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Spatial Discrepancy Analysis of Minefields Established Using Different Minelaying Methods

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Abstract

This study evaluates the spatial uniformity of minefields established by different minelaying methods using discrepancy-based metrics. Scatterable, row-based, and quasi-random layouts were compared in a common 200 × 200 m area for mine counts of 60, 120, and 180. Spatial quality was assessed using star discrepancy and L_2-star discrepancy. The results showed that scatterable minefields achieved the highest discrepancy values, while row-based layouts performed substantially better. The most favorable results were obtained for quasi-random layouts generated by the Halton and Hammersley sequences, with the Hammersley sequence producing the lowest discrepancy overall. The findings support the use of discrepancy as an objective tool for evaluating UAV-assisted minelaying.

KEY WORDS: *minefield; minelaying; spatial uniformity; discrepancy; L_2-star discrepancy; star discrepancy; low-discrepancy sequences; Halton sequence; Hammersley sequence; UAV minelaying*

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1. Introduction

Minefields represent a fundamental form of explosive obstacles and, in land warfare, consist of anti-tank mines, anti-personnel mines, or their combination [1]. The use of anti-personnel mines is significantly restricted by the Ottawa Convention, which regulates their production, storage, and employment in signatory states [2]. While explosive mine obstacles may be established on land and at sea, this work focuses on land-based minefields. Contemporary conflicts have demonstrated the development of modern minelaying approaches employing a broader range of assets than traditional systems.

The establishment of minefields should not be arbitrary but must be based on the chosen minelaying method, terrain characteristics, integration with fire support systems, and the anticipated manoeuvre of friendly and adversary forces. Pre-planned minefields are primarily constructed to protect key areas and critical infrastructure, and their presence is currently most evident in border regions of states neighbouring the Russian Federation.

Under tactical conditions, minefields are established using various minelaying assets, with established theory distinguishing between manual, mechanized, remote, and scatterable minelaying. Manual and mechanized minelaying enable the establishment of regular, deterministic minefields with defined spacing between individual mines. In contrast, rapid minelaying methods, particularly rocket- and artillery-based systems, result in less regular and seemingly random mine distributions.

Because of the war in Ukraine, new minelaying methods are emerging, especially those employing unmanned systems such as UAVs and UGVs [3]. These systems reduce the risk to personnel and enable precise deployment of mines in selected terrain sections [4]. However, the development of these capabilities simultaneously highlights the lack of quantitative tools for objective evaluation of the resulting mine distributions [5].

Existing approaches primarily focus on mine density and mine type but do not allow for comparison of spatial uniformity across different minelaying methods [5]. This paper therefore introduces discrepancy as a mathematical metric expressing the degree of spatial uniformity of mine placement and applies it to the comparison of selected minelaying methods using L_2-star and star discrepancy.

2. Discrepancy as a Measure of Minefield Spatial Uniformity

Unlike conventional Monte Carlo sampling, which relies on random point generation and may lead to local clustering, quasi-Monte Carlo methods aim to generate point sets with improved spatial uniformity. In the context of numerical integration, the objective is to approximate the integral over a bounded domain D by a finite set of points $P = \{p_1, \dots, p_n\}$ while minimizing the error [6]

$$\left|\frac{1}{n}\sum_{i=1}^{n} f(p_i) - \int_D f(x)dx\right| \tag{1}$$

The theoretical basis of quasi-Monte Carlo sampling is expressed by the error bound [6]

$$\left|\frac{1}{n}\sum_{i=1}^{n} f(p_i) - \int_D f(x)dx\right| \leq M(P)V(f), \tag{2}$$

where $M(P)$ denotes the discrepancy of the point set and $V(f)$ the variation of the function f. In general terms, discrepancy may be expressed as [6]:

$$M(P) = \|F_n(x) - F(x)\| \tag{3}$$

where $F_n(x)$ is the empirical distribution function of the point set and $F(x)$ is the corresponding ideal uniform distribution over the evaluated domain. Lower discrepancy values therefore indicate a more uniform spatial distribution of points [6]. In the present study, discrepancy was used to assess the spatial uniformity of mine positions through star discrepancy and L_2-star discrepancy, with L_2-star discrepancy adopted as the primary evaluation metric.

In practical terms, discrepancy can be understood as an indicator of how evenly points (mines) are distributed across a given area (minefield) in comparison with an ideal uniform arrangement. Lower discrepancy values correspond to a more balanced spatial coverage, while higher values indicate greater unevenness, such as clustering or empty regions. Within the present study, discrepancy is therefore interpreted as a measure of the spatial uniformity of mine positions.

Discrepancy is not represented by a single universal formula, but rather by a family of specific measures that quantify non-uniformity in different ways. The reason for this distinction is that spatial irregularity can be assessed from different perspectives. Some discrepancy measures emphasize the largest local departure from an ideal uniform distribution, whereas others reflect the overall deviation of the entire point set across the domain. In this sense, the individual forms of discrepancy do not represent separate components of one quantity, but alternative ways of evaluating spatial uniformity. For the purposes of this study, star discrepancy and L_2-star discrepancy were selected because together they capture both the worst local deviation and the global overall uniformity of mine positions. [7]

Among the available discrepancy measures, star discrepancy was introduced first because it captures the maximum deviation of the point distribution from an ideal uniform arrangement. [6]

$$D^*(P) = \sup_{x\in[0,1]^d}\left|\frac{N(x,P)}{n} - v_d([0,x])\right|, \tag{4}$$

where $P = \{p_1, \dots, p_n\}$ is the evaluated point set, $N(x,P)$ is the number of points falling into the interval $[0,x]$, and $v_d([0,x])$ denotes the volume of this region. In practical terms, star discrepancy identifies the worst local mismatch between the actual point distribution and an ideal uniform distribution. It is therefore sensitive to pronounced clustering or uncovered gaps within the evaluated area [8].

A generalized form of star discrepancy is the L_p-star discrepancy, which evaluates deviations from ideal uniformity over the entire domain using an L_p-norm. In the present study, the L_2-star discrepancy was applied in the form [6]:

$$L_2^*(P) = \left\{\int_{[0,1]^d}\left|\frac{N(x,P)}{n} - v_d([0,x])\right|^2 dx\right\}^{1/2}, \tag{5}$$

where $P = \{p_1, \dots, p_n\}$ denotes the evaluated point set, $N(x,P)$ is the number of points located in the region $[0,x]$, and $v_d([0,x])$is the volume of this region. Unlike star discrepancy, which reflects the maximum local deviation, L_2-star discrepancy aggregates deviations across the whole domain and therefore provides a more global measure of spatial uniformity. For this reason, it was adopted as the primary evaluation metric in the present study. [6]

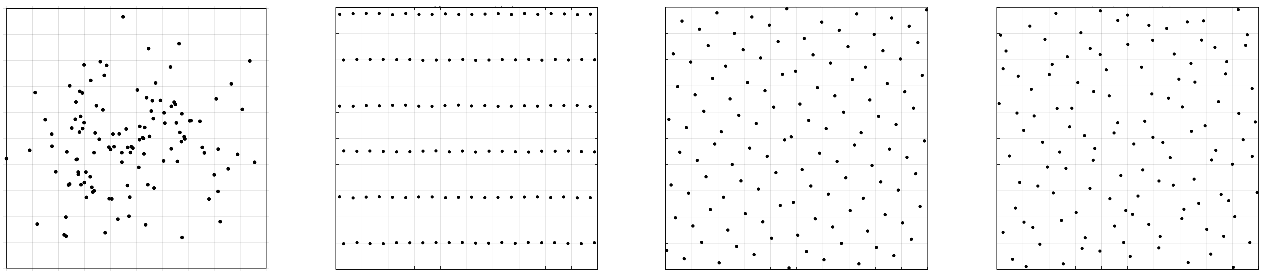
3. Methodology

The problem addressed in this study lies in the comparison of spatial uniformity achieved by different minelaying methods. A discrepancy-based evaluation approach was therefore adopted, as it enables the quantitative assessment of how evenly mines are distributed across the evaluated area and allows direct comparison among scatterable, row-based, and quasi-random layouts. All calculations were performed in MATLAB R2025b.

3.1 Evaluated minelaying categories

Three categories of minelaying were evaluated in this study, whereby the Halton and Hammersley sequences were considered two variants of the quasi-random approach. The first category was scatterable minelaying, representing remote minelaying systems, particularly rocket- and howitzer-based systems, which typically produce irregular spatial distributions of mines [9]. The second category was manual or mechanized minelaying, representing the regular placement of mines in rows by engineer units. The third category was an experimental minelaying approach based on unmanned platforms, particularly UAVs and, alternatively, UGVs, in which mine positions were generated using quasi-random sequences.

These three categories were selected to represent stochastic, regular, and quasi-random spatial patterns of mine placement under comparable evaluation conditions. In the simulation model, these categories were represented respectively by stochastic scatterable placement, regular row-based placement, and quasi-random point placement generated by low-discrepancy sequences (Fig. 1).



(a) (b) (c) (d)

Fig. 1. Illustrative examples of the evaluated minefield layouts: (a) scatterable deployment, (b) row-based deployment, (c) UAV-based minelaying using a Hammersley quasi-random sequence and (d) UAV-based minelaying using a Halton quasi-random sequence

3.2 Simulation domain and normalization

All evaluated minefield layouts were analysed within the same two-dimensional spatial domain in order to ensure direct comparability of the results. The evaluated area had fixed dimensions of 200 × 200 m for all minelaying categories and all simulated configurations. In each scenario, individual mine positions were represented as points in this bounded area.

To enable the application of standard discrepancy measures, the coordinates of mine positions were normalized to the unit square $[0,1]^2$. This transformation preserved the relative spatial arrangement of the points while removing the influence of absolute domain dimensions. As a result, both star discrepancy and L_2-star discrepancy could be computed under identical conditions for all evaluated minefield layouts. Only mine positions located within the evaluated area were included in the discrepancy analysis, while points outside the 200 × 200 m domain were excluded from further processing. This ensured that the calculated discrepancy reflected the effective spatial coverage achieved within the assessed area.

3.3 Experimental design

The analysis was carried out for three minelaying categories and three mine counts: 60, 120, and 180 mines. Each configuration was simulated in 1000 independent repetitions. For every repetition, the values of star discrepancy and L_2-star discrepancy were calculated and stored for subsequent statistical evaluation.

In total, the experimental design comprised 12 evaluated configurations and 12000 simulated minefield realizations. This structure made it possible to compare the effect of both minelaying method and mine count on the spatial uniformity of mine placement.

Scatterable minefield. For the scatterable configuration, mine positions were generated using a stochastic model intended to represent remote minelaying by rocket-based systems. The spatial distribution parameters were derived from previous observation and statistical analysis of a real minefield. Each rocket carried four mines, and the total mine counts of 60, 120, and 180 were obtained by varying the number of rockets and salvos accordingly.

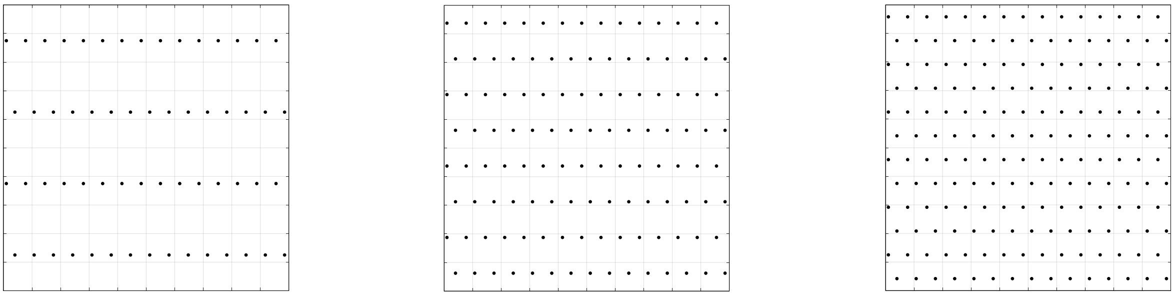
To account for variation in rocket impact locations, each impact centre was randomly displaced within a circular jitter area of radius 20 m around its reference epicentre. The mine positions associated with each rocket were subsequently generated from a bivariate normal distribution cantered at the corresponding impact point, with parameters $\sigma_x = 38.91$m, $\sigma_y = 38.97$m, and $\rho = 0.238$. This procedure yielded irregular minefield layouts corresponding to the stochastic nature of scatterable deployment. These parameters were derived from empirical observation and were therefore not selected arbitrarily.

Row minelaying. For the row-based minefield configuration, the total number of mines was specified first, and the number of rows was then fixed as 4, 8, and 12 for mine counts of 60, 120, and 180, respectively (Figure 2). The number of mines per row was kept constant at 15. The spacing between mines within a row was selected based on geometric verification in MATLAB and set to 13.5 m. Based on these predefined parameters, the inter-row spacing and the boundary offsets were subsequently derived so that the rows remained symmetrically distributed within the evaluated area.

Table 1. Geometric parameters of the row-based minefield configurations.

Number of mines	**Number of rows n**	**Mines per row**	**Inter-row spacing d_y [m]**	**Boundary offset l [m]**	**Within-row spacing d_x [m]**
60	4	15	50.0	25.0	13.5
120	8	15	25.0	12.5	13.5
180	12	15	16.67	8.33	13.5

After the nominal row-based positions had been established, each mine was additionally displaced by a random offset sampled uniformly within a circular error region of radius 2 m. This perturbation was introduced to enable repeated statistical evaluation of the row-based configuration. Without it, the layout would remain fully deterministic, and all runs would produce identical discrepancy values, leaving no variability to be represented in the boxplots. The main parameters of row minefields are listed in Table 1.



(a) (b) (c)

Fig. 2. Geometric configurations of the row-based minefield layout for: (a) 60 mines, (b) 120 mines, and (c) 180 mines.

Accordingly, mines were assumed to be placed in $n$parallel rows within a modelled area of height H. The spacing between adjacent rows was denoted by d_y, while the equal boundary offsets between the first and last rows and the field boundaries were denoted by l. Under this symmetric arrangement, the vertical geometry of the minefield was defined as

$$H = 2l + (n-1) \times d_y \tag{6}$$

where the term $(n-1) \times d_y$ represents the total distance between n rows. In this study, the inter-row spacing was set as

$$d_y = \frac{H}{n} \tag{7}$$

so that the spacing decreased proportionally with the number of rows while preserving the overall geometric character of the row-based layout. Substituting this relation into the previous equation yields

$$l = \frac{H}{2n} = \frac{d_y}{2} \tag{8}$$

The vertical position of the k-th row was then determined as

$$y_k = l + (k-1)d_y, k = 1,2,\dots,n \tag{9}$$

where y_k denotes the y-coordinate of the k-th row. This formulation does not represent a general property of all row-based minefields and has no direct doctrinal implication for real-world minefield establishment. It was introduced solely as a simplified geometric rule to unify the methodology and ensure consistent comparison of row-based layouts across different mine counts. To maintain a consistent row-based pattern across the evaluated configurations, the number of mines per row was kept constant and the total number of mines was varied by changing the number of rows.

Quasi-random sequences. For the quasi-random configuration, mine positions were generated using two-dimensional low-discrepancy sequences, specifically the Halton and Hammersley sequences, within a 200 × 200 m area. These sequences are deterministic point generators designed to cover a bounded domain more evenly than purely random placement and therefore to reduce clustering and uncovered regions [7]. For this reason, they were selected as representative models of quasi-random mine placement. [10]

In both cases, the points were not generated by independent random sampling, but by deterministic rules that gradually fill the evaluated area in a more uniform manner. The Halton sequence generates each coordinate from a different number base, which leads to a progressive distribution of points over the entire domain while avoiding excessive clustering [11]. The Hammersley sequence follows a similar principle, but one coordinate is generated systematically as an ordered subdivision of the interval, while the other is distributed using a low-discrepancy rule. As a result, both sequences produce point sets that are more evenly spread than purely random placement, although their internal construction differs [12].

For each repetition, a different block of the sequence was used. In addition, each generated point was displaced by a random offset sampled uniformly within a circular error region of radius 2 m. This positional perturbation was introduced for two reasons. First, it reflects practical emplacement constraints, since the exact intended location may not always be suitable for laying a mine under real conditions. Second, it prevents repeated evaluation of an unchanged deterministic layout. Because low-discrepancy sequences generate fixed spatial patterns, omission of this perturbation would result in identical minefield realizations and therefore identical discrepancy values across all repetitions. The perturbation thus made it possible to generate comparable but non-identical quasi-random layouts for statistical assessment. Points shifted outside the evaluated area were excluded from the discrepancy calculation, and the retained points were normalized to the unit square before computing star discrepancy and L_2-star discrepancy.

3.4 Statistical evaluation

For each simulated configuration, 1000 values of star discrepancy and 1000 values of L_2-star discrepancy were obtained from repeated runs. These values were statistically evaluated using boxplots, which enabled direct comparison of the central tendency and variability of discrepancy across the evaluated configurations.

The results were organized according to the three mine counts and the three minelaying categories, resulting in a total of 12 boxplot comparisons for each evaluated discrepancy measure. In the interpretation of results, L_2-star discrepancy was treated as the primary metric of overall spatial uniformity, while star discrepancy served as a complementary indicator of the worst local deviation.

4. Results

The results of the discrepancy analysis are presented in this section using boxplots and summary statistics for all evaluated configurations. The comparison focuses on the influence of both minelaying method and mine count on the spatial uniformity of mine placement. Since L_2^* was adopted as the primary metric of overall spatial uniformity and D^* as a complementary indicator of the worst local deviation, the results are presented separately for each measure and then summarized in a common numerical table.

4.1 L_2-star discrepancy across methods and mine counts

Figure 3 presents the distribution of L_2-star discrepancy values for all evaluated minelaying methods and mine counts. A consistent decrease in L_2-star discrepancy can be observed with increasing number of mines in all configurations, indicating improved spatial uniformity as the minefield becomes denser. However, substantial differences remained between the individual minelaying methods.

The scatterable configurations achieved the highest L_2-star discrepancy values across all three mine counts and therefore exhibited the lowest level of spatial uniformity. Although a slight improvement was observed as the number of mines increased from 60 to 180, the overall discrepancy remained markedly higher than in all other methods evaluated. This confirms that simple densification of a scatterable minefield does not remove the inherent irregularity of its stochastic spatial pattern.

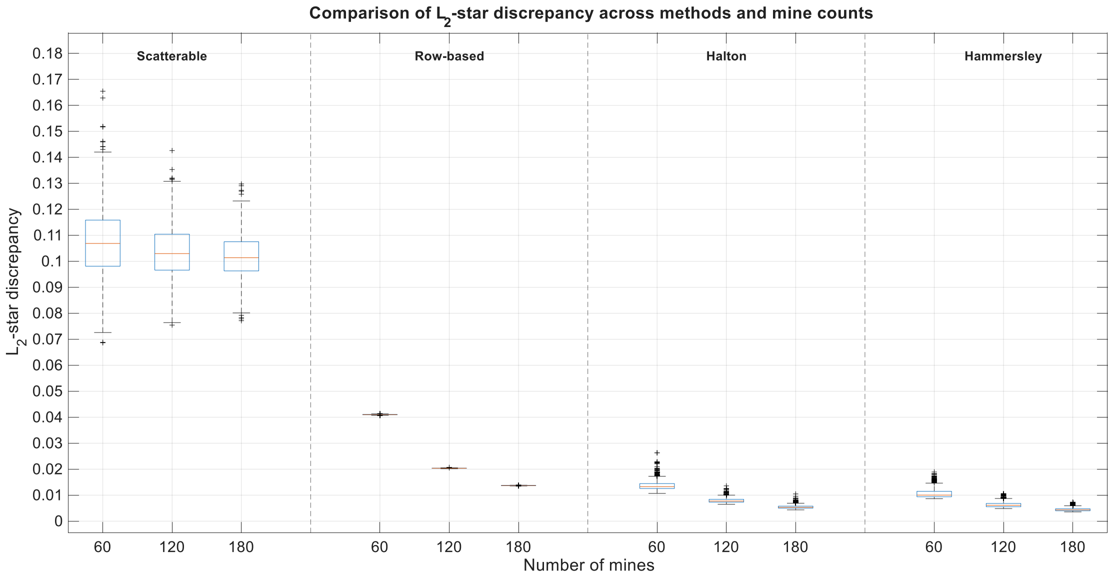


Fig. 3. Comparison of L_2-star discrepancy across minelaying methods and mine counts.

The row-based layouts produced substantially lower L_2-star discrepancy values than the scatterable configurations. At the same time, the discrepancy decreased systematically with increasing mine count, reflecting the more regular geometric structure of the row-based arrangement and its progressively denser coverage of the evaluated area.

Both quasi-random approaches outperformed the row-based layouts and achieved the lowest L_2-star discrepancy values overall. In both the Halton- and Hammersley-based configurations, discrepancy values decreased further as the number of mines increased. Among the evaluated methods, the Hammersley sequence yielded the lowest L_2-star discrepancy across all mine counts, followed by the Halton sequence. This indicates that quasi-random layouts, particularly those based on the Hammersley sequence, provided the highest overall spatial uniformity of mine placement in the present study.

4.2 Star discrepancy across methods and mine counts

Figure 4 confirms the trends observed for L_2-star discrepancy. Star discrepancy decreased with increasing mine count for all evaluated methods, while the overall ranking remained unchanged. Scatterable deployment consistently produced the highest values, indicating the largest local deviations from ideal uniformity. Row-based layouts performed substantially better, and both quasi-random approaches achieved the lowest values overall. Among them, the Hammersley-based layouts again yielded the best results. These findings indicate that the quasi-random configurations were superior not only in terms of global spatial uniformity, but also with respect to the worst local irregularities.

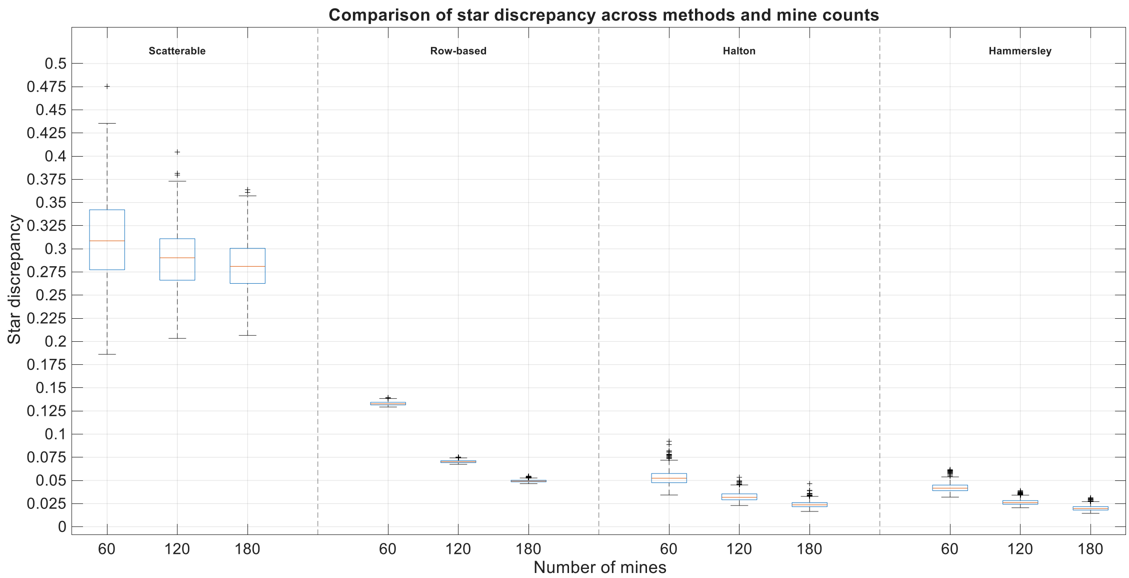


Fig. 4. Comparison of star discrepancy across minelaying methods and mine counts.

Table 2 provides the exact median and interquartile range values for both L_2^* and D^* across all evaluated configurations. These values confirm the trends visible in Figures 3 and 4, namely the highest discrepancy for scatterable deployment and the lowest values for the Hammersley-based quasi-random layouts.

Table 2. Median and interquartile range (IQR, i.e., the spread of the middle 50% of values) of L_2^* and D^* across the evaluated configurations.

Method	Mines	Median L_2^*	IQR L_2^*	Median D^*	IQR D^*
Scatterable	60	0.106874	0.017675	0.308632	0.064701
Scatterable	120	0.102966	0.013819	0.290338	0.044780
Scatterable	180	0.101368	0.011215	0.281041	0.037886
Row-based	60	0.041648	0.000069	0.135451	0.001334
Row-based	120	0.021066	0.000049	0.073249	0.001019
Row-based	180	0.014447	0.000041	0.052400	0.000873
Halton	60	0.013513	0.002089	0.053411	0.010721
Halton	120	0.008063	0.001222	0.033657	0.006831
Halton	180	0.005721	0.000843	0.025747	0.004695
Hammersley	60	0.010020	0.002118	0.041668	0.006092
Hammersley	120	0.006104	0.001279	0.026124	0.003925
Hammersley	180	0.004334	0.000769	0.019608	0.003700

5. Discussion

The presented results support the use of discrepancy-based evaluation for assessing minefield layouts established by different minelaying methods. In particular, they help clarify why quasi-random sequences should be considered in combat engineering, especially in obstacle employment and minefield establishment. In contemporary conflicts, unmanned aerial vehicles are increasingly employed for minelaying tasks, yet their doctrinal use still does not fully reflect their technical and tactical potential. In this respect, the present findings suggest that UAV-assisted minelaying may enable spatial deployment patterns extending beyond those assumed in the current doctrinal framework. [13]

The contrast between the evaluated layouts was most pronounced for scatterable deployment. Minefields established by remote or scatterable means are inherently stochastic, so increasing the number of mines does not necessarily lead to a proportional improvement in spatial coverage. Instead, clustering and uncovered gaps remain present across the evaluated area. As a result, scatterable configurations consistently produced the least favourable discrepancy values. Even with 180 mines, the improvement was limited because the stochastic character of the layout remained unchanged. Their main advantage therefore lies in deployment speed and tactical flexibility rather than spatial regularity.

Row-based minelaying follows the opposite principle. Rather than probabilistic placement, it relies on a predefined geometric arrangement in which each mine has a nominal position. This deterministic structure resulted in substantially lower discrepancy values than scatterable deployment. Discrepancy also decreased systematically with increasing mine count and number of rows, indicating improved spatial uniformity as the layout became denser. Even so, the 180-mine configuration did not achieve the best overall results, which suggests that a regular row-based pattern, although clearly superior to stochastic scatterable placement, is still not the most effective arrangement for maximizing spatial uniformity.

The most favourable results were obtained for the quasi-random layouts. This corresponds to the purpose of low-discrepancy sequences, which are designed to distribute points over a bounded domain as evenly as possible. Their advantage is that they avoid both the clustering typical of scatterable deployment and the rigid linear structure of row-based layouts. In this sense, quasi-random layouts combine deterministic generation with more balanced spatial coverage. Within this group, the Hammersley sequence achieved lower discrepancy values than the Halton sequence across all mine counts, indicating the most favourable spatial distribution under the adopted modelling assumptions.

After the introduction of local positional perturbation, the quasi-random layouts exhibited greater variability than the row-based configurations, but they still retained substantially lower discrepancy values overall. This variability should not be interpreted as inferior spatial quality. Rather, it reflects the fact that row-based layouts remained strongly constrained by their underlying geometry, whereas quasi-random layouts were generated from different sequence blocks and then locally perturbed, producing a broader set of non-identical realizations. Even under these conditions, the quasi-random layouts consistently achieved the lowest median values of both discrepancy measures.

An important finding is that both discrepancy measures produced the same ordering of the evaluated methods. Whereas L_2^* reflects the global spatial uniformity of the entire point set, D^* captures the worst local deviation from ideal uniformity. Their agreement therefore strengthens the robustness of the conclusions, showing that the superiority of the quasi-random layouts was manifested both at the level of overall spatial coverage and at the level of the largest local irregularities. From the perspective of minefield assessment, L_2^* may be regarded as the more informative primary metric, because it better represents the overall quality of spatial coverage across the full evaluated area. By contrast, D^* is most useful as a complementary indicator, since it highlights the most pronounced local irregularity within an otherwise broader spatial pattern.

Limitations. The present study has several limitations. It evaluated only the spatial uniformity of mine placement and not the full combat effectiveness of the resulting minefields. All configurations were analysed in a simplified two-dimensional area of fixed size, which does not reflect the complexity of real terrain and tactical conditions. The row-based layout was based on a study-specific geometric rule and should not be interpreted as a doctrinal standard. In addition, the quasi-random approach was represented only by the Halton and Hammersley sequences. The conclusions are therefore limited to the selected mine counts, evaluated area, and perturbation assumptions adopted in this study.

6. Conclusions

This study demonstrated that discrepancy-based metrics provide a suitable quantitative tool for evaluating the spatial uniformity of minefield layouts established by different minelaying methods. The obtained results showed clear and consistent differences between the evaluated approaches. Scatterable deployment produced the highest values of both L_2^* and D^*, indicating the lowest spatial uniformity and the greatest local irregularity. Row-based layouts achieved substantially better results but were still outperformed by quasi-random configurations. Among the evaluated quasi-random generators, the Hammersley sequence produced the lowest discrepancy values across all mine counts, followed by the Halton sequence. These results indicate that quasi-random placement can provide more uniform spatial coverage than both stochastic scatterable deployment and regular row-based layouts.

An important finding is that both discrepancy measures led to the same ordering of methods. Since L_2^* reflects global spatial uniformity and D^* captures the worst local deviation from ideal uniformity, their agreement strengthens the robustness of the conclusions. From the perspective of combat engineering, the presented results support the view that quasi-random sequences may represent a promising analytical and design tool for UAV-assisted minelaying, especially in situations where even spatial coverage is required than can be achieved by conventional scatterable deployment. The results therefore confirm the relevance of discrepancy as an objective metric for comparing minefield layouts and suggest that low-discrepancy sequences, particularly the Hammersley sequence, deserve further attention in future research on UAV-based obstacle emplacement.

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References

1. **Bilina M., Hasilová K., Žižka P.** Impact of Minefield Rows Spacing on Vehicle Hit Probability in a Simulated Minefield, 2025 International Conference on Military Technologies (ICMT).
2. **United Nations**, Treaty Series , vol. 2056, p. 211; C.N.163.2003.TREATIES-2 of 3 March 2003.
3. **Hrnčiar M., Kompan J., Nohel J.** The future of the battlefield: Technology-driven predictions in the land domain, Revista Científica General José María Córdova, 2025, vol. 23(49), p.277–296.
4. **Bogdanov P., Marinov M**. Combat Use of Remotely Operated Systems on the Tactical Level Based on the Conflict in Ukraine, Georgi Benkovski Higher Military Air Force School, 2024.
5. **Bilina M., Hasilová K., Palasiewicz T.** Drone Swarming and its Use in Minefield Laying Using Mathematical Methods, Challenges to National Defence in Contemporary Geopolitical Situation, 2024, vol. 1, no. 1.
6. **Hung Y. -C.** A review of Monte Carlo and quasi-Monte Carlo sampling techniques, WIREs Computational Statistics, 2023, vol. 16, no. 1.
7. **Drmota M.** The discrepancy of generalized Van-der-Corput–Halton sequences, Indagationes Mathematicae, 2015, vol. 26, no. 5.
8. **Estrada E.** Quasirandom geometric networks from low-discrepancy sequences, Physical Review E, 2017, vol. 96, no. 2.
9. **Blaha M., Šilinger K., Potužák L., Přikryl B**. Perspective Method for Determination of Fire for Effect in Tactical and Technical Control of Artillery Units, Proceedings of the 13th International Conference on Informatics in Control, Automation and Robotics, 2016.
10. **Pillichshammer F.** On the -Discrepancy of the Hammersley Point Set, Monatshefte für Mathematik, 2002, vol. 136, no. 1.
11. **Kirk M., Lemieux C.** An Improved Halton Sequence for Implementation in Quasi-Monte Carlo Methods, 2024, Winter Simulation Conference (WSC).
12. **Faure H., Pillichshammer F.** L p discrepancy of generalized two-dimensional Hammersley point sets, Monatshefte für Mathematik, 2008, vol. 158, no. 1.
13. **Bilina M., Bilinová I., Palasiewicz T., Žižka P., Grufík M.** Developments in Establishment of Minefields by UAVs: A Response to Conflict in Ukraine, 2025, International Conference on Military Technologies, Brno: Institute of Electrical and Electronics Engineers (IEEE).