





36 1. Introduction

37 Soil liquefaction is one of the most damaging earthquake-induced ground failure mechanisms in
38 saturated loose to medium-dense granular deposits. Its consequences may include excessive
39 settlement, lateral spreading, ground cracking, loss of bearing capacity, foundation distress, and
40 disruption of transportation and lifeline systems. For this reason, liquefaction assessment remains
41 a central component of geotechnical earthquake engineering and field-scale hazard evaluation. In
42 engineering practice, liquefaction is commonly interpreted using pointwise or profile-level scalar
43 descriptors, such as factor of safety against liquefaction, triggering probability, exceedance ratio,
44 liquefaction-prone area fraction, or depth-integrated severity measures (Seed & Idriss, 1971; Youd
45 & Idriss, 2001; Boulanger & Idriss, 2014). These descriptors quantify whether liquefaction-prone
46 conditions are expected and how much of a site or region may be affected.

47 However, scalar descriptors do not directly explain how liquefaction-prone zones are organized
48 across space. A given liquefaction-prone area fraction may correspond to many isolated local
49 patches, several clustered weak zones, or a spatially continuous field-scale weak domain. These
50 configurations are not equivalent from a geotechnical hazard perspective. Fragmented susceptible
51 zones may indicate localized investigation or mitigation needs, whereas continuous or spanning
52 weak-zone patterns may imply corridor-scale, waterfront-scale, or area-wide hazard significance.
53 Therefore, field-scale liquefaction interpretation requires not only a measure of hazard extent, but
54 also a measure of weak-zone organization.

55 This distinction is especially relevant in spatially variable soil deposits. Natural ground conditions
56 are heterogeneous because of depositional processes, stratigraphic variability, stress history,
57 groundwater conditions, and measurement uncertainty. Consequently, liquefaction resistance or
58 susceptibility may exhibit spatial correlation rather than independent point-to-point variation.
59 Random-field models provide a consistent probabilistic framework for representing such spatially
60 structured geotechnical variability (Vanmarcke, 1983; Fenton & Griffiths, 2008; Phoon &
61 Kulhawy, 1999; Lloret-Cabot et al., 2014), and advances in Gaussian Random Field generation
62 have broadened the simulation of heterogeneous ground behavior and spatially varying soil
63 properties (Liu et al., 2019). Previous probabilistic, stochastic, and geostatistical studies have
64 shown that spatial variability can influence liquefaction triggering, settlement, lateral spreading,
65 manifestation patterns, and the spatial distribution of unstable zones (Juang et al., 2000; Baise et
66 al., 2006; Baker & Faber, 2008; Popescu et al., 2005; Vivek & Raychowdhury, 2014; Montgomery
67 & Boulanger, 2017; Guan & Wang, 2022).

68 The need to distinguish hazard extent from hazard organization is also consistent with broader
69 findings in spatially correlated and networked systems. In such systems, local exceedance may
70 aggregate into connected domains whose geometry and continuity are not visible in scalar
71 summaries alone. Similar levels of local activation may therefore produce different macroscopic
72 connectivity states, from fragmented clusters to broader connected structures (Stauffer & Aharony,



2018; Sahimi, 1994). Percolation and complex-network studies further show that connectivity transitions may be continuous, abrupt, or hybrid, and that local abundance alone does not necessarily determine large-scale organization (Newman, 2010; Lee et al., 2018; Kryven, 2019). The emergence of larger connected domains may therefore be interpreted as a percolation-like reorganization process driven by spatial correlation and local activation level (Cao & Schwarz, 2012; D’Souza & Nagler, 2015).

In this context, connectivity-based descriptors provide a practical way to quantify weak-zone organization. Once a spatial resistance- or susceptibility-related field is thresholded into weak-zone and non-weak-zone domains, the resulting binary field can be examined in terms of connected components, dominant weak-zone ratio, fragmentation, cluster hierarchy, and spanning behavior. These descriptors quantify whether weak zones remain localized, cluster into larger domains, or develop field-scale continuity. The distinction is important because deformation-related consequences such as settlement, lateral spreading, and surface manifestation may depend not only on the presence of local liquefaction susceptibility, but also on the spatial continuity and arrangement of susceptible ground. (Youd et al., 2001; Uzielli et al., 2005; Maurer et al., 2014, 2015b).

This study develops a connectivity-based random-field framework for interpreting the spatial organization of low-resistance weak-zone fields under controlled equal-area conditions. The framework combines dataset-informed SPT_{N160} -based Gaussian Random Field realizations, lower-tail weak-zone thresholding, graph-based connectivity descriptors, dense $Pf-\theta$ transition mapping, and random-allocation null comparisons. This design isolates how spatial correlation reorganizes an equal amount of low-resistance ground into different weak-zone connectivity states. The central contribution is the explicit separation of weak-zone extent from weak-zone organization: Pf quantifies how much of the domain is classified as weak-zone area, whereas the connectivity metrics describe whether that area remains fragmented, clusters locally, becomes dominated by a major component, or spans the domain.

Accordingly, the objectives of this study are to: (1) generate dataset-informed spatially correlated SPT_{N160} -derived resistance fields using a Gaussian Random Field framework; (2) classify low-resistance weak-zone domains using controlled equal-area lower-tail thresholding; (3) quantify weak-zone organization using graph-based descriptors, including connected-component count, largest-component ratio, fragmentation index, top-3 cluster ratio, and spanning probability; (4) map the evolution of weak-zone organization across a dense $Pf-\theta$ parameter space; (5) compare spatially correlated GRF fields with random-allocation null fields having the same Pf ; and (6) examine whether the observed 2011 Christchurch manifestation field also exhibits non-random spatial organization beyond affected-area fraction.

The remainder of the paper is organized as follows. Section 2 presents the conceptual basis of the proposed framework. Section 3 describes the dataset-informed GRF generation, lower-tail equal-



110 area thresholding, dense Pf- θ transition mapping, random-allocation null model, and connectivity
 111 descriptors. Section 4 presents the synthetic transition results, null-model comparison, and
 112 Christchurch manifestation-field analysis. Section 5 summarizes the main conclusions and field-
 113 scale implications.

114 **2. Conceptual Framework: Extent–Organization Distinction in Weak-Zone Fields**

115 In this study, Pf is interpreted as the prescribed areal fraction of cells classified as low-resistance
 116 weak zones, whereas connectivity descriptors are used to quantify how those cells are spatially
 117 organized. This distinction is central to the proposed framework. Two fields may contain the same
 118 weak-zone area fraction but exhibit very different spatial configurations: many isolated patches,
 119 several clustered weak zones, one dominant connected component, or a spanning weak-zone
 120 domain. These configurations are not equivalent from a field-scale interpretation perspective.
 121 Fragmented patterns indicate spatially discontinuous weak zones, whereas clustered, dominant, or
 122 spanning patterns indicate increasing spatial continuity of low-resistance ground.

123 Once a continuous resistance-related field is thresholded into weak-zone and non-weak-zone
 124 domains, the resulting binary field can be interpreted as a spatial network of active cells. Each
 125 weak-zone cell is treated as an active node, and neighboring active cells define connected
 126 components. This representation allows the analysis to move from scalar abundance toward
 127 organization: whether weak-zone cells remain isolated, combine into local clusters, form a
 128 dominant connected structure, or span the analysis domain. In this sense, the framework uses
 129 percolation-inspired topology as an interpretation layer for field-scale liquefaction susceptibility
 130 patterns.

131 This organization-based view is consistent with spatially correlated and percolation-oriented
 132 systems, where local activation may aggregate into larger connected structures that are not captured
 133 by scalar abundance alone (Stauffer & Aharony, 2018; Sahimi, 1994; Newman, 2010). Related
 134 studies in complex networks also show that connectivity transitions may be continuous, abrupt, or
 135 hybrid, confirming that large-scale organization does not necessarily evolve linearly with local
 136 abundance (Lee et al., 2018; Kryven, 2019). In the present geotechnical context, these concepts are
 137 used as an interpretation layer for liquefaction-prone weak-zone patterns. The purpose is not to
 138 define a universal percolation threshold for liquefaction, but to assess whether susceptible zones
 139 remain localized or reorganize into more continuous weak-zone patterns. This distinction is
 140 relevant because deformation-related consequences such as settlement, lateral spreading, and
 141 surface manifestation may depend not only on the presence of local liquefaction susceptibility, but
 142 also on the spatial continuity and arrangement of susceptible zones (Youd et al., 2001; Uzielli et
 143 al., 2005; Maurer et al., 2014, 2015b).

144 The thresholded weak-zone field is represented as a regular lattice graph. Each weak-zone cell is
 145 treated as an active node, and edges are defined according to the adopted neighborhood rule.



146 Connected groups of active cells define weak-zone components. The descriptors used in this study
 147 are summarized in Table 1. The weak-zone area fraction P_f quantifies the areal extent of low-
 148 resistance ground. The connected component count N_c measures fragmentation. The largest
 149 connected component ratio Γ quantifies the dominance of the main weak-zone domain. The
 150 fragmentation index FI describes how strongly the weak-zone domain is partitioned relative to its
 151 total extent. The top-3 cluster ratio $T3$ measures whether weak-zone cells are concentrated within
 152 a small number of major clusters. Finally, the spanning indicator or spanning probability identifies
 153 whether a connected weak-zone component crosses the analysis domain. Together, these
 154 descriptors distinguish localized weak-zone occurrence from clustered, dominant, or domain-scale
 155 connected organization.

156 **Table 1.** Connectivity descriptors used to distinguish weak-zone extent from weak-zone
 157 organization.

Descriptor	Definition	Geotechnical interpretation
Weak-zone area fraction, (P_f)	Proportion of cells classified as low-resistance weak-zone cells.	Areal extent of weak-zone ground.
Connected component count, (N_c)	Number of separate connected weak-zone clusters	Degree of spatial fragmentation
Largest connected component ratio, (Γ)	Fraction of susceptible cells in the largest component	Dominance of the main weak-zone domain
Fragmentation index, (FI)	(N_c) divided by total susceptible cells	Partitioning of susceptible ground
Top-3 cluster ratio, ($T3$)	Fraction of susceptible cells in the three largest clusters	Concentration into major weak-zone domains
Spanning indicator/probability	Whether a connected component crosses the domain	Field-scale continuity or corridor-scale hazard potential

158 3. Methodology

159 3.1. Dataset-informed random-field model and equal-area thresholding

160 The methodology was designed to examine how spatial correlation influences the organization of
 161 low-resistance weak-zone fields under controlled equal-area conditions. Baseline statistics were
 162 derived from the cleaned SPT_{N160} dataset, while the investigation coordinates defined the spatial
 163 extent of the computational domain. These inputs were used to generate dataset-informed synthetic
 164 Gaussian Random Field realizations representing spatially variable resistance-related fields.
 165 Because lower SPT_{N160} values correspond to lower penetration resistance and greater liquefaction
 166 susceptibility, the lower P_f fraction of each realization was classified as the low-resistance weak-
 167 zone domain. Here, P_f represents the prescribed weak-zone area fraction used to compare topology
 168 under equal-area conditions.

169 The mean μ and standard deviation σ were computed from the cleaned SPT_{N160} values. The
 170 investigation coordinates were transformed into a local metric coordinate system and discretized



171 into a regular two-dimensional grid. The regular grid ensured direct comparability among
 172 realizations and provided a consistent basis for graph-based connectivity analysis. The adopted
 173 numerical setup is summarized in Table 2.

174 **Table 2. Numerical parameters and baseline statistics adopted in the stochastic simulations.**

Parameter	Value
μ	16.2231
σ	8.8675
Unique investigation locations	438
Domain X (m)	32393.64
Domain Y (m)	37405.97
Grid spacing, Δx (m)	50
Grid spacing, Δy (m)	50
Grid (n_x)	648
Grid (n_y)	749
Correlation lengths, (θ) (m)	25, 50, 75, 100, 150, 200, 300, 400, 600, 800, 1000, 1200, 1500
Target (Pf) values	0.05–0.70 at 0.05 intervals
GRF realizations per (Pf)–(θ) pair	50
Null-model realizations per (Pf)–(θ) pair	50
Connectivity rule	4-neighbor

175 Let $X(s)$ denote the SPT_{N160} -derived resistance field defined over the two-dimensional
 176 computational domain. For each realization, a spatially correlated standard Gaussian field was
 177 generated using a spectral Gaussian-filter-based procedure and then scaled using the dataset-
 178 derived mean and standard deviation of SPT_{N160} . The correlation length θ controls the characteristic
 179 distance over which neighboring cells tend to exhibit similar values. Smaller θ values generate
 180 short-range spatial variability, whereas larger θ values produce broader coherent domains. In this
 181 study, θ was treated as a scenario parameter to explore how different levels of spatial coherence
 182 influence weak-zone organization. The selected values span weak-to-strong spatial coherence and
 183 are consistent with the range of horizontal fluctuation scales reported in geotechnical random-field
 184 studies (Cami et al., 2020; Lloret-Cabot et al., 2014).

185 For each realization, the continuous SPT_{N160} -derived resistance field was transformed into a binary
 186 weak-zone domain using lower-tail quantile thresholding. This procedure ensured that each
 187 realization matched the prescribed weak-zone area fraction while allowing the spatial arrangement
 188 of weak zones to vary with the imposed correlation length:

189
$$I^{(k)}(s) = \begin{cases} 1, & X^{(k)}(s) \leq T_{pf}^k \\ 0, & X^{(k)}(s) > T_{pf}^k \end{cases} \quad (1)$$



190 where $X^{(k)}(s)$ is the SPT_{N160} -derived resistance field for the k -th realization, and T_{Pf}^k is the
191 realization-specific lower-tail threshold selected to produce the target weak-zone area fraction P_f .
192 Thus, $I^{(k)}(s)=1$ identifies cells belonging to the prescribed low-resistance weak-zone domain.

193 For each realization, the prescribed low-resistance weak-zone area fraction is computed as

$$194 \quad P_f^{(k)} = \frac{1}{M} \sum_{i=1}^M I_i^{(k)} \quad (2)$$

195 where M is the total number of cells in the domain and $I_i^{(k)}$ is the binary state of cell i in realization
196 k . Holding P_f constant across realizations enables the effect of spatial correlation on weak-zone
197 organization to be evaluated independently from the total weak-zone extent.

198 **3.2. Connectivity metrics and weak-zone organization classification**

199 After thresholding, each binary weak-zone field was analyzed using connected-component labeling
200 on a regular two-dimensional lattice. Weak-zone cells were treated as active nodes, and adjacency
201 was defined using a 4-neighbor rule. This conservative rule considers only horizontally and
202 vertically adjacent cells as connected and avoids assigning continuity through diagonal contact.
203 For each realization, P_f , N_c , Γ , FI , $T3$, and the spanning indicator were computed. The largest
204 connected component ratio is defined as

$$205 \quad \Gamma = \frac{|C_{max}|}{|D_f|} \quad (3)$$

206 where $|C_{max}|$ is the size of the largest connected component and $|D_f|$ is the total number of weak-
207 zone cells. To complement this measure, a fragmentation index is defined as

$$208 \quad FI = \frac{N_c}{|D_f|} \quad (4)$$

209 where N_c is the number of connected weak-zone components. The top-3 cluster ratio $T3$ was
210 computed as the fraction of liquefaction-prone cells contained within the three largest components.
211 The spanning indicator was assigned a value of 1 when at least one connected component crossed
212 the analysis domain from left to right or from top to bottom; otherwise, it was assigned 0. The
213 computational definitions are summarized in Table 3.

214

215

216



Table 3. Computational definitions of the connectivity descriptors used for weak-zone topology analysis.

Metric	Computational definition
P_f	Fraction of cells classified as weak-zone cells
N_c	Number of connected weak-zone components
Γ	Largest connected component size / total weak-zone cells
FI	$(N_c) / \text{total liquefaction-prone cells}$
T_3	Fraction of weak-zone cells in the three largest components
Spanning indicator	1 if any connected component spans left–right or top–bottom; otherwise 0

Ensemble-level organization states were assigned using the rule-based thresholds listed in Table 4. These thresholds were adopted to provide a consistent interpretation of the transition maps across the explored P_f – θ parameter space. The spanning regime was defined when the spanning probability exceeded 0.50, indicating that domain-scale continuity occurred in the majority of realizations. The Γ and T_3 thresholds were used to distinguish fields in which weak-zone cells were concentrated within one or a few major connected components from those distributed among many smaller clusters. The FI threshold was used to identify highly partitioned weak-zone patterns relative to the total number of weak-zone cells. Accordingly, the regime map should be read as a comparative classification of weak-zone organization across the simulated parameter space.

Table 4. Rule-based thresholds adopted for ensemble-level classification of weak-zone organization states.

Threshold name	Value	Interpretation
Spanning probability threshold	0.5	Spanning regime when at least half of realizations span the domain
Dominant (Γ) threshold	0.45	Dominant connected organization
Clustered (Γ) threshold	0.15	Clustered organization based on largest-component dominance
Clustered (T_3) threshold	0.45	Clustered organization based on concentration in top three components
Fragmented (FI) threshold	0.02	Highly partitioned weak-zone organization

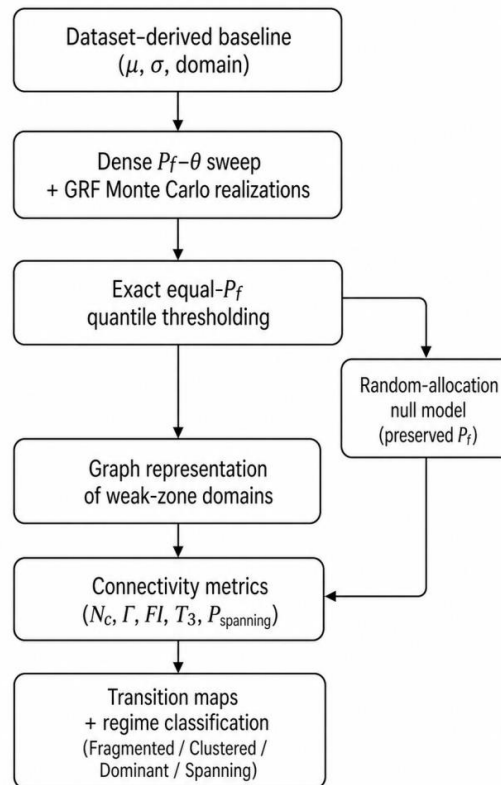


230 3.3. Dense P_f - θ transition mapping and random-allocation null model

231 To move beyond selected equal-area examples, the analysis was extended to a dense P_f - θ transition
232 space. The prescribed weak-zone area fraction was varied from 0.05 to 0.70 at 0.05 intervals, while
233 the spatial correlation length was varied from 25 m to 1500 m. For each parameter combination,
234 50 independent GRF realizations were generated and analyzed. Ensemble mean values of N_c , Γ ,
235 FI , $T3$, and spanning probability were then computed to map the transition from fragmented to
236 clustered and spanning weak-zone regimes.

237 A random-allocation null model was used to evaluate whether weak-zone organization can be
238 explained by areal abundance alone. For each P_f level, the number of weak-zone cells was
239 preserved, while their spatial positions were randomly reassigned across the domain. This
240 comparison provides a reference condition in which weak-zone extent is retained but spatial
241 correlation is removed. Differences between the GRF and null ensembles therefore isolate the
242 contribution of spatial correlation to fragmentation, cluster dominance, and spanning behavior.

243 The overall computational workflow is shown in Figure 1. It includes dataset-informed baseline
244 definition, spatially correlated field generation, lower-tail equal-area weak-zone thresholding,
245 dense transition mapping, random-allocation null modeling, graph-based connectivity analysis, and
246 organization-state interpretation.



247

248 **Figure 1.** Workflow of the proposed connectivity-based random-field framework, showing
 249 dataset-informed GRF simulation, lower-tail equal-area weak-zone thresholding, random-
 250 allocation null-model comparison, graph-based connectivity analysis, and transition mapping.

251 4. Results and Discussion

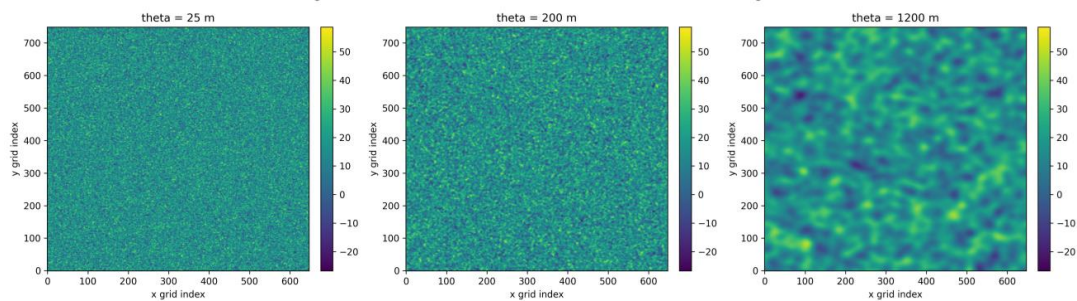
252 4.1. Correlation-driven evolution of spatial coherence

253 The generated SPT_{N160} -derived random fields exhibit a clear progression in spatial coherence as
 254 the imposed correlation length increases. At low θ , short-scale variability dominates the field,
 255 producing spatially irregular resistance patterns. As θ increases, neighboring cells become more
 256 similar and broader coherent domains emerge. This progression provides the physical basis for the
 257 subsequent weak-zone topology analysis, because lower-tail thresholding of increasingly coherent
 258 fields is expected to produce larger and more organized low-resistance clusters.

259 **Figure 2** illustrates this transition for representative fields generated at $\theta=25$, 200, and 1200 m. At
 260 $\theta=25$ m, the field is dominated by localized fluctuations and grid-scale heterogeneity. At $\theta=200$ m,
 261 local variability remains visible, but broader spatial continuity begins to develop. At $\theta=1200$ m,



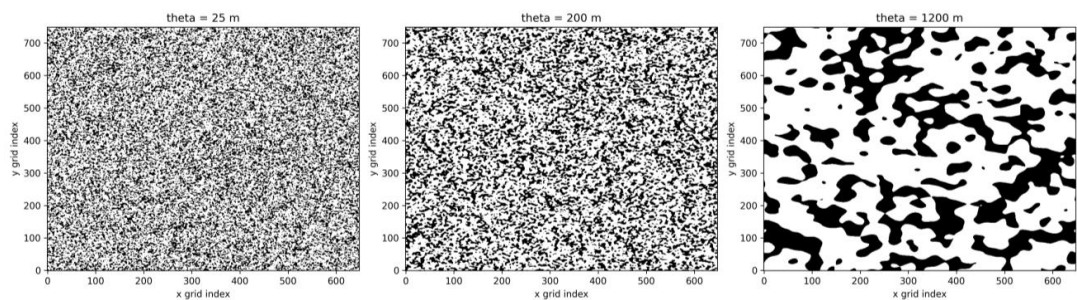
the field becomes substantially smoother, and larger coherent domains emerge across the analysis region. This change in spatial structure is important because the lower-tail regions extracted from smoother resistance fields are more likely to form connected weak-zone clusters.



265

Figure 2. Representative continuous SPT_{N160} -derived resistance fields generated under different horizontal correlation lengths θ , showing the increase in spatial coherence from weakly correlated to strongly coherent conditions.

The effect of spatial coherence becomes more evident after equal-area lower-tail thresholding (**Figure 3**). Figure 3 shows representative binary weak-zone fields generated with the same prescribed weak-zone area fraction but different correlation lengths. At low θ , weak-zone cells appear as many small and disconnected patches. As θ increases, these cells progressively merge into larger clusters, and at high θ , the binary pattern becomes broader and more coherent. Because the weak-zone area fraction is fixed in all cases, these changes reflect spatial organization rather than changes in weak-zone extent.



276

Figure 3. Binary low-resistance weak-zone fields obtained through controlled equal-area lower-tail thresholding under different correlation lengths. Black cells indicate the prescribed lower P_f fraction of the field, while white cells indicate the remaining domain.

280



4.2. Equal- P_f examples: same extent, different organization

A selected realization-level comparison is provided in Figure 4 and Table 5 to illustrate the non-equivalence between weak-zone extent and weak-zone organization. The selected cases have the same prescribed weak-zone area fraction, $P_f \approx 0.35$, but different correlation lengths. This comparison isolates the role of spatial correlation in reorganizing an equal amount of low-resistance ground into fragmented, clustered, or more coherent weak-zone patterns.

Table 5. Selected equal- P_f realizations used for realization-level comparison.

(θ) (m)	Realization	Target (P_f)	(N_c)	(Γ)	(FI)	(T3)	Organization state
25	12	0.35	6706	0.0054	0.0395	0.0138	Fragmented
200	3	0.35	2244	0.0143	0.0132	0.0361	Fragmented
1200	20	0.35	70	0.1547	0.0004	0.3712	Clustered

At $\theta=25$ m, the selected field contains 6706 connected components and has a largest-component ratio of only $\Gamma=0.0054$, indicating a highly fragmented weak-zone structure. At $\theta=200$ m, the number of components decreases to 2244, while Γ increases to 0.0143 and T3 increases to 0.0361, reflecting the onset of local aggregation. At $\theta=1200$ m, the number of components decreases sharply to 70, Γ increases to 0.1547, and T3 reaches 0.3712, indicating that a substantial fraction of weak-zone cells is concentrated within a small number of major clusters.

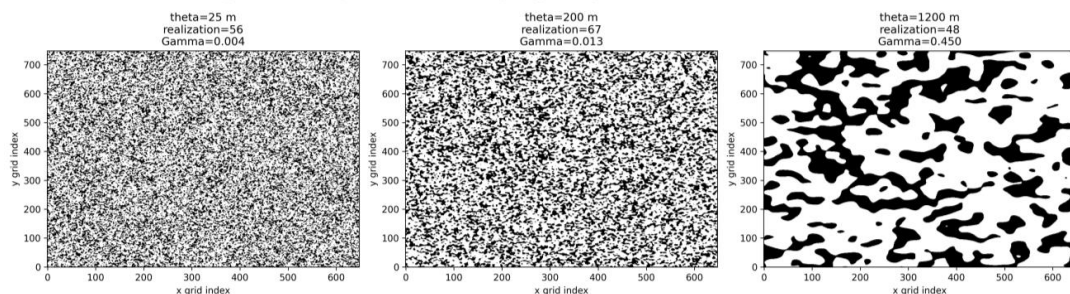


Figure 4. Selected equal- P_f binary weak-zone realizations for $P_f \approx 0.35$ under different correlation lengths: (a) $\theta=25$ m, realization 12, (b) $\theta=200$ m, realization 3, and (c) $\theta=1200$ m, realization 20. Black cells indicate low-resistance weak-zone cells, while white cells indicate the remaining domain.

This comparison shows that equal weak-zone area fraction can produce markedly different spatial configurations, ranging from highly fragmented patches to larger clustered weak-zone domains as the correlation length increases.

4.3. Connectivity transition across the P_f - θ parameter space

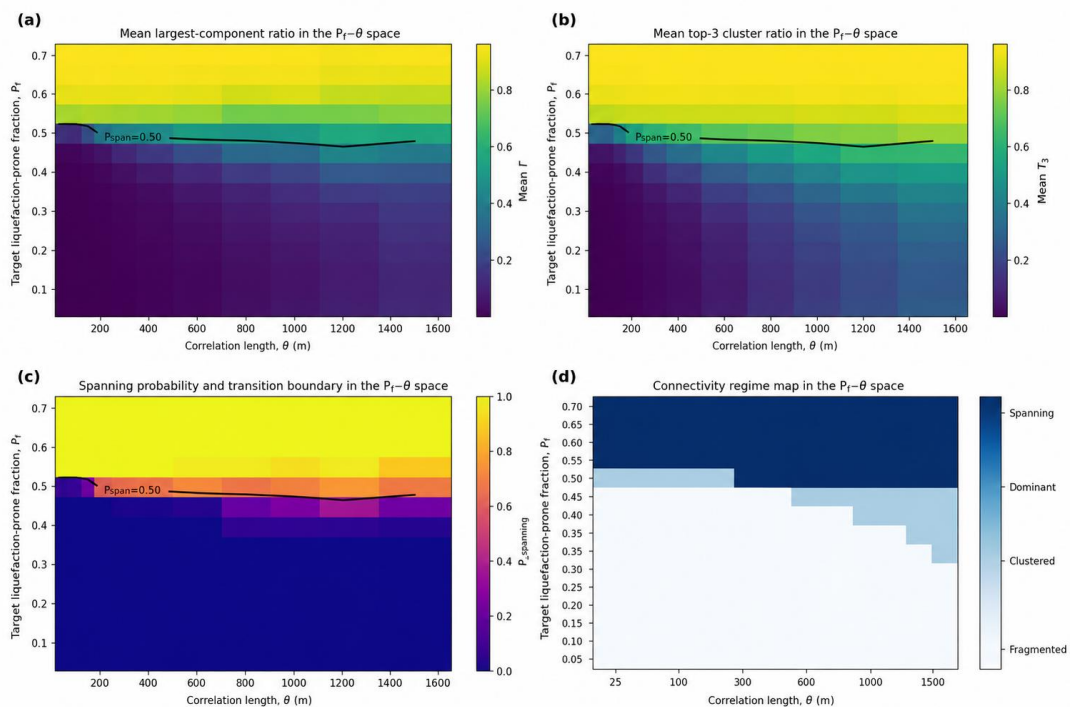


303 The dense P_f - θ transition analysis indicates that weak-zone organization is governed by the
 304 interaction between weak-zone abundance and spatial correlation. For $P_f \leq 0.35$, spanning
 305 probability remains zero across the explored range of correlation lengths, although increasing θ
 306 reduces fragmentation and promotes cluster coalescence. For $P_f = 0.40$ – 0.45 , the fields remain
 307 mostly below the spanning transition but show increasing cluster dominance at larger correlation
 308 lengths.

309 The clearest transition occurs around $P_f = 0.50$, where P_{spanning} rises above 0.50 once θ reaches
 310 approximately 200 m. For $P_f \geq 0.55$, the fields become spanning-dominated across nearly all
 311 correlation lengths. Thus, the intermediate P_f range marks the most sensitive transition zone, where
 312 changes in spatial correlation can shift the weak-zone field from fragmented or clustered
 313 organization toward field-scale continuity.

314 Figure 5 summarizes the ensemble-level response using transition maps of mean largest-
 315 component ratio Γ , mean top-3 cluster ratio T_3 , spanning probability P_{spanning} , and weak-zone
 316 organization state.

317



318



Figure 5. Connectivity transition maps in the P_f - θ parameter space: (a) mean largest-component ratio Γ , (b) mean top-3 cluster ratio T_3 , (c) spanning probability P_{spanning} with the $P_{\text{spanning}}=0.50$ transition boundary, and (d) weak-zone organization regime map.

These results show that P_f and θ play complementary roles. P_f controls the amount of low-resistance ground, whereas θ controls how that ground is spatially organized into fragmented, clustered, dominant, or spanning configurations. The same weak-zone fraction can therefore correspond to different topology states depending on the imposed correlation structure.

4.4. Random-allocation null-model comparison

The random-allocation null model provides a direct reference for separating weak-zone abundance from weak-zone organization. If the prescribed area fraction P_f were sufficient to explain the observed topology, the GRF and null fields would produce comparable connectivity metrics. Instead, the spatially correlated GRF fields consistently show lower fragmentation, larger dominant components, and stronger top-cluster concentration than random fields with the same number of weak-zone cells.

Figure 6 summarizes these differences across the P_f - θ parameter space. The fragmentation-index difference, $FI_{\text{GRF}} - FI_{\text{null}}$, is negative across the mapped domain, indicating that spatially correlated weak-zone fields are systematically less fragmented than random-allocation fields. In contrast, $\Gamma_{\text{GRF}} - \Gamma_{\text{null}}$ and $T_{3,\text{GRF}} - T_{3,\text{null}}$ are positive, showing that spatial correlation promotes larger dominant components and greater concentration of weak-zone cells within the largest clusters.

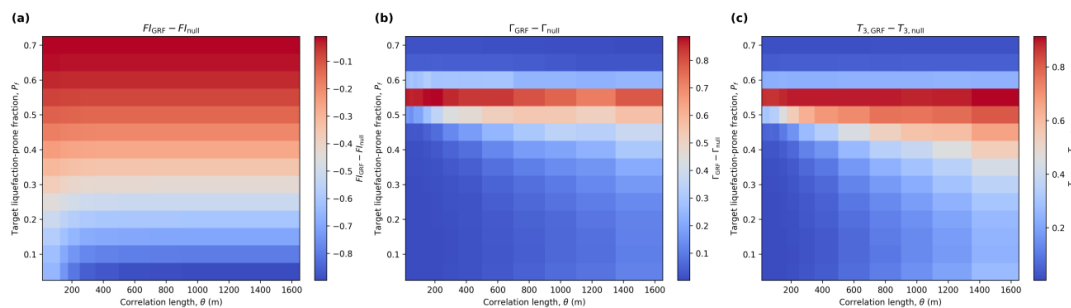


Figure 6. Difference maps comparing spatially correlated GRF fields with the random-allocation null model in the P_f - θ parameter space: (a) $FI_{\text{GRF}} - FI_{\text{null}}$, (b) $\Gamma_{\text{GRF}} - \Gamma_{\text{null}}$, and (c) $T_{3,\text{GRF}} - T_{3,\text{null}}$. Negative FI differences indicate reduced fragmentation in GRF fields, whereas positive Γ and T_3 differences indicate stronger connected-component dominance and cluster concentration.

This result indicates that spatial correlation does not merely smooth the resistance field; it reorganizes low-resistance cells into more coherent weak-zone structures. The null-model



345 comparison therefore reinforces the central extent–organization distinction: the amount of weak-
 346 zone area and the connectivity of that area are related but non-equivalent properties.

347 **4.5. Observational topology benchmark using the Christchurch manifestation field**

348 The observational topology benchmark was based on the Canterbury/Christchurch CPT-based
 349 liquefaction case-history dataset compiled by Geyin et al. (2021). The dataset includes liquefaction
 350 case histories from the September 2010 Mw7.1 Darfield, February 2011 Mw6.2 Christchurch, and
 351 February 2016 Mw5.7 Christchurch earthquakes, and provides geographic coordinates, processed
 352 CPT data, event-specific PGA, groundwater table depth, earthquake magnitude, and classified
 353 surface manifestation severity. The original dataset was compiled from the New Zealand
 354 Geotechnical Database and organized as a structured digital file suitable for liquefaction-triggering,
 355 manifestation, and spatial-response analyses.

356 In the present study, the dataset was not used to recalibrate liquefaction-triggering models or to
 357 validate the synthetic $SPT-N_{1,60}$ random-field simulations directly. Instead, only the spatial
 358 coordinates and surface manifestation severity classes were used to construct an independent
 359 observational topology benchmark. This allowed the analysis to examine whether real liquefaction
 360 manifestation patterns exhibit non-random spatial organization beyond affected-area fraction.

361 The 2011 Christchurch manifestation field was then converted into a graph-consistent point-based
 362 representation using a distance-based neighborhood definition derived from the observed point
 363 configuration, and the same family of connectivity descriptors was computed. In the original
 364 dataset, liquefaction manifestation severity was manually classified at CPT locations using high-
 365 resolution satellite imagery and reconnaissance reports available in the New Zealand Geotechnical
 366 Database. Classifications were assigned within an approximately 15 m radius around each CPT
 367 location and included none, minor, moderate, severe, lateral spreading, severe lateral spreading,
 368 and unknown.

369 To evaluate whether the descriptors are sensitive to field-outcome severity, the manifestation
 370 records were stratified into four severity-based binary definitions: any manifestation, moderate or
 371 worse manifestation, severe/lateral manifestation, and lateral-only manifestation. This severity-
 372 class comparison examines whether affected-area fraction and manifestation-field organization
 373 evolve consistently as the observed manifestation definition becomes more restrictive.

374 **Figure 7** presents the observed topology for the any-manifestation case. Although the
 375 manifestation fraction is high, indicating widespread liquefaction effects across the study area, the
 376 connected-component representation shows that widespread occurrence does not reorganize into a
 377 single dominant connected body. Instead, the manifested locations remain partitioned into many
 378 connected groups.

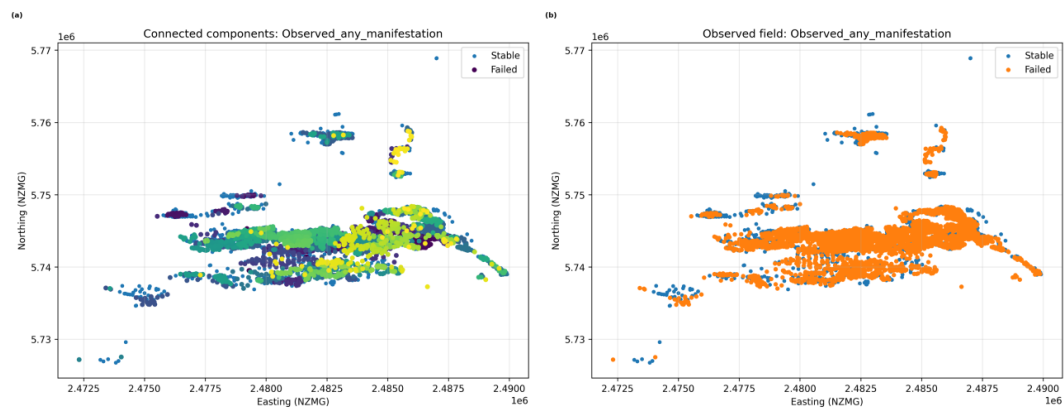


Figure 7. Observed manifestation connectivity of the 2011 Christchurch liquefaction field for the any-manifestation case: (a) connected-component representation and (b) binary observed manifestation field.

Figure 8 presents the corresponding topology for the severe/lateral manifestation subset. In this more restrictive case, the manifestation fraction decreases and the pattern becomes more selectively distributed. The connected-component map shows that severe or lateral manifestations remain organized as multiple disconnected clusters rather than as a single continuous manifestation domain.

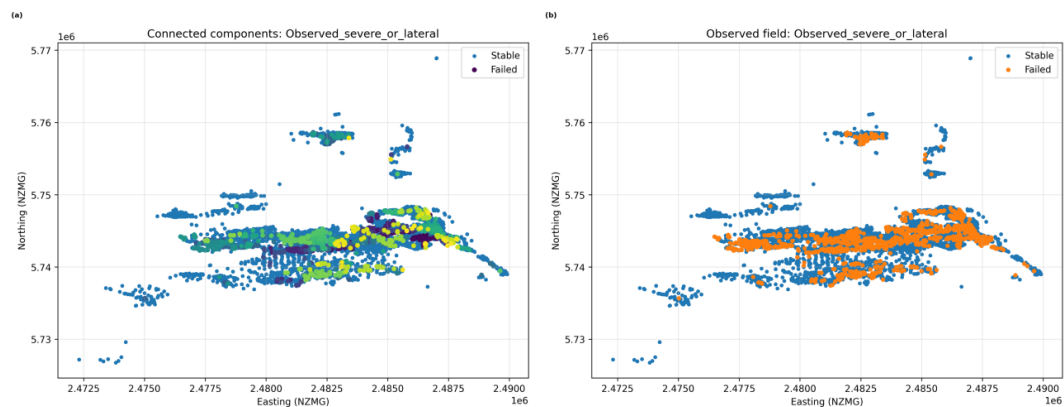


Figure 8. Observed manifestation connectivity of the 2011 Christchurch liquefaction field for the severe/lateral manifestation case: (a) connected-component representation and (b) binary observed manifestation field.



The computed metrics for the observed severity classes are summarized in Table 6. The any-manifestation case represents widespread field evidence of liquefaction, whereas the more restrictive definitions isolate progressively more severe or laterally deforming manifestations.

Table 6. Connectivity metrics computed for the observed 2011 Christchurch liquefaction manifestation field under the default neighborhood definition.

Scenario	Manifestation classes	Total locations	Manifested locations	Manifestation fraction	Connected components	Largest component size	(Γ)	(FI)	(T_3)
Any manifestation	1–5	5612	4722	0.841	1903	459	0.097	0.403	0.129
Moderate or worse	2–5	5612	2930	0.522	1199	237	0.081	0.409	0.124
Severe/lateral manifestation	3–5	5612	1311	0.234	689	66	0.05	0.526	0.098
Lateral-only manifestation	4–5	5612	905	0.161	494	34	0.038	0.546	0.076

As shown in Table 6, progressively more restrictive manifestation definitions reduce the affected fraction but do not produce a single connected manifestation domain. The manifestation fraction decreases from 0.841 for the any-manifestation case to 0.161 for the lateral-only subset. Over the same sequence, Γ decreases from 0.097 to 0.038, and T_3 decreases from 0.129 to 0.076, indicating that more severe field outcomes are not concentrated into one dominant connected component. Instead, FI increases from 0.403 to 0.546, showing that the more restrictive severity classes remain more fragmented. No spanning configuration is identified under the adopted neighborhood definition; however, this does not imply random spatial organization, as tested further using the permutation-based null model.

To test whether the observed manifestation organization can be explained by affected-area fraction alone, a permutation-based null comparison was performed. In this analysis, the number of manifested locations was preserved, while manifestation labels were randomly reassigned over the observed point set. Table 7 summarizes the observed-versus-null comparison for the any-manifestation and severe/lateral manifestation cases.

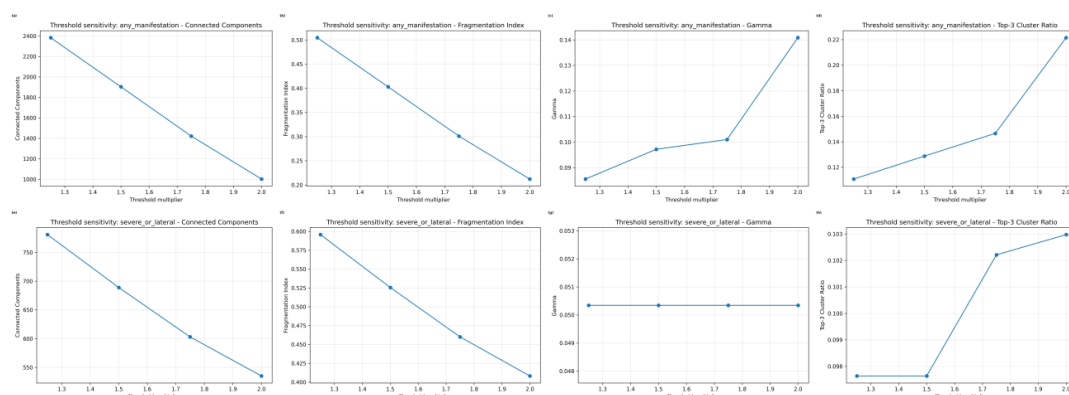


Table 7. Observed-versus-null connectivity comparison for the Canterbury/Christchurch liquefaction manifestation field.

Scenario	Metric	Observed	Null mean	Observed - null mean	Z-score	Empirical p-value
Any manifestation	N_c	1903	2221.286	-318.286	-18.8656	0.004
Any manifestation	Γ	0.0972	0.0808	0.0164	3.8118	0.004
Any manifestation	FI	0.403	0.4704	-0.0674	-18.8656	0.004
Any manifestation	T_3	0.1288	0.1046	0.0241	4.9209	0.004
Severe/lateral manifestation	N_c	689	990.39	-301.39	-20.0687	0.004
Severe/lateral manifestation	Γ	0.0503	0.0151	0.0353	8.2228	0.008
Severe/lateral manifestation	FI	0.5256	0.7554	-0.2299	-20.0687	0.004
Severe/lateral manifestation	T_3	0.0976	0.0365	0.0612	9.3163	0.004

The results in Table 7 show that the observed manifestation fields depart systematically from the random-allocation null model. For the any-manifestation case, the observed number of connected components is lower than the null expectation, while Γ and T_3 are higher. The same tendency is stronger for the severe/lateral manifestation subset, where N_c and FI are substantially lower than the null expectation, while Γ and T_3 are markedly higher. These results indicate that the observed field is less fragmented and more clustered than would be expected from random label allocation with the same manifestation count. Therefore, the Christchurch results provide real-case support for the central interpretation of the study: affected-area fraction alone does not determine manifestation-field organization.

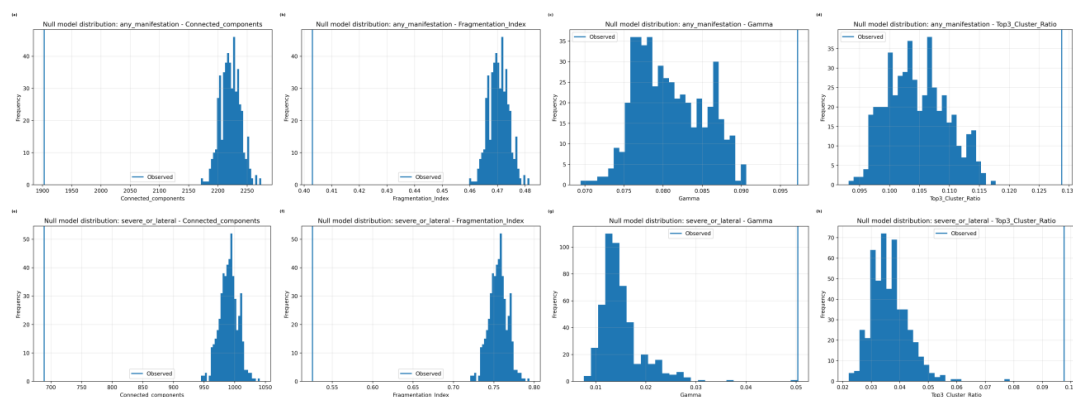
The robustness of this interpretation was further examined by varying the neighborhood-threshold multiplier used in graph construction. Figure 9 shows that increasing the neighborhood threshold reduces the number of components and the fragmentation index, while increasing Γ and T_3 , as expected. However, the qualitative interpretation remains stable: the observed manifestation field does not reduce to a single dominant spanning structure under the explored neighborhood definitions.



428

429 **Figure 9.** Sensitivity of the observed Christchurch connectivity metrics to the neighborhood-
 430 threshold multiplier used in graph construction. The upper row shows the any-manifestation case,
 431 and the lower row shows the severe/lateral manifestation case. Columns show connected
 432 component count, fragmentation index, largest connected component ratio Γ , and top-3 cluster
 433 ratio.

434 Figure 10 further supports this interpretation by showing the permutation-based null distributions
 435 for the observed connectivity metrics. The observed values are consistently displaced from the null
 436 distributions, confirming that the Christchurch manifestation organization departs from random
 437 label allocation with the same manifestation count.



438

439 **Figure 10.** Permutation-based null-model comparison for the Canterbury/Christchurch
 440 manifestation-field connectivity metrics. The null distributions were generated by randomly
 441 reallocating manifestation labels while preserving the number of manifested locations. Vertical
 442 lines indicate the observed metric values for the any-manifestation and severe/lateral manifestation
 443 scenarios.



444 Taken together, the Christchurch analyses provide a real-case confirmation of the central extent–
 445 organization distinction developed in this study. The severity-class results show that decreasing
 446 manifestation abundance does not simply scale the spatial pattern; instead, more restrictive field-
 447 outcome definitions remain fragmented and non-spanning. The permutation-based null model
 448 further shows that the observed manifestation structures depart from random allocation with
 449 preserved manifestation count. These findings indicate that real liquefaction manifestation fields
 450 contain spatial organization that is not captured by affected-area fraction alone. Accordingly,
 451 connectivity descriptors provide a complementary interpretation layer for post-earthquake
 452 liquefaction datasets, linking observed field outcomes to the broader weak-zone organization
 453 framework proposed in this study.

454 **4.6. Engineering implications for field-scale liquefaction hazard interpretation**

455 The principal engineering implication of the results is that similar areal liquefaction hazard should
 456 not automatically be interpreted as similar field-scale consequence. The synthetic GRF analyses
 457 show that fields with the same prescribed susceptible-area fraction may differ substantially in
 458 fragmentation, cluster dominance, and spanning behavior. The dense P_f – θ transition maps further
 459 show that weak-zone organization can shift from fragmented to clustered or spanning regimes
 460 depending on the interaction between susceptible-area abundance and spatial correlation.

461 This distinction is relevant for distributed geotechnical systems, urban waterfronts, port areas,
 462 transportation corridors, lifelines, and large development sites. A fragmented weak-zone pattern
 463 may imply localized investigation or targeted mitigation, whereas a clustered, dominant, or
 464 spanning pattern may suggest broader zoning, corridor-scale assessment, or system-level
 465 interpretation. Thus, susceptible-area fraction should be read as a measure of hazard abundance,
 466 while Γ , FI, T3, and P_{spanning} should be read as descriptors of field-scale organization.

467 From a geotechnical perspective, a connected weak-zone pattern may be interpreted as the lateral
 468 continuity of low-resistance or liquefaction-susceptible ground conditions. Such continuity is
 469 relevant because field-scale ground deformation may become spatially coherent when susceptible
 470 zones are not isolated. In this sense, the connectivity descriptors do not directly predict settlement,
 471 lateral spreading, or structural damage; rather, they indicate whether the spatial arrangement of
 472 weak zones may support localized, cluster-scale, or system-scale hazard interpretation. This
 473 distinction is particularly important for waterfronts, transportation corridors, buried lifelines, and
 474 distributed infrastructure systems, where the continuity of susceptible ground may influence the
 475 scale at which mitigation or zoning decisions are made.

476 To translate the connectivity states into engineering interpretation, **Table 8** summarizes the
 477 practical meaning of fragmented, clustered, dominant connected, and spanning weak-zone
 478 organizations.

479

480



Table 8. Engineering interpretation of weak-zone organization states.

Weak-zone organization state	Geotechnical interpretation	Possible engineering implication
Fragmented	Liquefaction-prone cells occur as many isolated or weakly connected local patches	Localized investigation, targeted ground improvement, point-scale screening
Clustered	Susceptible cells form grouped weak-zone patches but without a dominant connected domain	Cluster-scale zoning, local-to-district scale mitigation prioritization
Dominant connected	A substantial proportion of susceptible cells belongs to one major connected weak-zone domain	Area-wide hazard interpretation, corridor-scale assessment, coordinated mitigation planning
Spanning	A connected liquefaction-prone domain extends across the analysis region	System-level interpretation for lifelines, waterfronts, transport corridors, and distributed infrastructure

As indicated in Table 8, the practical meaning of a liquefaction-prone field changes with its organization state. A fragmented pattern suggests that susceptible ground is spatially discontinuous and may require localized investigation or targeted treatment. A clustered pattern indicates that susceptible zones are grouped into larger local domains, which may be more relevant for district-scale zoning or cluster-based mitigation. A dominant connected or spanning pattern has broader field-scale significance because a substantial portion of the susceptible area is organized into one major weak-zone system or extends across the domain. Such cases may require corridor-scale, waterfront-scale, or system-level interpretation rather than isolated point-scale screening.

The transition boundary identified in the Pf- θ space provides a useful conceptual basis for field-scale hazard interpretation. It indicates the conditions under which liquefaction-prone zones are likely to remain localized, become clustered, or form domain-scale weak-zone continuity. In practical applications, this information can complement conventional liquefaction indicators by identifying whether mapped susceptible zones are spatially isolated or organized into larger connected systems.

Overall, the results support a connectivity-aware interpretation of spatial liquefaction hazard. The central contribution is the distinction between hazard extent and hazard organization. Scalar descriptors remain necessary for quantifying how much ground is susceptible, but connectivity metrics provide additional information on how that susceptible ground is arranged across the field. This distinction is particularly important where field-scale or infrastructure-scale consequences depend on the continuity of weak zones rather than on susceptible-area fraction alone.



502 5. Conclusions

503 This study developed a connectivity-based random-field framework for interpreting the spatial
 504 organization of low-resistance weak-zone fields under controlled equal-area conditions. The main
 505 contribution is the explicit separation of weak-zone extent from weak-zone organization. While
 506 conventional scalar descriptors quantify how much ground is potentially susceptible, the proposed
 507 topology-based approach shows how that weak-zone area is spatially arranged: fragmented,
 508 clustered, dominantly connected, or spanning.

509 The results demonstrate that equal weak-zone area does not imply equal field-scale organization.
 510 Under the same prescribed P_f , weakly correlated fields remained highly fragmented, whereas larger
 511 correlation lengths promoted cluster coalescence, dominant connected components, and, at
 512 sufficiently high weak-zone fractions, spanning configurations. The dense P_f - θ transition maps
 513 showed that the clearest connectivity transition occurs around $P_f=0.50$, where spanning probability
 514 exceeds 0.50 once θ reaches approximately 200 m. Lower- P_f fields remain fragmented across the
 515 explored correlation-length range, whereas $P_f \geq 0.55$ produces spanning-dominated organization
 516 across nearly all tested correlation lengths.

517 The random-allocation null model further demonstrated that weak-zone organization cannot be
 518 explained by liquefaction-prone area fraction alone. Spatially correlated GRF fields produced
 519 lower fragmentation, stronger largest-component dominance, and greater concentration into major
 520 clusters than random fields with the same P_f . This result establishes weak-zone connectivity as a
 521 distinct field-scale property arising from the interaction between susceptible-area abundance and
 522 spatial correlation.

523 The Christchurch manifestation-field analysis provided an observational topology benchmark for
 524 the proposed interpretation. The severity-class comparison showed that progressively more
 525 restrictive manifestation definitions reduced affected-area fraction but did not produce a single
 526 dominant connected manifestation domain. The observed-versus-null comparison further showed
 527 that real manifestation patterns depart from random label allocation with preserved manifestation
 528 count. These findings indicate that real liquefaction manifestation fields also contain spatial
 529 organization that is not captured by affected-area fraction alone.

530 The main conclusions of the study are summarized as follows:

- 531 1. **Hazard extent and weak-zone organization are non-equivalent.** P_f quantifies how much
 532 of the domain is classified as liquefaction-prone, but it does not describe whether the
 533 susceptible ground is fragmented, clustered, dominantly connected, or spanning.
- 534 2. **Spatial correlation drives connectivity transitions.** Increasing θ promotes aggregation of
 535 susceptible cells into larger connected weak-zone domains, with the transition most
 536 pronounced at intermediate susceptible-area fractions.



- 537 3. **Equal Pf may correspond to different field-scale implications.** Fields with identical
 538 liquefaction-prone area fraction can exhibit substantially different connectedness,
 539 fragmentation, and spanning behavior depending on the spatial correlation structure.
- 540 4. **The null model confirms non-random weak-zone organization.** Spatially correlated
 541 fields systematically depart from random allocation with the same susceptible-area fraction,
 542 indicating that connectivity is not a trivial consequence of area abundance.
- 543 5. **Observed manifestation fields require organization-aware interpretation.** The
 544 Christchurch results show that real liquefaction manifestations may be widespread and non-
 545 random while still remaining partitioned rather than forming a single dominant connected
 546 body.
- 547 6. **Connectivity descriptors complement conventional liquefaction indicators.** Metrics
 548 such as N_c , Γ , FI, T3, and spanning probability provide information on the spatial
 549 arrangement of susceptible ground that scalar measures alone cannot capture.

550 The framework provides a field-scale organization layer that can be applied after liquefaction-
 551 prone or low-resistance weak zones have been identified. In this role, connectivity descriptors help
 552 distinguish whether susceptible zones remain localized, cluster into larger weak-zone domains, or
 553 develop domain-scale continuity. This organization-aware interpretation is particularly useful for
 554 distributed geotechnical systems, where the continuity of susceptible ground may influence the
 555 scale of investigation, zoning, or mitigation decisions.

556 Several limitations should be acknowledged. The controlled GRF analyses were based on two-
 557 dimensional SPT- $N_{1,60}$ -derived resistance fields rather than direct site-specific liquefaction
 558 triggering simulations; similarly, Pf should be interpreted as an areal classification fraction, not as
 559 a point-level probability of failure. The imposed correlation length was treated as a scenario
 560 parameter to explore weak-to-strong spatial coherence conditions. The organization regimes were
 561 synthesized using rule-based thresholds, which provide a consistent basis for comparing topology
 562 states across the simulated Pf- θ space. The Christchurch application was used as an observational
 563 topology benchmark, rather than as a direct validation of the synthetic GRF model, because the
 564 Canterbury dataset is CPT-based and represents event-specific surface manifestation observations.

565 Future work may extend the framework by incorporating anisotropic and three-dimensional
 566 random fields, depth-dependent triggering calculations, CPT- or SPT-based CSR-CRR
 567 procedures, alternative neighborhood definitions, and calibration against observed ground
 568 deformation or infrastructure performance. Such extensions would allow the proposed connectivity
 569 descriptors and regime classifications to evolve from an interpretive topology layer toward
 570 performance-based decision support for liquefaction hazard zoning and mitigation prioritization.
 571 Overall, the study shows that spatial liquefaction hazard should be interpreted through both extent
 572 and organization. This distinction is particularly important for distributed geotechnical systems,
 573 where similar areal liquefaction hazard may imply different field-scale consequences depending
 574 on weak-zone continuity and spatial organization.

575

576



577 Data Availability Statement: All data and models analyzed during the current study are available
 578 from the corresponding author on reasonable request.

579 Declaration of interest statement: The authors declare that they have no known competing financial
 580 interests or personal relationships that could have appeared to influence the work reported in this
 581 paper.

582 **References**

583 Baise, L. G., Higgins, R. B., & Brankman, C. M. (2006). Liquefaction Hazard Mapping—
 584 Statistical and Spatial Characterization of Susceptible Units. *Journal of Geotechnical and*
 585 *Geoenvironmental Engineering*, 132(6). [https://doi.org/10.1061/\(asce\)1090-](https://doi.org/10.1061/(asce)1090-0241(2006)132:6(705))
 586 [0241\(2006\)132:6\(705\)](https://doi.org/10.1061/(asce)1090-0241(2006)132:6(705))

587 Baker, J. W., & Faber, M. H. (2008). Liquefaction Risk Assessment Using Geostatistics to account
 588 for Soil Spatial Variability. *Journal of Geotechnical and Geoenvironmental Engineering*, 134(1).
 589 [https://doi.org/10.1061/\(asce\)1090-0241\(2008\)134:1\(14\)](https://doi.org/10.1061/(asce)1090-0241(2008)134:1(14))

590 Boulanger, R. W., & Idriss, I. M. (2014). *CPT and SPT based liquefaction triggering procedures*
 591 (Report No. UCD/CGM-14/01). Center for Geotechnical Modeling, University of California,

592 Cami, B., Javankhoshdel, S., Phoon, K.-K., & Ching, J. (2020). Scale of fluctuation for spatially
 593 varying soils: Estimation methods and values. *ASCE-ASME Journal of Risk and Uncertainty in*
 594 *Engineering Systems, Part A: Civil Engineering*, 6(4), 03120002.
 595 <https://doi.org/10.1061/AJRUA6.0001083>

596 Cao, L., & Schwarz, J. M. (2012). Correlated percolation and tricriticality. *Physical Review E -*
 597 *Statistical, Nonlinear, and Soft Matter Physics*, 86(6).
 598 <https://doi.org/10.1103/PhysRevE.86.061131>

599 D'Souza, R. M., & Nagler, J. (2015). Anomalous critical and supercritical phenomena in explosive
 600 percolation. *Nature Physics*, 11(7). <https://doi.org/10.1038/nphys3378>

601 Fenton, G. A., & Griffiths, D. V. (2008). *Risk assessment in geotechnical engineering*. John Wiley
 602 & Sons. <https://doi.org/10.1002/9780470284704>

603 Geyin, M., Maurer, B. W., Bradley, B. A., Green, R. A., & van Ballegooy, S. (2021). CPT-based
 604 liquefaction case histories compiled from three earthquakes in Canterbury, New Zealand.
 605 *Earthquake Spectra*, 37(4), 2920–2945. <https://doi.org/10.1177/8755293021996367>



- 606 Guan, Z., & Wang, Y. (2022). CPT-based probabilistic liquefaction assessment considering soil
 607 spatial variability, interpolation uncertainty and model uncertainty. *Computers and Geotechnics*,
 608 141. <https://doi.org/10.1016/j.compgeo.2021.104504>
- 609 Juang, C. H., & Jiang, T. (2000). Assessing probabilistic methods for liquefaction potential
 610 evaluation. *Proceedings of Sessions of Geo-Denver 2000 - Soil Dynamics and Liquefaction 2000*,
 611 GSP 107, 295. [https://doi.org/10.1061/40520\(295\)10](https://doi.org/10.1061/40520(295)10)
- 612 Kryven, I. (2019). Bond percolation in coloured and multiplex networks. *Nature Communications*,
 613 10(1). <https://doi.org/10.1038/s41467-018-08009-9>
- 614 Lee, D., Kahng, B., Cho, Y. S., Goh, K.-I., & Lee, D.-S. (2018). Recent advances of percolation
 615 theory in complex networks. *Journal of the Korean Physical Society*, 73(2), 152–164.
 616 <https://doi.org/10.3938/jkps.73.152>
- 617
- 618 Lloret-Cabot, M., Fenton, G. A., & Hicks, M. A. (2014). On the estimation of scale of fluctuation
 619 in geostatistics. *Georisk*, 8(2). <https://doi.org/10.1080/17499518.2013.871189>
- 620
- 621 Liu, Y., Li, J., Sun, S., & Yu, B. (2019). Advances in Gaussian random field generation: A review.
 622 *Computational Geosciences*, 23(5), 1011–1047. <https://doi.org/10.1007/s10596-019-09867-y>
- 623
- 624 Maurer, B. W., Green, R. A., Cubrinovski, M., & Bradley, B. A. (2014). Evaluation of the
 625 Liquefaction Potential Index for Assessing Liquefaction Hazard in Christchurch, New Zealand.
 626 *Journal of Geotechnical and Geoenvironmental Engineering*, 140(7).
 627 [https://doi.org/10.1061/\(asce\)gt.1943-5606.0001117](https://doi.org/10.1061/(asce)gt.1943-5606.0001117)
- 628
- 629 Maurer, B. W., Green, R. A., Cubrinovski, M., & Bradley, B. A. (2015a). Fines-content effects on
 630 liquefaction hazard evaluation for infrastructure in Christchurch, New Zealand. *Soil Dynamics and*
 631 *Earthquake Engineering*, 76. <https://doi.org/10.1016/j.soildyn.2014.10.028>
- 632
- 633 Maurer, B. W., Green, R. A., Cubrinovski, M., & Bradley, B. A. (2015b). Assessment of CPT-
 634 based methods for liquefaction evaluation in a liquefaction potential index framework.
 635 *Géotechnique*, 65(5), 328–336. <https://doi.org/10.1680/geot.SIP.15.P.007>
- 636 Montgomery, J., & Boulanger, R. W. (2017). Effects of Spatial Variability on Liquefaction-
 637 Induced Settlement and Lateral Spreading. *Journal of Geotechnical and Geoenvironmental*
 638 *Engineering*, 143(1). [https://doi.org/10.1061/\(asce\)gt.1943-5606.0001584](https://doi.org/10.1061/(asce)gt.1943-5606.0001584)
- 639
- 640 Newman, M. E. J. (2010). *Networks: An introduction*. Oxford University Press.
 641 <https://doi.org/10.1093/acprof:oso/9780199206650.001.0001>
- 642
- 643 Phoon, K. K., & Kulhawy, F. H. (1999). Characterization of geotechnical variability. *Canadian*
 644 *Geotechnical Journal*, 36(4). <https://doi.org/10.1139/t99-038>



- 645 Popescu, R., Prevost, J. H., & Deodatis, G. (2005). 3D effects in seismic liquefaction of
 646 stochastically variable soil deposits. *Geotechnique*, 55(1).
 647 <https://doi.org/10.1680/geot.2005.55.1.21>
- 648 Sahimi, M. (1994). *Applications of percolation theory*. Taylor & Francis.
 649 <https://doi.org/10.1201/9781482272444>
- 650 Seed, H. B., & Idriss, I. M. (1971). Simplified procedure for evaluating soil liquefaction potential.
 651 *Journal of the Soil Mechanics and Foundations Division*, 97(9), 1249–1273.
 652 <https://doi.org/10.1061/JSFEAQ.0001662>
- 653 Stauffer, D., & Aharony, A. (2018). *Introduction to percolation theory* (2nd ed.). CRC Press.
 654 <https://doi.org/10.1201/9781315274386>
- 655 Uzielli, M., Vannucchi, G., & Phoon, K. K. (2005). Random field characterization of stress-
 656 normalised cone penetration testing parameters. *Geotechnique*, 55(1).
 657 <https://doi.org/10.1680/geot.2005.55.1.3>
- 658 Vanmarcke, E. (1983). *Random fields: analysis and synthesis*, 1983. In MIT Press, Cambridge,
 659 MA.
- 660 Vivek, B., & Raychowdhury, P. (2014). Probabilistic and spatial liquefaction analysis using CPT
 661 data: A case study for Alameda County site. *Natural Hazards*, 71(3).
 662 <https://doi.org/10.1007/s11069-013-0976-4>
 663
- 664 Youd, T. L., & Idriss, I. M. (2001). Liquefaction Resistance of Soils: Summary Report from the
 665 1996 NCEER and 1998 NCEER/NSF Workshops on Evaluation of Liquefaction Resistance of
 666 Soils. *Journal of Geotechnical and Geoenvironmental Engineering*, 127(4).
 667 [https://doi.org/10.1061/\(asce\)1090-0241\(2001\)127:4\(297\)](https://doi.org/10.1061/(asce)1090-0241(2001)127:4(297))