The multi-criteria decision approach for dense point cloud fusion - the case study of wooden cultural heritage objects

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Abstract: This study presents a methodology for dense point cloud fusion based on Multi-Criteria Decision-Making (MCDM) techniques, applied to heritage documentation. Photogrammetric reconstruction was conducted using both classical Multi-View Stereo (MVS) algorithms, including Agisoft Metashape, RealityScan, and OpenMVS, as well as a learning-based method (VIS-MVS Net). UAV imagery of historical buildings from the Museum of the Kielce Countryside served as input data, while terrestrial laser scanning (TLS) provided reference datasets. Point cloud quality was evaluated based on completeness, density, and geometric accuracy, with additional metrics assessing surface roughness, planarity, and variance. The proposed fusion approach employed the CRITIC method to assign objective weights to geometric descriptors and used TOPSIS and OWA algorithms to compute point quality scores and merge multiple datasets. The MCDM-based fusion method effectively integrated point clouds of varying origins, preserving structural fidelity and surface smoothness while compensating for missing data. The developed methodology provides a systematic and objective framework for integrating multi-source point clouds, supporting advanced heritage documentation and metrological applications.

1. Introduction

The application of photogrammetry for heritage documentation has a long-established history (Stylianidis & Remondino, 2017). Over the past few decades, photogrammetry has experienced a resurgence of interest, primarily due to significant advancements in image processing technology. Traditionally associated with generating 3D vector drawings, photogrammetry has evolved to generate dense point clouds and 3D meshes, requiring less user interaction. The emergence of Multi-View Stereo (MVS) methods has enabled the generation of dense point clouds from photogrammetric data. However, challenges remain, particularly in texture-less or reflective surfaces, due to MVS's reliance on hand-crafted pixel-level features, which can lead to ambiguity. Researchers have attempted to address these limitations through semantic constraints (e.g., Murtiyoso et al., 2022; Stathopoulou et al., 2021) and, more recently, through learning-based approaches (e.g., Stathopoulou and Remondino, 2023).

MVS has a well-established role in heritage documentation (Grilli and Remondino, 2019; Murtiyoso and Grussenmeyer, 2017), and several studies have explored the potential of learning-based methods (Wei et al., 2020). In this context, the present paper aims to analyse the application of classical and deep learning-based methods for generating dense point clouds of heritage objects. The following approaches were examined: (1) classical MVS algorithms implemented in commercial software such as Agisoft Metashape, RealityScan, as well as in the open-source library OpenMVS; and (2) a learning-based approach implemented in the VIS-MVS Net library.

In this work, we propose a point cloud fusion method based on parameters characterising the properties of the clouds, employing Multi-Criteria Decision-Making (MCDM) techniques (Triantaphyllou, 2000). Specifically, we utilise methods such as TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and OWA (Ordered Weighted Averaging), which enable systematic evaluation and aggregation of multiple criteria to support robust, objective decision-making during the fusion process.

2. Related Works

Image-based reconstruction has become a mainstay for three-dimensional documentation of architecture and cultural heritage, with SfM–MVS delivering dense point clouds efficiently and at low cost using cameras (Storeide et al., 2023; Markiewicz et al., 2025). Yet the geometric quality of purely photogrammetric point clouds is sensitive to illumination, texture, and network geometry, often yielding non-uniform density, gaps, and elevated noise (Schonberger & Frahm, 2016; Markiewicz et al., 2024).

Terrestrial laser scanning (TLS) offers high accuracy and stable geometry, typically producing homogeneous point distributions; however, it comes at a higher cost and requires longer acquisition and processing times, particularly for complex objects that necessitate multi-station campaigns and demanding registration (Shaojing et al., 2025).

These trade-offs are acute for wooden heritage, where irregular geometry, intricate details, and variable reflectance, often affected by ageing, complicate both imaging and scanning. Photogrammetry may introduce artefacts and discontinuities, whereas TLS, despite its accuracy, can lack completeness or rich colour. Comparative assessments confirm that no single technique ensures completeness, uniform density, and geometric stability simultaneously (Capolupo, 2021).

Consequently, growing attention is given to multi-sensor integration (e.g., TLS + UAV), which can leverage complementary strengths while mitigating individual weaknesses. Integration frameworks demonstrate gains in completeness and geometric quality, but also reveal practical limitations in registration and data harmonisation (Abdelazeem et al., 2021). Studies further show that fusing photogrammetric and TLS point clouds can reduce duplication and noise while preserving structural detail. For example, weighted spatial fusion, which combines local and global information, has been proposed for heterogeneous datasets (Abdelazeem et al., 2021; Poku-Agyemang et al., 2025).

Robust quality assessment is pivotal for such fusion. Commonly used indicators quantify completeness, density, and geometric accuracy (often via cloud-to-cloud or cloud-to-mesh comparisons against a TLS reference), which underpin many SfM–MVS vs TLS evaluations in heritage contexts (Capolupo, 2021). Beyond these global metrics, local descriptors, e.g., surface roughness, planarity, and local variance, characterise geometric quality without explicit references and support no-reference assessment that exploits density, colour cues, and angular consistency (e. g., Weinmann et al., 2017).

Despite the wide range of available quality indicators, most existing studies analyse individual metrics separately or limit their assessment to simple comparisons. Approaches in which multiple quality criteria are formally integrated into a single, coherent decision-making process that enables the selection or weighting of points from different data sources are rarely encountered. In particular, there is a lack of methods that provide an objective determination of the relative importance of individual criteria and a formal procedure for selecting points of the highest geometric quality in the context of point cloud fusion.

Current fusion practices are largely algorithmic, relying on ICP variants, voxel-based merging, confidence maps, or heuristic density/distance filters, as well as reconstruction-oriented pipelines (e.g., MLS or Poisson Surface Reconstruction) that tend to smooth data rather than truly fuse measurements (Cui et al., 2020; Grifoni et al., 2024; Sutherland et al., 2023). A common limitation is the absence of a formal mechanism that simultaneously accounts for multiple quality criteria and their interrelationships, which complicates generalisation across datasets of varying provenance and quality.

Multi-Criteria Decision Making (MCDM) directly addresses such problems by balancing competing criteria through explicit weighting. In TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), alternatives are ranked by distance to ideal and anti-ideal solutions, while OWA (Ordered Weighted Averaging) aggregates ordered criterion values to control optimism vs pessimism. MCDM has a strong record in GIS, spatial data quality analysis, and algorithm selection (Malczewski et al., 2003; Ramya & Devadas, 2019), yet remains underexplored for 3D point-level quality analysis. Introducing objective weighting, such as CRITIC, in combination with ranking and compromise procedures (e.g., TOPSIS, OWA), offers a principled approach to fusing heterogeneous point clouds while accounting for their uneven geometric quality. This opportunity motivates the present study.

3. The methodology of data processing

3.1 Test site description

The dataset used for the analysis consisted of images of historical buildings from the Museum of the Kielce Countryside, captured using the DJI Mini 2 Unnamed Aerial Vehicle (UAV). Reference data included point clouds obtained from terrestrial laser scanning (TLS) using a Leica BLK 360. For evaluation purposes, four Test Sites (Fig. 1) representing different geometries, sizes, and structural complexities were selected: (1) a wooden church from Rogów, erected in log construction made of larch wood on oak foundations, with slender twin, and (2) a brick-and-wood manor granary from Rogów, featuring a mixed masonry and timber construction. Each case study presents distinct challenges related to 3D reconstruction, particularly concerning hand-crafted MVS.

Figure 1. Test Sites: (1) Church from Rogów; (2) Manor granary from Rogów. [source: fotopolska.eu]

3.2 MCDM approach to point cloud fusion

The proposed fusion methodology integrates MCDM techniques, specifically TOPSIS and OWA, to identify the most suitable points for data fusion. In the initial stage, each point cloud is characterised by a set of auxiliary geometric descriptors normalised to the range [0, 1]. These descriptors include roughness, planarity, linearity, surface variance, and curvature. The relative importance of each descriptor is subsequently determined automatically using the CRITIC (Criteria Importance Through Intercriteria Correlation) method, which establishes objective weighting factors based on the contrast and mutual correlation of the criteria. After weighting, each point is evaluated within the [0, 1] interval using an MCDM approach to obtain a final point quality score.

The process of determining the point quality score on the example of the TOPSIS method:

1. **Construction of a decision matrix**

The process begins by constructing a decision matrix, where each row represents the value of normalised parameters *for a point.*

2. **Decision matrix weighting**

For each parameter, the weight is computed using the CRITIC method:

$$w_j = \frac{\sigma_j \sum_{k=1}^{m}(1 - r_{jk})}{\sum_{l=1}^{m}\left(\sigma_l \sum_{k=1}^{m}(1 - r_{lk})\right)} \quad (1)$$

Each point parameter value is multiplied by the corresponding weight.

$$v_{ij} = w_j \, x_{ij} \quad (2)$$

3. **Estimation of the Ideal and Anti-Ideal solutions**

The Ideal point A+ and Anti-Ideal point A- can be defined as:

$$A^+ = \{\max(v_{1j}, v_{2j}, \ldots, v_{nj})\} \text{ for each } j \quad (3)$$

$$A^- = \{\min(v_{1j}, v_{2j}, \ldots, v_{nj})\} \text{ for each } j \quad (4)$$

4. **Distance to ideal solution calculation**

The Euclidean distances of each point to Ideal and Anti-Ideal points are computed using:

$$D_i^+ = \sqrt{\sum_j (v_{ij} - A_j^+)^2}, \quad (5)$$

$$D_i^- = \sqrt{\sum_j (v_{ij} - A_j^-)^2} \quad (6)$$

5. **Points ranking**

Each point is ranked by proximity to the ideal solution.

$$S_i^{\mathrm{TOPSIS}} = \frac{D_i^-}{D_i^+ + D_i^-} \quad (7)$$

The point cloud is then voxelised, and within each voxel, the *n* highest-ranked points are selected according to their computed scores to form the final set of candidate fusion points.

3.3 The proposed methodology of data processing

To conduct a comprehensive assessment of the effectiveness of point cloud fusion, the following selected criteria were analysed: (1) completeness of the resulting point cloud, (2) point cloud density, (3) accuracy of shape representation (including planarity, surface roughness and normal vector variance).

The planarity metric measures how closely points in a local neighbourhood lie on a two-dimensional plane. It is derived from the eigenvalues of the covariance matrix computed from the 3D coordinates of those points. Planarity values range from 0 (poor) to 1 (ideal), with higher values indicating better alignment of points to a plane.

The surface roughness parameter describes elevation variation among neighbouring points. It helps identify spatial irregularities and potential noise in the point cloud. In this study, higher roughness values may indicate artefacts or inconsistencies. Roughness is typically calculated as the deviation of points from the best-fit plane, often linked to the smallest eigenvalue.

Normal Vector Variance is a geometric descriptor that measures the angular variability of surface normals within a local neighbourhood. It serves as an indicator of surface smoothness or irregularity: (1) low variance denotes a smooth, planar surface with consistent normal directions; (2) high variance suggests surface roughness, noise, or complex geometries such as edges or corners.

4. Results

4.1 The quality assessment of the MVS point clouds generated with different algorithms

The initial analysis involved a visual assessment of the generated point clouds (Figs 2 and 3) to evaluate the completeness and accuracy of the shape representation. Based on the studies conducted, it can be clearly concluded that the worst results were obtained for the point cloud generated using the learning-based VIS-MVS Net algorithm. When analysing the remaining point clouds, it is evident that all methods allow for a complete or nearly complete reconstruction of the body and roof of the analysed test sites.

Software/Methods	Number of points in point clouds	
	1st test site	2nd test site
Agisoft Metashape	7 865 239	7 787 974
RealityScan	6 902 507	3 073 691
OpenMVS-PB	8 617 532	2 487 299
VIS-MVS Net	15 283 960	14 883 959
TLS	15 369 676	10 421 207

Table 1. Number of points in the difference point clouds

Table 1 presents the number of points in the dense point clouds from TLS and generated using different MVS methods. The VIS-MVS Net algorithm produced the most points, suggesting a high level of detail. However, this did not translate into better reconstruction quality, as shown in Figures 2 and 3.

OpenMVS-PB achieves the best shape fidelity, followed by Agisoft Metashape and RealityScan, while VIS-MVS Net shows the highest variability. These findings underscore the significance of algorithm selection for applications that require precise surface geometry, such as heritage documentation or structural analysis.

(a) Agisoft Metashape (b) RealityScan (c) OpenMVS-PB (d) VIS-MVS Net (e) TLS

Figure 2. Visual assessment of point cloud quality - Test Site 1

(a) Agisoft Metashape (b) RealityScan (c) OpenMVS-PB (d) VIS-MVS Net (e) TLS

Figure 3. Visual assessment of point cloud quality - Test Site 2

4.2 The quantitative result of point cloud fusion with OWA and TOPSIS approaches

Previously, all point clouds from MVS methods (OpenMVS-PBM, OpenMVS-SGM, Agisoft Metashape, or RealityScan) were merged, excluding the VIS-MVS Net cloud, which is characterised by high noise. Subsequently, using the same parameters, the VIS-MVS Net cloud was added to the previously fused dataset. Finally, the TLS-derived point cloud was incorporated similarly. Figures 4, 5, 6, and 7 present the classification points in fused point clouds obtained using the OWA and TOPSIS approaches, illustrating which points were selected from each source dataset.

Table 2 presents the number of points in the fused dense point clouds. OWA and TOPSIS select nearly identical proportions of points across datasets, indicating similar effectiveness of both methods. Additionally, configurations that fuse multiple data sources consistently yield the highest point counts, showing that multimodal merging most strongly enriches the final point clouds.

Dataset	Number of points in point clouds fusion – Test Site 1	
	OWA	TOPSIS
MVS Fusion	6 876 097	6 876 097
MVS+TLS	13 076 811	13 076 730
MVS+VIS-MVS NET	12 919 858	12 919 855
MVS+VIS-MVS NET+TLS	17 060 514	17 361 839

Dataset	Number of points in point clouds fusion – Test Site 2	
	OWA	TOPSIS
MVS Fusion	7 403 934	7 403 934
MVS+TLS	11 366 491	11 366 491
MVS+VIS-MVS NET	9 801 367	9 801 367
MVS+VIS-MVS NET+TLS	12 905 517	12 992 506

Table 2. Number of points in the point clouds after fusion

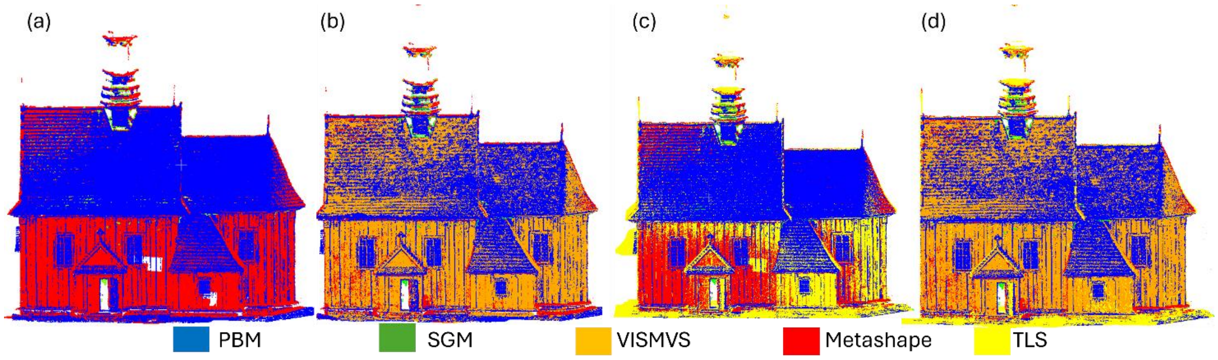


Figure 4. Point classification according to source clouds – Test Site 1 and fusion method OWA (a) OpenMVS -PB, SGM and Agisoft (Hand-crafted - HC MVS), (b) HC-MVS with VIS Net, (c) HC-MVS with TLS and (d) All MVS point cloud with TLS

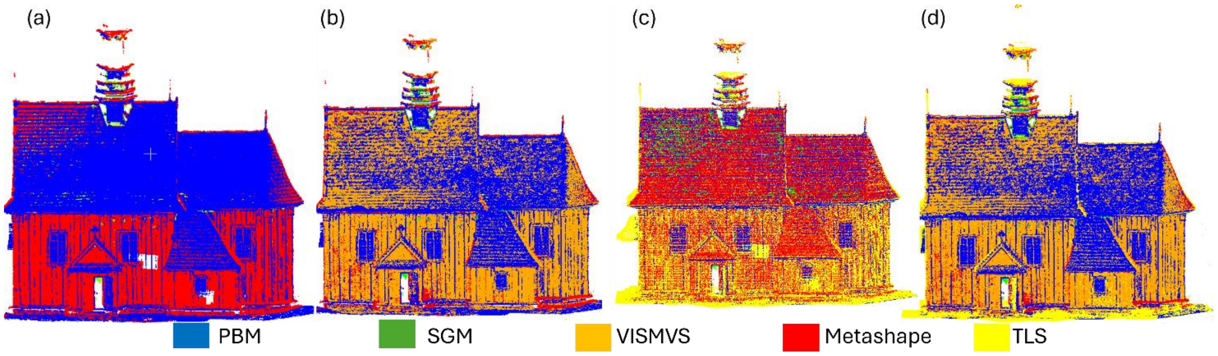


Figure 5. Point classification according to source clouds – Test Site 1 and fusion method TOPSIS (a) OpenMVS -PB, SGM and Agisoft (Hand-crafted - HC MVS), (b) HC-MVS with VIS Net, (c) HC-MVS with TLS and (d) All MVS point cloud with TLS

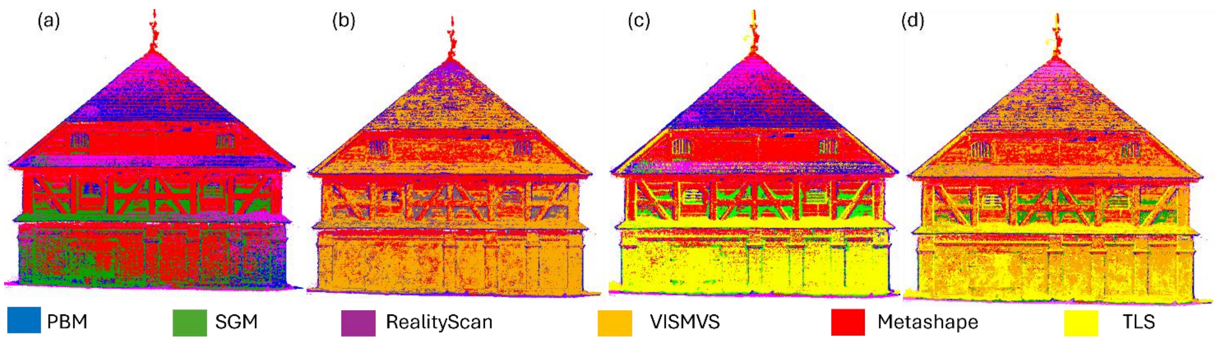


Figure 6. Point classification according to source clouds -Test Site 2 and fusion method OWA (a) OpenMVS -PB, SGM and Agisoft (Hand-crafted - HC MVS), (b) HC-MVS with VIS Net, (c) HC-MVS with TLS and (d) All MVS point cloud with TLS)

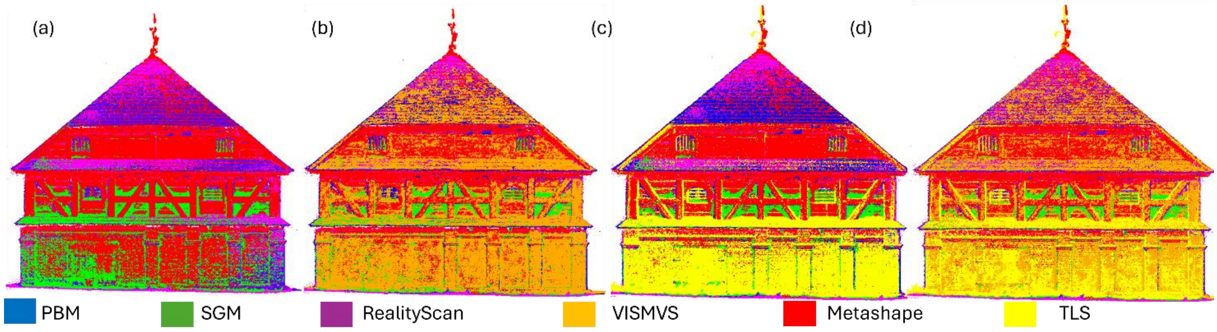
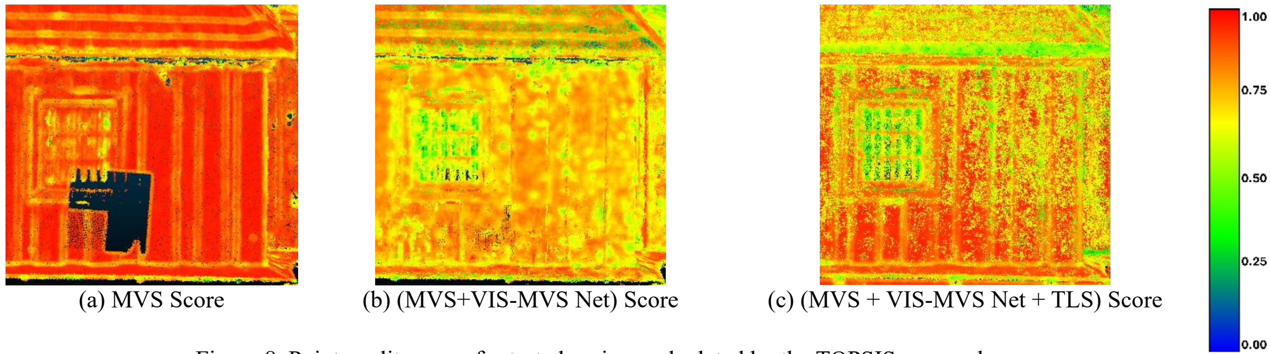


Figure 7. Point classification according to source clouds -Test Site 2 and fusion method TOPSIS (a) OpenMVS -PB, SGM and Agisoft (Hand-crafted - HC MVS), (b) HC-MVS with VIS Net, (c) HC-MVS with TLS and (d) All MVS point cloud with TLS)



(a) MVS Score (b) (MVS+VIS-MVS Net) Score (c) (MVS + VIS-MVS Net + TLS) Score

Figure 8. Point quality score for tested regions calculated by the TOPSIS approach.

4.3 The qualitative result of point cloud fusion with OWA and TOPSIS approaches

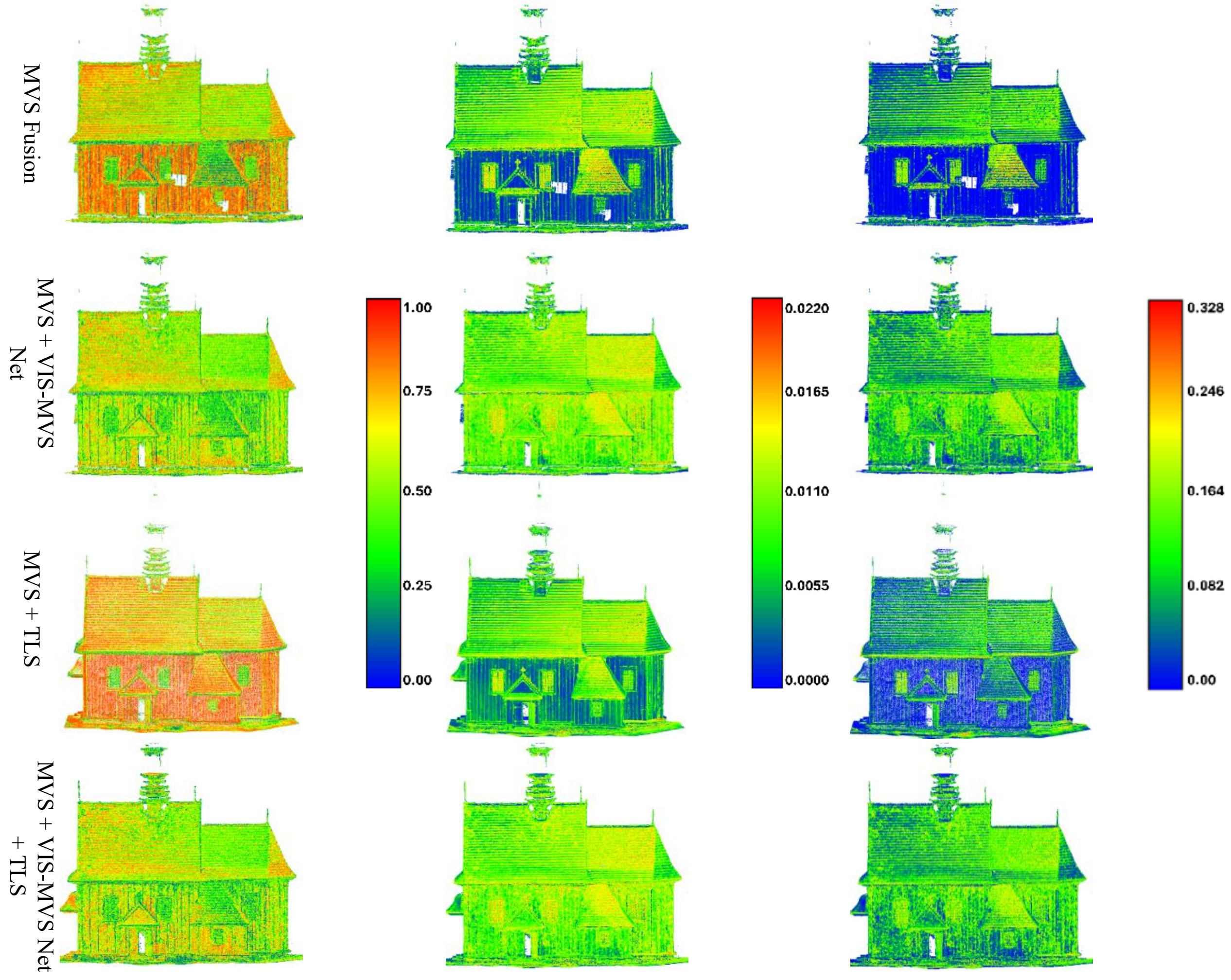
To assess the quality of the fusion, test regions were designated within the point clouds. In these regions, points were removed, noise was introduced, and cloud density was modified (Figure 8). These fields served as a basis for evaluating the fusion of multiple point clouds. Additionally, the quality parameters, namely planarity, surface roughness, and normal vector variance, were computed for the final fused point clouds. The comparative analysis was presented in Table 3 and Figures 9 and 10. The graphical results are presented only for the TOPSIS approach.

For Test Site 1, the results in Table 3 show that TOPSIS are characterised by higher planarity values than OWA across all variants; typically increasing the mean planarity by 0.002 – 0.007. The median values follow the same trend, confirming a systematic, albeit small, advantage of TOPSIS in surface flatness representation. In terms of roughness, both OWA and TOPSIS yield near-identical means and medians, with differences visible only to the fourth decimal place, indicating that the choice of decision strategy does not materially affect local surface irregularities for this dataset. The surface variance parameter also shows a slight improvement under TOPSIS across all variants, with mean values reduced by approximately 0.001–0.002 compared with OWA. Standard deviations (σ) for all three parameters remain very similar between the two methods, indicating comparable internal variability and stable distributions. Overall, for Test Site 1, TOPSIS provides slightly better geometric consistency, particularly in planarity and surface variance. Still, the improvement is limited, and MVS Fusion remains the best-performing configuration across methods.

For Test Site 2, the differences between OWA and TOPSIS are slight but consistent. As in Test Site 1, TOPSIS achieves slightly higher planarity values, with mean differences on the order of 0.001 – 0.004. Roughness values show minimal deviation between the two methods, with means and medians essentially identical (variations occur at the fourth decimal place). The surface variance metric shows minimal improvement under TOPSIS, typically lowering the mean by 0.001–0.002 while maintaining nearly identical standard deviations. Across all variants, these differences do not exceed levels that would meaningfully change the interpretation of reconstruction quality.

As in Test Site 1, the ranking of variants remains unchanged: MVS Fusion achieves the best overall balance of planarity, roughness, and surface variance for both OWA and TOPSIS. Thus, for Test Site 2, TOPSIS offers a slight but consistent advantage, particularly in planarity and surface variance, while roughness remains effectively unaffected by the choice of method.

Across both datasets, TOPSIS performs marginally better than OWA in planarity and surface variance, while roughness remains nearly identical between the two methods. However, the differences are minor in magnitude and do not change the hierarchy among merging variants. In all cases, MVS Fusion remains the highest-quality solution, regardless of dataset or aggregation method.



(a) planarity (b) roughness (c) surface variance

Figure 9. Shape variance analysis of point cloud quality after fusion - Test Site 1 (TOPSIS)

Test site	Method	Fusion approach	Planarity			Roughness			Surface_var		
			Mean	Median	Standard dev. (σ)	Mean	Median	Standard dev. (σ)	Mean	Median	Standard dev. (σ)
1	OWA	MVS Fusion	0.718	0.772	0.195	0.0078	0.0075	0.0043	0.064	0.047	0.059
		MVS+TLS	0.716	0.773	0.193	0.0082	0.0077	0.004	0.067	0.049	0.058
		MVS+VIS-MVS NET	0.671	0.709	0.163	0.0103	0.0102	0.003	0.093	0.085	0.05
		MVS+VIS-MVS NET+TLS	0.68	0.721	0.176	0.0099	0.0099	0.0036	0.088	0.079	0.056
	TOPSIS	MVS Fusion	0.72	0.774	0.195	0.0078	0.0075	0.0043	0.064	0.047	0.059
		MVS+TLS	0.719	0.776	0.193	0.0082	0.0077	0.004	0.067	0.049	0.058
		MVS+VIS-MVS NET	0.674	0.712	0.162	0.0103	0.0102	0.003	0.092	0.083	0.05
		MVS+VIS-MVS NET+TLS	0.687	0.727	0.173	0.0098	0.0098	0.0035	0.086	0.078	0.054
2	OWA	MVS Fusion	0.786	0.835	0.152	0.0068	0.0064	0.0028	0.044	0.033	0.038
		MVS+TLS	0.701	0.769	0.201	0.0093	0.0086	0.0039	0.08	0.06	0.061
		MVS+VIS-MVS NET	0.748	0.791	0.147	0.0086	0.0084	0.0028	0.066	0.057	0.041
		MVS+VIS-MVS NET+TLS	0.678	0.739	0.193	0.0102	0.0097	0.0037	0.092	0.077	0.06
	TOPSIS	MVS Fusion	0.787	0.835	0.151	0.0068	0.0064	0.0028	0.044	0.033	0.038
		MVS+TLS	0.703	0.77	0.199	0.0092	0.0086	0.0039	0.08	0.06	0.062
		MVS+VIS-MVS NET	0.751	0.793	0.145	0.0085	0.0083	0.0028	0.065	0.056	0.04
		MVS+VIS-MVS NET+TLS	0.682	0.741	0.19	0.0101	0.0097	0.0037	0.092	0.076	0.06

Table 3. Summary of geometric quality metrics (planarity, roughness, and surface variance) for all merging variants

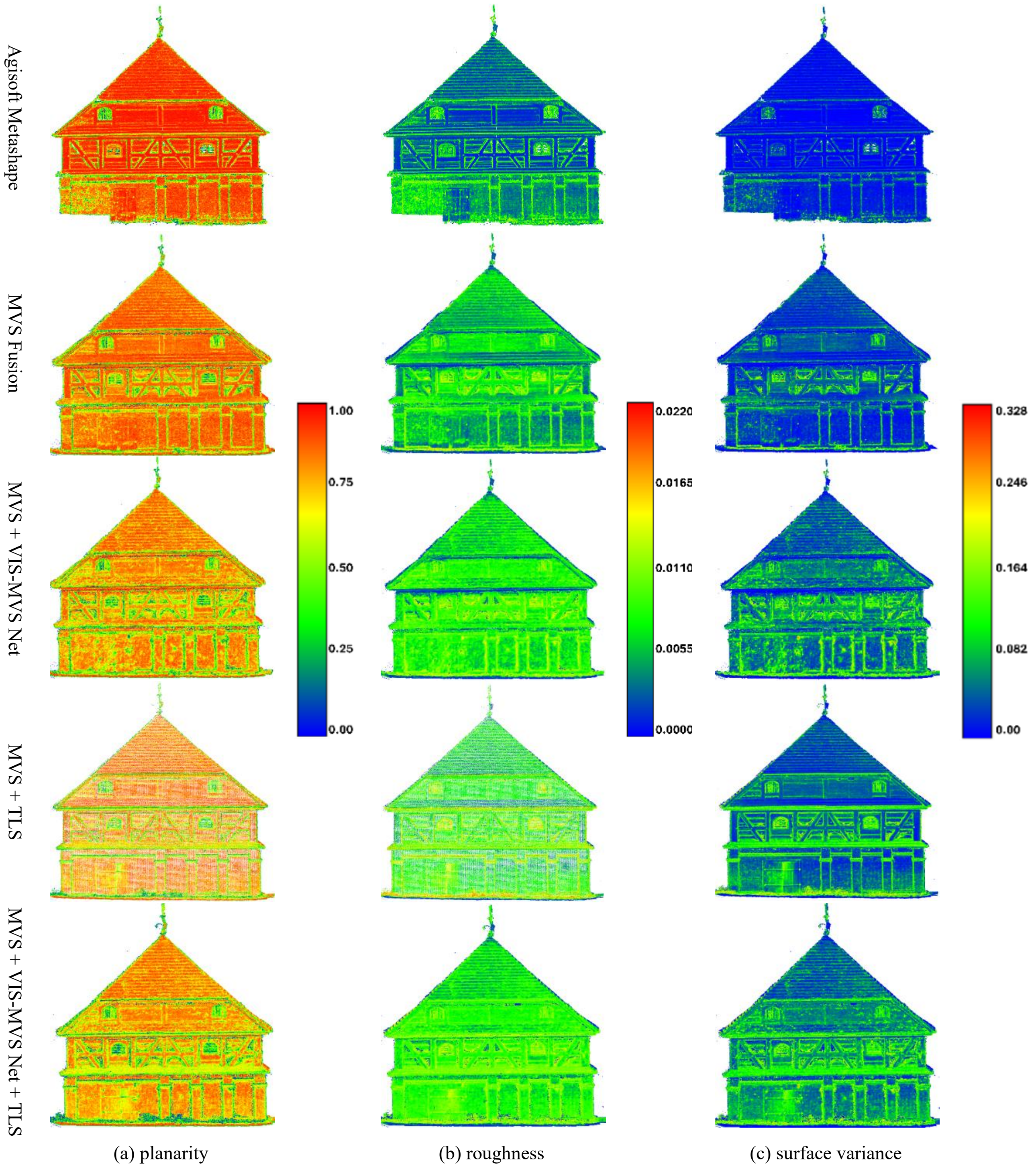


Figure 10. Shape variance analyses of point cloud quality after fusion - Test Site 2 (TOPSIS)

5. Conclusions

This study proposed a framework for dense point cloud fusion based on Multi-Criteria Decision-Making (MCDM) techniques, with a particular focus on heritage documentation of wooden architectural objects. By integrating objective criterion weighting (CRITIC) with ranking and aggregation strategies (TOPSIS and OWA), the presented methodology provides a systematic and reproducible approach for selecting and fusing points from heterogeneous datasets of varying geometric quality.

The comparative analysis of classical hand-crafted MVS algorithms, a learning-based MVS approach, and terrestrial laser scanning demonstrated that no single acquisition or reconstruction method ensures optimal completeness, density, and geometric fidelity simultaneously. The proposed MCDM-based fusion strategy proved effective in integrating multiple point clouds while preserving structural detail and mitigating local artefacts. Both TOPSIS and OWA allow for comparable fusion outcomes, selecting nearly identical proportions of points from the individual datasets.

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The utilisation of VIS-MVS Net and TLS data in the fusion process increased point cloud completeness and density, but did not universally improve local geometric quality. In several cases, integrating lower-quality or noisier datasets increased surface variance and reduced planarity, highlighting the importance of quality-driven point selection rather than unconditional data merging. These results underline the strength of the proposed framework in objectively filtering and prioritising points based on multiple, interrelated geometric descriptors rather than relying on heuristic or purely algorithmic fusion strategies.

Future work will focus on extending the framework to semantic descriptors, adaptive voxel strategies, and large-scale multi-temporal datasets, supporting the development of robust digital twins and long-term monitoring solutions for cultural heritage assets.

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References

Abdelazeem, M., Elamin, A., Afifi, A., & El-Rabbany, A. (2021). Multi-sensor point cloud data fusion for precise 3D mapping. The Egyptian Journal of Remote Sensing and Space Science, 24(3), 835-844.

Capolupo, A. (2021). Accuracy assessment of cultural heritage models extracting 3D point cloud geometric features with RPAS SfM-MVS and TLS techniques. Drones, 5(4), 145.

Cui, Y., Chen, R., Chu, W., Chen, L., Tian, D., Li, Y., & Cao, D. (2021). Deep learning for image and point cloud fusion in autonomous driving: A review. IEEE Transactions on Intelligent Transportation Systems, 23(2), 722-739.

Grifoni, E., Vannini, E., Lunghi, I., Faraioli, P., Ginanni, M., Santacesarea, A., & Fontana, R. (2024). 3D multimodal point clouds data fusion for metrological analysis and restoration assessment of a panel painting. Journal of Cultural Heritage, 66, 356-366.

Grilli, E., Remondino, F., 2019. Classification of 3D Digital Heritage. Remote Sens. 11, 847. https://doi.org/10.3390/rs11070847

Malczewski, J., Chapman, T., Flegel, C., Walters, D., Shrubsole, D., & Healy, M. A. (2003). GIS–multi-criteria evaluation with ordered weighted averaging (OWA): case study of developing watershed management strategies. Environment and Planning A, 35(10), 1769-1784.

Markiewicz, J., Karwel, K., & Murtiyoso, A. (2024). The critical evaluation of Multi-View Stereo approaches in 3D dense reconstruction for Cultural Heritage objects. Journal of Modern Technologies for Cultural Heritage Preservation, 1(3).

Markiewicz, J., Kot, P., Georgopoulos, A., Bocheńska, A., Muradov, M., Hess, M., ... & Antoniou, A. (2025). Transforming architectural heritage documentation: developing integrated European recommendations for safeguarding and preservation. npj Heritage Science, 13(1), 622.

Murtiyoso, A., Grussenmeyer, P., 2017. Documentation of heritage buildings using close-range UAV images: dense matching issues, comparison and case studies. Photogramm. Rec. 32, 206–229. https://doi.org/10.1111/phor.12197

Murtiyoso, A., Pellis, E., Grussenmeyer, P., Landes, T., Masiero, A., 2022. Towards Semantic Photogrammetry: Generating Semantically Rich Point Clouds from Architectural Close-Range Photogrammetry. Sensors 22, 966. https://doi.org/10.3390/s22030966

Poku-Agyemang, K. N., & Reiterer, A. (2025). Weighted multiple point cloud fusion. PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science, 93(1), 65-78.

Ramya, S., & Devadas, V. (2019). Integration of GIS, AHP and TOPSIS in evaluating suitable locations for industrial development: A case of Tehri Garhwal district, Uttarakhand, India. Journal of Cleaner Production, 238, 117872.

Schonberger, J. L., Frahm, J.-M., 2016. Structure-from-Motion Revisited. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), 4104–4113

Shaojing, S. O. N. G., Xinjian, L. I., & Feiyi, F. A. N. G. (2025). A Review of Point Cloud Fusion Technology: Methods, Applications, and Challenges. 14(3), 1-20.

Stathopoulou, E.K., Battisti, R., Cernea, D., Remondino, F., Georgopoulos, A., 2021. Semantically Derived Geometric Constraints for MVS Reconstruction of Textureless Areas. Remote Sens. 13, 1053. https://doi.org/10.3390/rs13061053

Stathopoulou, E.K., Remondino, F., 2023. A survey on conventional and learning-based methods for multi-view stereo. Photogramm. Rec. 38, 374–407. https://doi.org/10.1111/phor.12456

Storeide, M. S. B., George, S., Sole, A. & Hardeberg, J. Y.Standardization of digitised heritage: a review of implementations of 3D in cultural heritage. Herit. Sci. 11, 1–22 (2023).

Stylianidis, E. & Remondino, F. 3D Recording, Documentation and Management of Cultural Heritage (Whittles Publishing, 2017).

Sutherland, N., Marsh, S., Priestnall, G., Bryan, P., & Mills, J. (2023). Infrared thermography and 3D-data fusion for architectural heritage: a scoping review. Remote Sensing, 15(9), 2422.

Triantaphyllou, E., 2000. Fuzzy Multi-Criteria Decision Making. pp. 241–262. https://doi.org/10.1007/978-1-4757-3157-6_13

Wei, Z., Wang, Y., Yi, H., Chen, Y., Wang, G., 2020. Semantic 3D Reconstruction with Learning MVS and 2D Segmentation of Aerial Images. Appl. Sci. 10, 1275. https://doi.org/10.3390/app10041275

Weinmann, M., Jutzi, B., & Mallet, C. (2017). Geometric features and their relevance for 3D point cloud classification. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 4, 157-164.