.891; top-10% overlap = 0.589
MPI 0.20/0.80	Spearman = 0.519; top-10% overlap = 0.356

The MPI weight-sensitivity results indicate that priority rankings remain highly stable when demand and residual variability are assigned comparable or demand-dominant weights. However, strongly uncertainty-dominant weighting substantially modifies the top-priority set. This suggests that the MPI can be adapted to different planning preferences while retaining stable priority structure for the baseline and balanced configurations.

As a compact spatial-organization check, connected-component analysis was also applied to the binary high-demand fields. At the p80 threshold, all five scenario fields produce high-demand domains dominated by a single connected component, with a largest component ratio of 1.000 in each case. The corresponding high-demand grid fractions are 0.141 for S1, 0.137 for S2, 0.429 for S3, 0.114 for S4, and 0.179 for S5. This indicates that high-demand zones form coherent exceedance regions rather than isolated grid-cell anomalies. This check is used here only as a supporting spatial concentration indicator within the resilience-oriented workflow.

Together, the persistence, scenario-sensitivity, MPI, rank-variability, and robustness outputs translate the monitoring-updated demand fields into adaptation-oriented spatial information. Persistent zones represent stable priorities across the scenario set, scenario-sensitive zones identify locations whose criticality depends on the assumed source configuration, and MPI highlights areas where elevated demand and residual variability coincide.

4.4. Digital-Twin-Oriented Updating and Uncertainty Propagation

To evaluate the updateability of the proposed workflow, the monitoring archive was divided into cumulative model versions ending in 2010, 2015, 2020, and 2025. For each version, the reference ground-motion representation, station-level residuals, spatial residual field, scenario forecasts, and monitoring-priority indicators were recomputed. This analysis evaluates how the monitoring-informed regional demand representation evolves as the observation archive expands. The model-version results are summarized in **Table 8**.



Table 8. Digital-twin-oriented model-version tracking.

Version	Period	Records	Stations	Events	(R ²)	RMSE	Spatial update stations	MPI mean	MPI max
v1	1977–2010	632	55	311	0.554	0.937	19	0.546	0.883
v2	1977–2015	4,413	102	933	0.674	0.829	88	0.503	0.811
v3	1977–2020	29,906	117	2,537	0.63	0.804	106	0.418	0.948
v4	1977–2025	37,077	119	2,974	0.633	0.801	108	0.419	0.937

The number of usable records increases from 632 in the first version to 37,077 in the final version. The number of stations increases from 55 to 119, while the number of spatial-update stations increases from 19 to 108. Model performance also improves from the first to the final version, with RMSE decreasing from 0.937 to 0.801. The final two versions have very similar RMSE values, indicating that the reference representation becomes increasingly stable as the archive matures.

The sequential update log in Table 9 shows how the regional representation changes as new monitoring records are incorporated.

Table 9. Sequential update log for the digital-twin-oriented model versions.

Transition	Records added	Residual delta RMSE	MPI delta RMSE	MPI rank Spearman	Top 10% MPI overlap
v1 → v2	3,781	0.209	0.111	0.828	0.675
v2 → v3	25,493	0.171	0.122	0.825	0.558
v3 → v4	7,171	0.027	0.011	0.996	0.89

The largest changes occur in the earlier updates, when monitoring coverage and event sampling expand substantially. In contrast, the transition from v3 to v4 produces only minor changes. The residual-field delta RMSE decreases to 0.027, the MPI delta RMSE decreases to 0.011, the MPI rank correlation reaches 0.996, and the top-10% priority overlap reaches 0.890. These results indicate that the monitoring-informed priority structure becomes highly stable in the final model version.

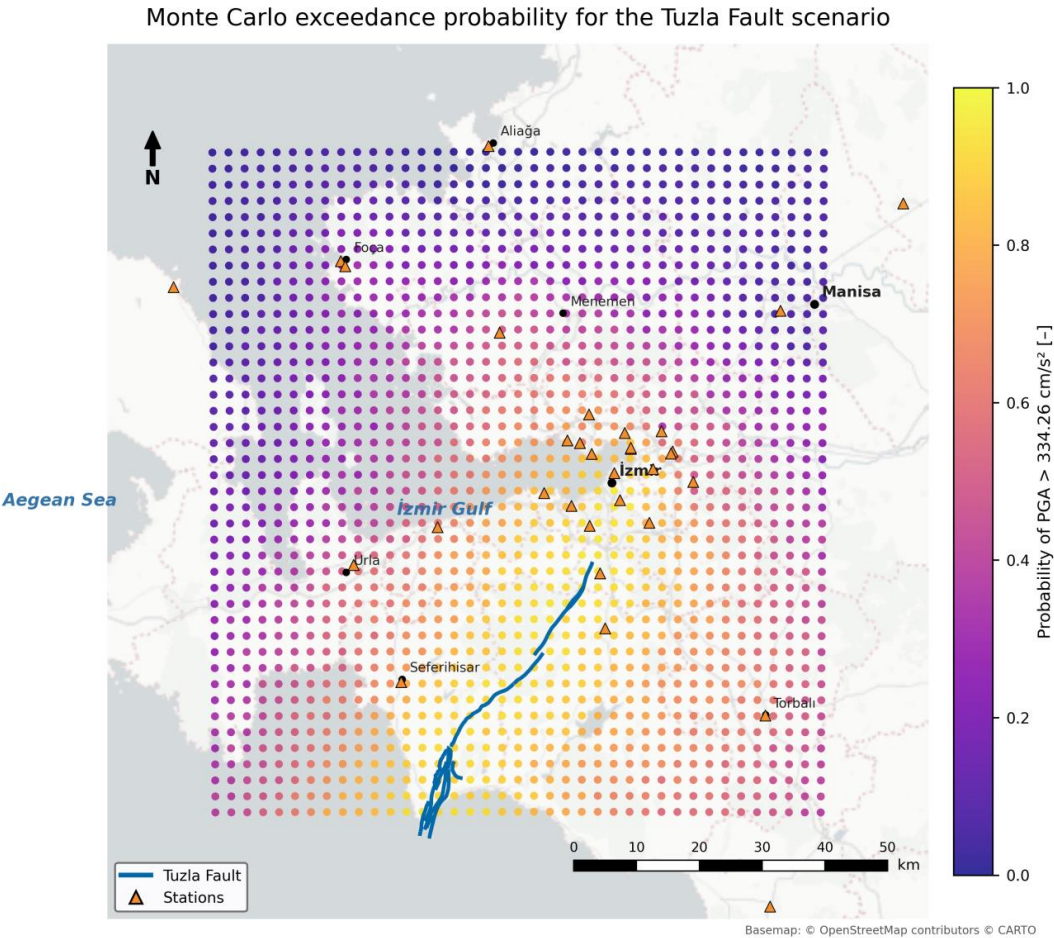
Uncertainty propagation was evaluated using Monte Carlo simulation of the residual-variability layer. For each scenario, 500 realizations were generated and exceedance probabilities were calculated relative to the p80 high-demand threshold, $PGA_c=334.26$. The Monte Carlo results are summarized in **Table 10**.



Table 10. Monte Carlo uncertainty propagation summary.

Scenario	Mean MC PGA	Max MC PGA	Mean exceedance probability	Max exceedance probability	Grid fraction ($P_{exc}>0.50$)	Grid fraction ($P_{exc}>0.80$)
S1	251.6	1194.83	0.218	0.854	0.142	0.007
S2	241.96	810.81	0.216	0.83	0.137	0.001
S3	487.48	2035.63	0.452	0.962	0.429	0.162
S4	194.43	823.95	0.155	0.808	0.115	0.001
S5	273.76	1307.11	0.225	0.944	0.179	0.053

The Monte Carlo results confirm the deterministic scenario ranking. The Tuzla Fault scenario, S3, remains the dominant source configuration under residual-variability propagation, with the highest mean exceedance probability of 0.452 and the largest fraction of grid points with $P_{exc}>0.50$, equal to 0.429. It also has the largest fraction of grid points with $P_{exc}>0.80$, equal to 0.162. The spatial distribution of $P_{exc,3}(x)$ for this scenario is shown in **Figure 7**, where elevated exceedance probabilities form a broad footprint over the central and southern parts of the prediction domain. This probability pattern is consistent with the deterministic updated PGA forecast and the persistence structure obtained from the scenario ensemble.



581

582 **Figure 7.** Monte Carlo exceedance-probability map for the Tuzla Fault scenario

583 Taken together, the digital-twin-oriented model-version tracking and Monte Carlo analyses extend
584 the sense–forecast–adapt sequence from deterministic scenario mapping toward updateable and
585 uncertainty-aware interpretation. The cumulative model versions indicate that the regional demand
586 representation can be progressively revised as additional monitoring records become available,
587 while the uncertainty propagation analysis illustrates how residual variability can be translated into
588 probabilistic exceedance information. These results suggest that accumulated strong-motion
589 observations can support an updateable, scenario-responsive, and adaptation-oriented spatial
590 demand representation for proactive seismic resilience planning.

591 **5. Discussion**

592 The central implication of this study is the repositioning of strong-motion monitoring data from
593 retrospective observation toward proactive scenario updating. Instead of using recorded motions



only as event-specific measurements or post-event constraints, the proposed workflow converts station-level residual tendencies into a regional correction field that can modify future scenario-based PGA forecasts. This provides an updateable spatial demand representation in which accumulated monitoring records inform not only what has happened, but also how alternative future earthquake scenarios may be interpreted for resilience planning.

5.1. Field-Based Interpretation of Scenario Demand

Ground-motion prediction is commonly evaluated at individual sites, whereas regional resilience problems are inherently spatial. The results of this study indicate that the interpretation of seismic demand changes when the output is treated as a spatial field rather than as a set of independent station-level estimates. The selected scenarios differ not only in their mean and maximum PGA values, but also in the spatial extent and organization of elevated demand. The high-demand grid ratios show that the Tuzla Fault scenario generates the broadest high-demand footprint, followed by the Yenifoça Fault scenario, whereas the İzmir, Seferihisar, and Gülbahçe scenarios produce more localized high-demand patterns. These source-dependent differences should be viewed within the broader tectonic setting of Türkiye, where rotation of the proposed deep structure has been linked to the accumulation of geodynamic stress, particularly in interpretations of the 2023 eastern Türkiye earthquake sequence (Eppelbaum et al., 2024).

This finding is consistent with the broader literature on spatially correlated ground-motion fields. Previous studies have shown that spatial correlation of ground-motion residuals can significantly affect regional hazard and portfolio loss estimates because nearby sites do not respond independently during an earthquake (Jayaram and Baker, 2009). More recent studies further emphasize that spatial correlation may be influenced by source, path, and site effects, and that spatially coherent ground-motion fields are essential for regional seismic risk interpretation (Chen and Baker, 2019; Schiappapietra and Douglas, 2020; Bodenmann et al., 2023). The present study builds on this spatial-field perspective, but uses it in a forecasting-oriented manner. The objective is not to estimate a new spatial correlation model, but to update, compare, and interpret scenario-dependent demand fields for proactive resilience planning.

The connected-component results provide a supporting spatial-organization check within this field-based interpretation. At the p_{80} threshold, the high-demand regions are dominated by a main connected footprint rather than by isolated grid-cell anomalies. This supports the interpretation that the scenario forecasts produce spatially coherent high-demand domains. However, connectedness is used here only as a concentration indicator; a detailed analysis of fragmentation, spanning, or threshold-transition behavior is beyond the scope of the present study.

5.2. Role and Interpretation of the Residual Updating Layer

A central feature of the proposed framework is the use of monitoring-derived residuals as an updateable regional correction layer. The reference ground-motion representation provides a transparent baseline for estimating expected PGA from magnitude, source-to-site distance, and site-condition information. Station-level residuals then quantify systematic deviations between recorded and predicted motions. By interpolating these residual tendencies over the prediction



633 domain, the monitoring archive is converted into a spatial correction field that can be combined
634 with alternative future source scenarios.

635 This interpretation is closely related to recent developments in regionalized and non-ergodic
636 ground-motion modelling. In such approaches, systematic source, path, and site effects are treated
637 as spatially structured components rather than as purely random variability. Spatially varying
638 coefficient models and non-ergodic ground-motion formulations have shown that allowing model
639 terms to vary geographically can capture repeatable regional effects and reduce unexplained
640 variability in ground-motion prediction (Landwehr et al., 2016; Lavrentiadis et al., 2023). Non-
641 ergodic site-response studies similarly emphasize that local recordings can constrain systematic
642 site effects and improve site-specific or region-specific ground-motion estimates (Stewart et al.,
643 2017). The residual layer used in the present study follows the same general motivation: repeated
644 observations are used to identify spatially persistent departures from a reference model.

645 The proposed implementation is intentionally simpler than a full non-ergodic ground-motion
646 model. It does not decompose residuals into separate source, path, and site terms. Instead, it
647 constructs a traceable regional correction surface that can be regenerated as the monitoring archive
648 expands. This design is consistent with the broader idea of continuous model updating, in which
649 ground-motion representations are revised as new observations become available rather than being
650 treated as static models (Stafford, 2019). In the present workflow, updating occurs at the level of
651 spatial residual correction: new strong-motion records can modify station-level residual tendencies,
652 update the residual field, and revise the resulting scenario-based demand forecasts.

653 The leave-one-station-out validation indicates that station-level residual tendencies cannot be
654 predicted with high precision from spatial position alone. This result defines the appropriate
655 interpretation of the residual layer. It should not be viewed as a precise local residual predictor for
656 individual stations. Rather, it functions as a low-bias regional correction layer that transfers
657 accumulated monitoring information into scenario-based spatial demand forecasts.

658 Importantly, the residual correction modifies demand levels without eliminating the primary
659 influence of source configuration. The scenario hierarchy remains physically interpretable after
660 updating, with the strongest demand patterns still governed by the assigned source magnitude,
661 geometry, and distance structure. The monitoring-derived layer therefore acts as an empirical
662 regional adjustment to the source-controlled baseline fields, providing a practical basis for
663 proactive seismic-demand screening.

664 5.3. Adaptation-Oriented Indicators for Proactive Resilience

665 The persistence, scenario-sensitivity, monitoring-priority, and rank-variability indicators constitute
666 the adaptation-oriented layer of the proposed framework. Their main value is that they prevent the
667 forecast ensemble from being reduced to a single deterministic PGA map. A single scenario map
668 may identify where shaking is high under one assumed source, but it cannot distinguish between
669 locations that are repeatedly critical, strongly source-dependent, uncertainty-influenced, or
670 unstable in their relative priority. The proposed indicators make these distinctions explicit and
671 therefore provide an intermediate decision-support layer between seismic monitoring and full
672 regional risk assessment.



673 This interpretation is aligned with resilience-oriented planning. Seismic resilience is not limited to
674 estimating physical damage; it also involves preparedness, consequence reduction, functionality
675 preservation, and recovery. [Bruneau et al. \(2003\)](#) framed community seismic resilience in terms of
676 reducing failure probabilities, reducing consequences, and reducing recovery time. In this context,
677 the indicators developed here operate upstream of direct damage or loss estimation. They identify
678 where elevated demand, source sensitivity, spatial concentration, and residual variability are
679 located before exposure and vulnerability models are introduced.

680 The proposed workflow therefore complements, rather than replaces, full seismic risk platforms. It
681 provides a demand-side screening layer that can help identify where more detailed vulnerability,
682 exposure, or loss analyses should be prioritized. Such outputs may serve as input or pre-processing
683 information for risk-oriented tools such as OpenQuake, which combine hazard, exposure, and
684 vulnerability models for seismic risk calculation ([Silva et al., 2014](#)). In this sense, the framework
685 supports proactive resilience planning by translating monitoring-informed scenario forecasts into
686 spatially explicit prioritization information.

687 **5.4. Digital-Twin-Oriented Updating and Uncertainty-Aware Forecasting**

688 The model-version tracking experiment provides the updateable component of the proposed
689 workflow. Rather than treating the regional demand model as a static product, the framework
690 allows the reference ground-motion representation, residual correction layer, residual-variability
691 layer, scenario forecasts, and adaptation indicators to be regenerated as the monitoring archive
692 expands. This creates a regional sensing-to-forecasting logic in which each cumulative model
693 version represents an updated virtual description of spatial seismic demand.

694 This interpretation is consistent with recent developments in city, geospatial, and disaster-risk
695 digital twins. City digital twins have been discussed as tools for urban resilience because they can
696 integrate heterogeneous spatial data, support scenario exploration, and improve the communication
697 of risk-relevant information to decision-makers ([Therias and Rafiee, 2023](#)). Disaster-risk twinning
698 studies similarly emphasize dynamic data integration, virtual representation, uncertainty
699 communication, and decision-support outputs for managing hazard-affected environments ([Lagap
700 and Ghaffarian, 2024; Wang and Wang, 2025](#)).

701 The present study transfers this logic from individual structural assets to a regional seismic-demand
702 field. The physical system is the İzmir Basin and its surrounding active-fault environment. The
703 sensing layer is the strong-motion monitoring archive. The virtual representation consists of the
704 reference ground-motion model, residual correction field, residual-variability layer, and scenario-
705 based PGA fields. The updating mechanism is residual-based monitoring assimilation through
706 cumulative model-version regeneration. The decision layer is represented by persistence, scenario
707 sensitivity, monitoring priority, rank variability, spatial concentration, and exceedance-probability
708 outputs. The correspondence between the proposed workflow and the main digital-twin
709 components is summarized in **Table 11**.

710

711



Table 11. Digital-twin interpretation of the proposed monitoring-informed seismic-demand forecasting workflow.

Digital-twin component	Implementation in the present study
Physical system	İzmir Basin, surrounding active-fault environment, and regional strong-motion monitoring network
Sensing layer	Accumulated event–station strong-motion records, station metadata, and Vs30 information
Digital / virtual system	Reference ground-motion representation, residual correction field, residual-variability field, and scenario-based PGA fields
Physical-to-virtual updating	Residual-based monitoring assimilation and cumulative model-version regeneration
Virtual-to-physical forecasting / decision support	Scenario PGA forecasts, persistence, scenario sensitivity, monitoring priority, rank variability, spatial concentration, and exceedance probability
Uncertainty representation	Residual-variability layer, Monte Carlo uncertainty propagation, and exceedance-probability mapping
Current optimization-related output	Monitoring or inspection priority and identification of high-demand or high-variability zones
Future operational extension	Event-based or near-real-time updating, sensor-placement optimization, exposure/vulnerability coupling, and intervention prioritization

As shown in **Table 11**, the proposed workflow should be interpreted as a digital-twin-oriented regional seismic-demand forecasting framework rather than as a fully operational real-time digital twin. It implements two core functions of a digital-twin logic: physical-to-virtual updating through monitoring-derived residual assimilation, and virtual-to-physical decision support through scenario forecasts and adaptation indicators. Real-time streaming, automated sensor-placement optimization, exposure/vulnerability coupling, and optimization-based intervention planning remain future operational extensions.

The sequential model-version results indicate that this virtual demand representation becomes more stable as the monitoring archive expands. The largest changes occur between earlier model versions, when the number of records and spatial-update stations increases substantially. In contrast, the transition from the 2020 version to the 2025 version produces only minor changes, with an MPI rank correlation of 0.996 and a top-10% priority overlap of 0.890. This suggests that the monitoring-informed priority surface stabilizes as the observation archive matures.

The Monte Carlo analysis extends the same framework into uncertainty-aware forecasting. Residual variability is propagated into exceedance-probability maps, and the Tuzla Fault scenario remains the dominant source configuration under this uncertainty propagation. The agreement between deterministic ranking and Monte Carlo exceedance results indicates that the main scenario hierarchy is robust with respect to residual variability. At the same time, exceedance-probability maps communicate the demand footprint in a form that is more directly interpretable for planning than deterministic PGA values alone.



734 Together, the model-version tracking and Monte Carlo analyses show how the proposed workflow
735 can be updated and interpreted under uncertainty. New records can revise the residual correction
736 layer, source scenarios can be re-evaluated, and adaptation indicators can be regenerated
737 accordingly. This supports a basin-scale sense–forecast–adapt logic in which sensing updates the
738 regional demand representation, forecasting evaluates alternative future demand states, and
739 adaptation indicators support proactive resilience planning.

740 **5.5. Limitations and Future Extensions**

741 The present implementation prioritizes transparency, updateability, and interpretability. For this
742 reason, the reference ground-motion representation is kept parsimonious and uses first-order
743 predictors, including magnitude, source-to-site distance, and VS30. This design makes the residual
744 updating process traceable and reproducible, but it also limits the level of physical detail
745 represented in the baseline model. Future extensions may incorporate more detailed source, path,
746 and site terms, including basin-depth proxies, frequency-dependent site response, event-specific
747 random effects, spatially varying coefficients, and non-ergodic adjustments.

748 The residual correction layer should be interpreted as a regional screening and forecasting surface
749 rather than as a precise local residual predictor. The leave-one-station-out validation indicates that
750 station-level residual tendencies are difficult to reconstruct from spatial position alone, which is
751 expected because residuals represent the remaining unexplained component after the main ground-
752 motion predictors have been considered. Future implementations may improve this layer by
753 incorporating geological units, basin geometry, station metadata, Bayesian hierarchical residual
754 models, or Gaussian-process formulations with physically informed covariance structures.

755 The scenario sources are represented using dissolved fault traces and a depth-adjusted distance
756 proxy to enable consistent comparison among the selected source configurations. This
757 representation is suitable for the scenario-comparison objective of the present study, but it does not
758 capture the full complexity of earthquake rupture. Further developments may include finite-fault
759 rupture geometry, directivity effects, hypocentre variability, rupture segmentation, magnitude–
760 rupture scaling uncertainty, and alternative source-distance metrics.

761 The uncertainty propagation analysis focuses on residual variability and translates this information
762 into exceedance-probability maps. This provides an uncertainty-aware interpretation of the
763 forecasted demand fields, but it does not exhaust the full uncertainty space. Future work may
764 broaden the uncertainty treatment by incorporating alternative source models, epistemic
765 uncertainty in ground-motion modelling, site-response uncertainty, and spatially correlated
766 random-field simulations.

767 Finally, the adaptation-oriented indicators are intended to support screening, prioritization, and
768 proactive planning, not to replace exposure, vulnerability, damage, or loss modelling. Direct
769 integration with exposure, vulnerability, lifeline dependency, and recovery models would extend
770 the workflow from spatial demand forecasting toward full resilience quantification. Such
771 developments would allow the sense–forecast–adapt framework to support both early-stage
772 regional prioritization and more detailed operational decision-support applications.



773 6. Conclusions

774 This study developed a monitoring-informed sense–forecast–adapt workflow for spatial seismic-
775 demand forecasting in the İzmir Basin. The proposed framework converts accumulated strong-
776 motion observations into a regional residual correction layer, embeds this layer within active-fault-
777 based scenario forecasts, and translates the resulting demand fields into adaptation-oriented spatial
778 indicators for proactive seismic resilience planning.

779 The results show that regional strong-motion observations can be used as an empirical updating
780 layer for forward scenario forecasting. By aggregating event–station residuals at the station level
781 and interpolating them over the prediction domain, the monitoring archive is transformed into a
782 spatial correction surface that modifies scenario-based demand fields. The leave-one-station-out
783 validation indicates that this residual surface should be interpreted as a regional correction layer
784 rather than as a precise local residual predictor. Its main value lies in transferring accumulated
785 monitoring information into spatial demand forecasts in a traceable and low-bias manner.

786 The scenario comparison highlights the importance of source configuration in controlling the
787 spatial footprint of forecasted demand. Among the five scenario sources, the Tuzla Fault scenario
788 consistently produces the strongest and broadest monitoring-updated demand pattern. The
789 Yenifoça Fault scenario represents the main secondary demand case, whereas the İzmir,
790 Seferihisar, and Gülbahçe scenarios generate more localized high-demand patterns. These results
791 support the use of multiple physically interpretable source scenarios when evaluating regional
792 seismic-demand fields.

793 The adaptation-oriented indicators provide information beyond that available from deterministic
794 PGA maps alone. Persistence, scenario sensitivity, monitoring / inspection priority, rank
795 variability, and spatial concentration metrics distinguish locations that are repeatedly critical,
796 source-dependent, uncertainty-influenced, or spatially coherent. The robustness analyses further
797 indicate that the main spatial interpretations remain stable under reasonable changes in threshold
798 selection and priority-index weighting, while the connected-component check shows that high-
799 demand areas form coherent spatial footprints rather than isolated grid-cell anomalies.

800 The cumulative model-version experiment supports the updateable character of the workflow. As
801 the monitoring archive expands, the residual and priority fields evolve and become increasingly
802 stable in the most recent model versions. This provides a digital-twin-oriented interpretation of the
803 framework, in which the regional virtual demand representation can be revised as new strong-
804 motion records become available. The Monte Carlo simulations further extend the workflow into
805 uncertainty-aware forecasting by translating residual variability into exceedance-probability maps.
806 The resulting probabilistic outputs preserve the main deterministic scenario hierarchy, with the
807 Tuzla Fault scenario remaining the dominant source configuration.

808 Overall, the study shows that monitoring-derived residual updating, scenario-based demand
809 forecasting, adaptation-oriented indicators, model-version tracking, and exceedance-probability
810 mapping can be integrated into a single field-based workflow. The proposed approach provides an
811 updateable basis for identifying persistent, source-sensitive, spatially coherent, and uncertainty-
812 influenced seismic-demand zones in monitored basin environments. In this form, the workflow can



813 support proactive seismic resilience planning by linking regional monitoring archives with future
814 scenario evaluation and spatial decision-support indicators.

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823 References

824 Bodenmann, L., Baker, J. W., and Stojadinović, B.: Accounting for path and site effects in spatial
825 ground-motion correlation models using Bayesian inference, *Nat. Hazards Earth Syst. Sci.*, 23,
826 2387–2402, <https://doi.org/10.5194/nhess-23-2387-2023>, 2023.

827 Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O’Rourke, T. D., Reinhorn, A. M., Shinozuka,
828 M., Tierney, K., Wallace, W. A., and von Winterfeldt, D.: A framework to quantitatively assess
829 and enhance the seismic resilience of communities, *Earthq. Spectra*, 19, 733–752,
830 <https://doi.org/10.1193/1.1623497>, 2003.

831 Campbell, K. W. and Bozorgnia, Y.: NGA-West2 ground motion model for the average horizontal
832 components of PGA, PGV, and 5% damped linear acceleration response spectra, *Earthq. Spectra*,
833 30, 1087–1115, <https://doi.org/10.1193/062913EQS175M>, 2014.

834 Chen, Y. and Baker, J. W.: Spatial correlations in CyberShake physics-based ground motion
835 simulations, *Bull. Seismol. Soc. Am.*, 109, 2447–2458, <https://doi.org/10.1785/0120190065>, 2019.

836 Coşkun, S., Dondurur, D., Çifçi, G., Aydemir, A., Güngör, T., and Drahor, M. G.: Investigation on
837 the tectonic significance of İzmir, Uzunada Fault Zones and other tectonic elements in the Gulf of
838 İzmir, western Turkey, using high resolution seismic data, *Mar. Petrol. Geol.*, 83, 73–83,
839 <https://doi.org/10.1016/j.marpetgeo.2017.03.010>, 2017.

840 Du, A. and Padgett, J. E.: Post-event regional seismic risk assessment via vector-IM-based record
841 updating, in: *Bridge Maintenance, Safety, Management, Life-Cycle Sustainability and Innovations*,
842 edited by: Yokota, H. and Frangopol, D. M., CRC Press, 586,
843 <https://doi.org/10.1201/9780429279119-375>, 2021.

844 Emre, Ö., Duman, T. Y., Özalp, S., Elmacı, H., Olgun, Ş., and Şaroğlu, F.: Active fault map of
845 Turkey with an explanatory text, 1:1,250,000 scale, General Directorate of Mineral Research and
846 Exploration, Ankara, Türkiye, 2013.



- 847 Engler, D. T., Thompson, E. M., Maurer, B. W., Geyin, M., Burgi, P. M., Allstadt, K., and Jaiswal,
848 K. S.: Updating regional-scale geospatial liquefaction models with locally available geotechnical
849 data, *Seismol. Res. Lett.*, 96, 3365–3378, <https://doi.org/10.1785/0220250134>, 2025.
- 850 Eppelbaum, L. V., Ben-Avraham, Z., Katz, Y. I., Cloetingh, S., and Kaban, M. K.: Giant quasi-
851 ring mantle structure in the African–Arabian junction: Results derived from the geological–
852 geophysical data integration, *Geotectonics*, 55, 58–82,
853 <https://doi.org/10.1134/S0016852121010052>, 2021.
- 854 Eppelbaum, L. V., Katz, Y. I., and Ben-Avraham, Z.: The reasons for enormous accumulation of
855 the geodynamic tension in Eastern Turkey: A multidisciplinary study, *Geol. Geophys. Earth Sci.*,
856 2, 1–28, <https://doi.org/10.58396/gges020202>, 2024.
- 857 Eppelbaum, L. V., Katz, Y. I., and Ben-Avraham, Z.: Giant quasi-ring mantle structure beneath the
858 Eastern Mediterranean: Interpretation of new seismic tomography, magnetic field, and
859 paleobiogeographic data, *Geotectonics*, 59, 101–126,
860 <https://doi.org/10.1134/S001685212570013X>, 2025.
- 861 Goda, K. and Atkinson, G. M.: Probabilistic characterization of spatially correlated response
862 spectra for earthquakes in Japan, *Bull. Seismol. Soc. Am.*, 99, 3003–3020,
863 <https://doi.org/10.1785/0120090007>, 2009.
- 864 Huang, D. and Wang, G.: Region-specific spatial cross-correlation model for stochastic simulation
865 of regionalized ground-motion time histories, *Bull. Seismol. Soc. Am.*, 105, 272–284,
866 <https://doi.org/10.1785/0120140198>, 2015.
- 867 Jayaram, N. and Baker, J. W.: Correlation model for spatially distributed ground-motion intensities,
868 *Earthq. Eng. Struct. Dyn.*, 38, 1687–1708, <https://doi.org/10.1002/eqe.922>, 2009.
- 869 Kaklamanos, J., Baise, L. G., and Boore, D. M.: Estimating unknown input parameters when
870 implementing the NGA ground-motion prediction equations in engineering practice, *Earthq.*
871 *Spectra*, 27, 1219–1235, <https://doi.org/10.1193/1.3650372>, 2011.
- 872 Kwak, D. Y. and Ahn, J.-K.: Update of mainshock intensity map using aftershock records collected
873 from temporary seismic stations: Case study of 2017 M5.4 Pohang earthquake, *Earthq. Spectra*,
874 42, <https://doi.org/10.1002/esp4.70048>, 2026.
- 875 Lagap, U. and Ghaffarian, S.: Digital post-disaster risk management twinning: A review and
876 improved conceptual framework, *Int. J. Disaster Risk Reduct.*, 110, 104629,
877 <https://doi.org/10.1016/j.ijdrr.2024.104629>, 2024.
- 878 Landwehr, N., Kuehn, N. M., Scheffer, T., and Abrahamson, N. A.: A nonergodic ground-motion
879 model for California with spatially varying coefficients, *Bull. Seismol. Soc. Am.*, 106, 2574–2583,
880 <https://doi.org/10.1785/0120160118>, 2016.



- 881 Lavrentiadis, G., Abrahamson, N. A., Kuehn, N. M., Bozorgnia, Y., Goulet, C. A., Babič, A.,
882 Macedo, J., Dolšek, M., Gregor, N., Kottke, A. R., Lacour, M., Liu, C., Meng, X., Phung, V.-B.,
883 Sung, C.-H., and Walling, M.: Overview and introduction to development of non-ergodic
884 earthquake ground-motion models, *Bull. Earthq. Eng.*, 21, 5121–5151,
885 <https://doi.org/10.1007/s10518-022-01485-x>, 2023.
- 886 Loth, C. and Baker, J. W.: A spatial cross-correlation model of ground motion spectral
887 accelerations at multiple periods, *Earthq. Eng. Struct. Dyn.*, 42, 397–417,
888 <https://doi.org/10.1002/eqe.2212>, 2013.
- 889 Mizutani, Y., Sugai, M., and Mori, Y.: Fourier amplitude spectrum at arbitrary points estimated by
890 Kriging method, in: *Proceedings of the 13th International Conference on Applications of Statistics
891 and Probability in Civil Engineering (ICASP13)*, Seoul, South Korea, Paper 468, 2019.
- 892 Özener, H., Doğru, A., and Acar, M.: Determination of the displacements along the Tuzla Fault,
893 Aegean Region–Turkey: Preliminary results from GPS and precise leveling techniques, *J. Geodyn.*,
894 67, 13–20, <https://doi.org/10.1016/j.jog.2012.06.001>, 2013.
- 895 Park, J., Bazzurro, P., and Baker, J. W.: Modeling spatial correlation of ground motion intensity
896 measures for regional seismic hazard and portfolio loss estimation, in: *Proceedings of the 10th
897 International Conference on Applications of Statistics and Probability in Civil Engineering
898 (ICASP10)*, Tokyo, Japan, 8 pp., 2007.
- 899 Sato, T. and Imabayashi, H.: Real time conditional simulation of earthquake ground motion,
900 *Earthq. Eng. Eng. Seismol.*, 1, 27–38, 1999.
- 901 Schiappapietra, E. and Douglas, J.: Modelling the spatial correlation of earthquake ground motion:
902 Insights from the literature, data from the 2016–2017 Central Italy earthquake sequence and
903 ground-motion simulations, *Earth-Sci. Rev.*, 203, 103139,
904 <https://doi.org/10.1016/j.earscirev.2020.103139>, 2020.
- 905 Silva, V., Crowley, H., Pagani, M., Monelli, D., and Pinho, R.: Development of the OpenQuake
906 engine, the Global Earthquake Model’s open-source software for seismic risk assessment, *Nat.
907 Hazards*, 72, 1409–1427, <https://doi.org/10.1007/s11069-013-0618-x>, 2014.
- 908 Stafford, P. J.: Continuous integration of data into ground-motion models using Bayesian updating,
909 *J. Seismol.*, 23, 39–57, <https://doi.org/10.1007/s10950-018-9792-3>, 2019.
- 910 Stewart, J. P., Afshari, K., and Goulet, C. A.: Non-ergodic site response in seismic hazard analysis,
911 *Earthq. Spectra*, 33, 1385–1414, <https://doi.org/10.1193/081716EQS135M>, 2017.
- 912 Şengöçmen Geçkin, B., Sözbilir, H., Özkaymak, Ç., and Softa, M.: Active tectonics of Gülbahçe
913 Fault Zone (GBFZ) by using geomorphic indices, İzmir Province, western Anatolia, Turkey, Afyon
914 Kocatepe Univ. J. Sci. Eng., 21, 1195–1209, <https://doi.org/10.35414/akufemubid.946298>, 2021.



915 Tamhidi, A., Kuehn, N. M., Ghahari, S. F., Rodgers, A. J., Kohler, M. D., Taciroglu, E., and
916 Bozorgnia, Y.: Conditioned simulation of ground-motion time series at uninstrumented sites using
917 Gaussian process regression, *Bull. Seismol. Soc. Am.*, 112, 331–347,
918 <https://doi.org/10.1785/0120210054>, 2022.

919 Thelen, A., Zhang, X., Fink, O., Lu, Y., Ghosh, S., Youn, B. D., Todd, M. D., Mahadevan, S., Hu,
920 C., and Hu, Z.: A comprehensive review of digital twin—part 1: Modeling and twinning enabling
921 technologies, *Struct. Multidiscip. Optim.*, 65, 354, <https://doi.org/10.1007/s00158-022-03425-4>,
922 2022.

923 Thelen, A., Zhang, X., Fink, O., Lu, Y., Ghosh, S., Youn, B. D., Todd, M. D., Mahadevan, S., Hu,
924 C., and Hu, Z.: A comprehensive review of digital twin—part 2: Roles of uncertainty quantification
925 and optimization, a battery digital twin, and perspectives, *Struct. Multidiscip. Optim.*, 66, 1,
926 <https://doi.org/10.1007/s00158-022-03410-x>, 2023.

927 Therias, A. and Rafiee, A.: City digital twins for urban resilience, *Int. J. Digit. Earth*, 16, 4164–
928 4190, <https://doi.org/10.1080/17538947.2023.2264827>, 2023.

929 Torzoni, M., Tezzele, M., Mariani, S., Manzoni, A., and Willcox, K. E.: A digital twin framework
930 for civil engineering structures, *Comput. Method. Appl. M.*, 418, 116584,
931 <https://doi.org/10.1016/j.cma.2023.116584>, 2024.

932 Vanmarcke, E. H. and Fenton, G. A.: Conditioned simulation of local fields of earthquake ground
933 motion, *Struct. Saf.*, 10, 247–264, [https://doi.org/10.1016/0167-4730\(91\)90018-5](https://doi.org/10.1016/0167-4730(91)90018-5), 1991.

934 Vanmarcke, E. H., Heredia-Zavoni, E., and Fenton, G. A.: Conditional simulation of spatially
935 correlated earthquake ground motion, *J. Eng. Mech.*, 119, 2333–2352,
936 [https://doi.org/10.1061/\(ASCE\)0733-9399\(1993\)119:11\(2333\)](https://doi.org/10.1061/(ASCE)0733-9399(1993)119:11(2333)), 1993.

937 Viallet, E., Humbert, N., and Mottier, P.: Updating a probabilistic seismic hazard assessment with
938 instrumental and historical observations based on a Bayesian inference, *Nucl. Eng. Des.*, 350, 112–
939 127, <https://doi.org/10.1016/j.nucengdes.2019.04.034>, 2019.

940 Wang, Z. and Wang, Z.: Risk twin: Real-time risk visualization and control for structural systems,
941 *Struct. Multidiscip. Optim.*, 68, 85, <https://doi.org/10.1007/s00158-025-04014-x>, 2025.

942 Worden, C. B., Wald, D. J., Allen, T. I., Lin, K., Garcia, D., and Cua, G.: A revised ground-motion
943 and intensity interpolation scheme for ShakeMap, *Bull. Seismol. Soc. Am.*, 100, 3083–3096,
944 <https://doi.org/10.1785/0120100101>, 2010.

945

946