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Assessment of the Efficiency of Lidar Data Reduction Methods in the Generation of Digital Elevation Models

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ABSTRACT: Digital Elevation Models (DEMs) have become an indispensable tool for a wide range of surface investigations, facilitating critical engineering and scientific assessments. While there are several methods for acquiring input data, LiDAR technology offers a significant advantage by providing a highly efficient and cost-effective means of data acquisition. The technology produces dense point clouds, enabling the construction of high resolution and high quality DEMs. However, the inherent density and large volume of these point clouds present significant data processing challenges, potentially introducing errors into the final DEM. While numerous data reduction methods for LiDAR point clouds have been proposed, previous studies have yielded inconclusive results regarding the optimal method for generating DEMs from LiDAR data, highlighting the need for further research to establish best practices in the field of earth surface analysis. The main objective of the present study is to assess the most relevant LiDAR data reduction methods and new proposals in order to determine which of them are more technically feasible. To this end, a bibliographical study was carried out on the nine selected methods, which allowed their comparison by means of a criteria-based matrix. According to the results obtained, it was determined that the methods with the best performance in LiDAR data reduction are the PpC method, the OptD method, the Uniform 3D Grids and the RpA algorithm.

KEYWORDS: Data Reduction Model**,** Digital Elevation Models, LiDAR, PpC method, OptD method, RpA algorithm.

I. INTRODUCTION

The revolution brought about by the incorporation of Digital Elevation Models (DEM) in various fields related to land surface studies has resulted in important changes in sciences, activities and disciplines such as cartography, disaster management, hydrology, agriculture, engineering and urban planning, among others, for which these have proven to be fundamental tools. However, the large number of points composing the original LiDAR point clouds entails a significant challenge in terms of processing, storage, analysis and representation. It is therefore essential to reduce the data to optimize these processes and obtain high quality and operationally efficient DEMs.

As a rule, DEMs used to be generated by indirect methods, such as photogrammetry or digitizing, which rely on pre-existing images or maps, or by direct methods, such as altimetry, GPS or topography, which provide primary and high-resolution data. Nevertheless, the advent of LiDAR has dramatically changed the field. By measuring the distance to the surface with laser pulses, LiDAR provides high-precision, high-resolution data directly from the ground, overcoming the limitations of previous methods and becoming the tool of choice for generating high-quality DEMs.

Nowadays, airborne LiDAR has been established as the standard technique to obtain data for DEM generation, as it provides reliable and accurate models over large areas and offers 3D information in an efficient way (Yilmaz and Uysal, 2017). Among the highlights of this technology are its potential to generate a point cloud in which all the morphological characteristics of the terrain under study are preserved. These points are used to form a cloud containing billions of data. In many cases, the resulting amount of information can be excessive and not cost-effective for obtaining a representative model, regardless of the high quality of the measurement in short periods of time. It is therefore not practical to use all the information obtained, so it is necessary to apply methods that reduce the point cloud without jeopardizing the representativeness of the information (Paredes, Salina, Martínez and Jiménez, 2013).

Viewed from this perspective, the accuracy of the DEM in the reproduction of a terrain under study is conditioned by different factors. First, the accuracy of the model, which depends on the irregularities and characteristics of the surface; this factor is handled as uncertainty, i.e., as a non-tangible aspect that can be corrected in the model construction process. Similarly, the interpolation methods to generate the digital surface has an important effect to consider. This factor will be associated with the methods or techniques used to adequately represent reality. Finally, the attributes related to the input data, namely the accuracy, density and distribution of the input data. The latter is directly related to the quality of measurement, filtering and point cloud reduction (Błaszczak-Bąk and Sobieraj,2018).

The steadily increasing resolution of LiDAR data, although providing a more detailed representation of the terrain, has increased the computational burden associated with the storage, processing, and analysis of these data due to the large volume of information generated (Yilmaz and Uysal, 2017). In view of this situation, the need to optimize computational resources has arisen, which has driven the development of data reduction algorithms that allow the generation of high quality DEMs from representative subsets of the original point cloud. Despite the existence of several methodological proposals in the scientific literature, further research is needed to establish standardized and efficient protocols for LiDAR data reduction.

There are a large number of studies on DEM generation that have explored a wide range of topics, including model accuracy, identification and analysis of factors that affect its generation, and the assessment of procedures to obtain a more accurate model by comparing existing methods and proposing new techniques. Based on these, there is a general consensus that the topographic characteristics of the terrain and the quality of the LiDAR data are fundamental for the quality of the final DEM. In this regard, studies such as Buján et al. (2019) have highlighted the importance of iterative methods to accurately represent high slope areas and have underlined the need to consider the accuracy, distribution and density of LiDAR points in the model generation process.

It is thus understood that the reduction of point cloud density is essential to optimize computational resources and facilitate the extraction of relevant information (Yilmaz & Uysal, 2017). Likewise, evidence on data density reduction shows that, compared to the DEM constructed from the total LiDAR dataset, there is no significant decrease in accuracy when constructing the DEM from the reduced dataset (Sayed, Taie & El-Khoribi, R. 2016). By applying data reduction techniques, it is possible to generate more manageable and accurate DEMs, allowing for more detailed analyses and generating higher quality mapping products (Santecchia & Span, 2020). The increasing demand for high-resolution LiDAR data makes research in data reduction methods an active and relevant field of study (Becek & Boguslawsk, 2018).

In terms of DEM generation, there are quite a number of methods and algorithms available, but the comparative evaluation of their performance and the identification of the most suitable methodology for specific situations is still a pending issue. As pointed out by Yilmaz & Uysal (2017), the high density of LiDAR point clouds, although beneficial in terms of detail, leads to difficulties in managing and processing the data. Therefore, it is essential to perform evaluations and comparisons to select the most efficient and accurate reduction methods for each particular application or case.

Taking into account the above, this research addresses the comparative evaluation of different LiDAR data reduction methods in order to determine their efficiency in the generation of Digital Elevation Models. This will be done through an exhaustive literature review, the theoretical foundations and applicability of each method are analyzed to establish selection criteria based on their efficiency, accuracy and ability to preserve relevant topographic features. By addressing theoretical, practical and methodological aspects, a rigorous and objective evaluation of the different alternatives available will be carried out

II. METHOD

This research involved a documentary study to compare and analyze different methods used for reducing LiDAR data, which is essential for generating various Digital Elevation Models (DEMs). The aim was to determine the precision, accuracy, and effectiveness of each method in specific cases. The study considered relevant contributions in this field to build a knowledge base on the fundamentals and applicability of each data reduction method. Both established methods widely accepted in the scientific community and newly emerging techniques with potential were examined. After selecting the studies to be analyzed, relevant information was identified to evaluate the suitability of each method for data reduction.

The collected information was used to carry out a comparative analysis describing each of the LiDAR data reduction methods, identifying the fundamentals that support them and determining the feasibility of their application. Similarly, each of the methods is compared and analyzed with the purpose of determining the ideal method or methods for LiDAR data reduction by means of a criteria-based matrix, which allow decision making using criteria or conditions established to assign a valuation to the problem to be evaluated in order to determine the best option, based on the Pugh Selection Matrix or Criteria-Based Matrix (Madke & Jaybhaye, 2016). The feasibility and effectiveness criteria for the assessment were determined on the basis of the literature review and its results, and the level of importance of each criterion was subsequently established on the basis of a scoring scale. Subsequently, the feasibility criteria were compared resulting in the Weighting Factor (WF) and the Option Weight (OW), which were used to determine the final assessment of each of the methods.

III. LIDAR DATA REDUCTION METHODS

A. V-W Method optimized by Błaszczak.

The Visvalingam-Whyatt (V-W) algorithm, also known as Line generalization by repeated elimination of points method, operates on a delimited region, progressively eliminating points based on an effective area criterion. This method, initially proposed by Visvalingam and Whyatt in 1993 to simplify coastal lines, is based on the idea that iterative elimination of points with the minimum triangular area leads to a generalized representation of the line, significantly reducing the number of points required without a perceptible loss of detail (Visvalingam and Whyatt, 1993). At each iteration, the areas of adjacent triangles are recalculated to ensure that the simplification is carried out gradually and consistently (Melnyk et al., 2016).

Visvalingam and Williamson (1994) proposed a line simplification algorithm that has had a significant impact on the field of automated mapping. By applying the algorithm to data from roads, the author demonstrated its ability to generate simplified line representations that preserve the essential characteristics of the original objects. The efficiency of the algorithm, which yields balanced generalizations from a single tolerance parameter, makes it an ideal tool for the production of multi-scale mapping (Visvalingam and Williamson, 1994). They also came up with a number of improvements to the algorithm to optimize the generalization of centerlines, thus broadening its range of applications. In the following table, some generalities of this method are shown.

TABLE 1. GENERALITIES OF V-W METHOD OPTIMIZED BY BŁASZCZAK

Method	Description	Effectiveness
V-W Method optimized by Błaszczak	• Consists of the initial selection of the topographic bands and the tolerance range that determines the degree of reduction. • The surface of the calculated effective area corresponds to the triangles that are compared with the tolerance triangle, whose size will determine the number of points to eliminate. • It is characterized by creating a generalized line of triangles starting from the closest points. • In general, it reduces the number of points without creating new entities.	• It speeds up point processing. • The use of the reduction method optimizes the generation of the digital model while preserving its accuracy. • It maintains the characteristics of the terrain.

B. Uniform 3D Grids Method.

The uniform 3D-Grids method uniformly reduces the point cloud by subdividing the space into cubic cells of equal size and eliminates the points that would become part of each 3D cell, but keeps the information of one of the points per grid (Yilmaz et al., 2017). It is basically based on two factors: the number of initial cells and the size of the user-defined tolerance. However, the tolerance is the main factor in data reduction; for example, when the tolerance value is smaller, the greater the number of points remaining, and vice versa (Lee et al., 2001). This way of processing requires complex calculations for each element of the model; therefore, the reduction process is usually slow (Gomes, 2018). This method reduces the data by selecting a representative point and discarding other points of the grid; in addition, it uses point normal values on the surface of the object of study from which non-uniform 3D grids are generated using the standard deviation of the normal values; it is capable of handling the entire surface of a 3D object based on a single or multiple point clouds. In the case that the object requires multiple point clouds it is essential to register a single coordinate system for the entire modelling (Lee, Woo, and Suk, 2001).

Additionally, Yilmaz et al. (2017) developed a study in which they managed to evaluate the effect of the 3D-Grids method on the accuracy in the construction of a DTM derived from a LiDAR point cloud; that is, they examined to what extent the point cloud can be reduced while maintaining the effective accuracy for the construction of the DTM, the results of their work allow them to argue that the proposed method is feasible because better representations of the terrain are obtained and the point cloud can be reduced up to 50% of the density level while maintaining the accuracy of the model. In Table 2, the generalities of the method are presented.

TABLE 2. GENERALITIES OF UNIFORM 3D-GRIDS METHOD

Method	Description	Effectiveness
Uniform 3D-Grids Method	• It reduces the amount of point cloud data by subdividing (octree structure) the spatial model into cubic cells of equal size and eliminating all but one point per cell.	• It maintains accuracy, but is generally very slow for point data acquisition. • Up to 50% reduction of LiDAR data while maintaining the accuracy of the digital model.

C. Randomized Algorithms for Data Reduction

Data reduction is essentially the compression of the original data (X) along the MNIJ dimensions into a reduced representation (XR). This compressed data is then subjected to a factorization in order to obtain a low-rank matrix approximation of the original X. The main objective and challenge of data reduction is to ensure that XR faithfully preserves all the crucial information (variance) contained in the original data X. (Cruz, Amigo, Barbin & Kucheryavskiy, 2022).

The LiDAR data reduction algorithm begins by overlaying a grid of 1 square meter cells on the LiDAR data, while maintaining spatial georeferencing. The first cell in the grid is selected and a LiDAR point is randomly selected from the set of all points within that cell. This random selection process continues within the selected cell until either a LiDAR point within the slope green region is identified or all points within the cell have been examined, or there are no points to remove in the cell. If one of these conditions is met, the algorithm proceeds to the next grid cell, starting from left to right and top to bottom. The rationale behind this approach is the recognition that fewer LiDAR points are necessary to accurately represent flat terrain compared to areas with significant topographic variation. (Sharma, Xu, Sugumaran & Oliveira, 2016).

TABLE 3. GENERALITIES OF RANDOMIZED ALGORITHMS (RANDOMIZED DATA REDUCTION)

Method	Description	Effectiveness
Randomized Algorithms (Randomized Data Reduction)	• This algorithm randomly removes points from the cloud based on a specified percentage of total points to be reduced.	• Reduction up to 50% of the data while maintaining the accuracy of the DEM.

D. Becek and Boguslawski Q-tree Method

Developed by Finkel and Bentley in 1974, the quadtree is a data structure suitable for storing information for retrieval in composite keys. The Q-tree allows the space to be divided into adaptive cells depending on the distribution of information, for example, a two-dimensional region into 4 quadrants NW (north-west), NE (north-east), SW (south-west) and SE (south-east) or 1, 2, 3 and 4 respectively, each quadrant having a node corresponding to it, these nodes can store a record and subdivide up to four descendants (subtrees) (Finkel and Bentley, 1974). In short, it is a 2D method that consists of dividing a region or study area into 4 equal quadrants, each quadrant is assigned a node that has a two-dimensional key, and from this node a subdivision into 4 subtrees, the subdivision is repeated until there are no points left to store or the intended selection criterion is met (Martinez, 2019).

TABLE 4. GENERALITIES OF Q-TREE METHOD

Method	Description	Effectiveness
Q-tree Method	• Subdivide into quadrants (sheets) in a continuous manner until the smallest size of a sheet is reached or when the covered space of this sheet satisfies one of the criteria of σ_T. • The σ_T criterion determines the size of the sheets.	• A highly accurate DEM is generated and terrain features are maintained.

E. OptD-Single Method

The OptD (Optimum Dataset) method, proposed by Błaszczak-Bąk (2016), offers an efficient solution for data reduction by optimally selecting a subset that retains the most relevant information for a given task. This method, which is based on single- or multi-criteria optimization, has been successfully applied in the reduction of large complex datasets. Błaszczak-Bąk, Sobieraj-Żłobińska, and Wieczorek, (2018) proved the effectiveness of OptD-single in generating accurate models from reduced datasets, while maintaining an adequate level of detail in the regions of greatest interest. The authors suggested that OptD-multi could further expand the scope of this technique in the future.

The OptD-single method requires that the data set meets a strictly defined condition. This variant of the method is valid for large data sets and its algorithm consists of 12 steps; among all of them, the most important steps for the compression of the method are mentioned: a) Establishing optimization criterion (f), e.g., numbers of points in reduced dataset, standard deviation for the dataset, b) the initial width of the mesh steps (nL) can be chosen appropriately or triangles can be used: the number of points to be reduced from the total of the set, b) the initial width of strips (L) must be chosen appropriately or, if necessary, triangles can also be used, for this purpose some parameters can be taken into account such as the average distance between points in the measurement set or directly determine the width of strips by means of a fixed interval, c) Selecting the cartographic line generalization method, e.g. the D-P or V-W (Błaszczak-Bąk, Sobieraj-Żłobińska, and Kowalik, 2017; Błaszczak-Bąk and Sobieraj-Żłobińska, 2018). The OptD method uses both linear object generalization methods for calculations in a vertical plane, which allows accurately verifying each elevation.

TABLE 5. GENERALITIES OF OPTD-SINGLE METHOD

Method	Description	Effectiveness
OptD-Single Method	• The OptD-single method allows the selection of the optimal reduced data set in terms of number of measurement points for a given criterion; in other words, it allows the reduction of large data sets by means of an optimization criterion.	• Generates an optimal and accurate DEM. • Maintains the essential characteristics of the terrain. • Generates different densities based on terrain characteristics and the procedure is automatic.

F. Generalities of RpA- Single Method

LiDAR point cloud density reduction is essential to optimize the processing and analysis of these large datasets. Buján (2018) introduced the Random per Area (RpA) method as an effective tool for this purpose. Based on area-based random sampling, this method allows obtaining subsets of points that retain the general characteristics of the original cloud. Although the RpA method does not consider the spatial structure of the data, its simplicity and efficiency make it an attractive option for applications requiring rapid point density reduction. Future research could explore the combination of the RpA method with spatial filtering techniques to improve reduction accuracy.

TABLE 6. GENERALITIES OF RPA- SINGLE METHOD

Method	Description	Effectiveness
RpA- Single Method	• It randomly reduces the point density at the area level, not taking into account neither the point distribution nor the returns of the LiDAR sensor. • The unit of reduction is the entire area containing data.	• The original features are maintained in reduced point clouds.

G. SRpC Method

Semi-Ramdom per Cell (SRpC) is an adaptation of the method used by Buján, González, Barreiro, Santé, Corbelle and Miranda (2013). This method proposes a data reduction by random selection guided by the type of return (information provided by the laser pulse of a LiDAR sensor), during which the distribution of points is not taken into account. Ideally, the data should belong to the same return and be obtained from flights carried out in the same area, at the same time and with the same flight parameters, but with different pulse densities. However, González, Diéguez, and Miranda (2012) suggest that a set of LiDAR points can be artificially reconstructed through random cell (grid) selection or selection from a subset consisting of points with equal returns.

TABLE 7. GENERALITIES OF SRPC METHOD

Method	Description	Effectiveness
SRpC Method	• It reduces the points in a semi-random manner at the cell level with homogeneous density, by considering the returns (first and last), but does not take into account the distribution of the points. • The area containing the data is divided into cells, then based on the number of points set, the points per cell are selected.	• It does not perform well in the distribution of points and in the ratio of terrestrial to non-terrestrial points. • Some limitations to obtain desired density

H. ThinData Method

ThinData is an algorithm for the generation of output data sets with consistent pulse densities over the entire coverage area. Acording to Marchesan et al. (2020), it randomly reduces the number of pulses according to the desired size. by first analyzing the input data (specified by DataFile) and determining the current pulse density within each cell of a defined grid (CellSize). Based on these calculations, ThinData estimates a retention rate for each cell to achieve the desired pulse density. The algorithm identifies individual pulses by recognizing new first returns or any subsequent returns (2nd, 3rd, 4th, etc.) that do not have corresponding previous returns within the same pulse sequence. This algorithm enables LIDAR data to be thinned to specific pulse densities. This feature is useful when comparing analysis results from multiple LIDAR acquisitions collected with different pulse densities. (Mcgaughey, 2016).

TABLE 8. GENERALITIES OF THINDATA METHOD

Method	Description	Effectiveness
Thindata Method	• ThinData allows LiDAR point cloud densities to be adjusted to a specified level, which is particularly helpful when comparing analyses across datasets acquired at different point densities, ensuring consistency in the evaluation process	• Did not perform well in the distribution of points and proportion of ground and non-ground points. • Limitations in obtaining the desired density.

I. PpC Method

The Proportional per Cell PpC method has been designed and implemented to overcome some of the limitations of the SRpC method, its main purpose is to simulate the actual capture of points without the need for additional data such as; for example, the scan angle of each point, capture sequence among others, this in order to reduce the influence of the method in the accuracy of digital models. The reduction of points takes place according to the distribution of points and the type of return, allowing two types of return: the first and the final return. Buján (2018) argues that the procedure of the method is performed by the following sequence: 1) calculation of the weighted average of the density of points 2) selection of points in each cell, the value of 4 is set as part of trial and error after a visual analysis of the results obtained from a point cloud with homogeneous density; 3) the size of the cell on which the data reduction will be conducted is determined 4) the selection ratio is calculated.

TABLE 9. GENERALITIES OF PPC METHOD

Method	Description	Effectiveness
PpC Method	• The actual point capture is simulated without the need for additional data. • Point density is reduced to cell level, considering both point distribution and return type.	• The influence of the method on the accuracy of DEMs is minimized. • Many of the original features of the DEM after point reduction are kept.

IV. RESULTS

In order to obtain the results of this study, four criteria of feasibility and effectiveness were determined, which served as the basis for the comparison of the nine methods or algorithms considered, namely, 1. Conservation of terrain characteristics, referring to the algorithm's ability to maintain the essential characteristics of the terrain and guaranteeing its accuracy; 2. Density level, which establishes the ability of the algorithm to reduce the point cloud in different desired densities without presenting limitations; 3. Reduction conditions, related to factors or criteria that determine the reduction of points based on the terrain characteristics or in favor of a better result; and 4. Better performance over other methods, which refers to the efficiency of this method over the other algorithms to which it was compared.

The methodology for the comparison of different LiDAR data reduction methods was built around the criteria-based matrix or Pugh selection matrix. For this, the relevant factors or criteria were determined. Then, a level of importance was assigned to the criteria. Next, a criteria-based matrix between the different methods with respect to the selected criteria was elaborated, based on the results of this, the level of importance of each of these criteria was established in order to obtain an effective and feasible method, which yielded the Weighting Factor. Next, the reduction methods were compared with each of the criteria and the Option Weight was obtained. Finally, the weighting factor was multiplied by the Option Weight to arrive at the final Rating of the methods considered in this research.

TABLE 10. FINAL ASSESSMENT OF LIDAR REDUCTION METHODS

	Conservation of terrain characteristics	Density level	Reduction conditions	Better performance	Final Assesment
	WF x OW	WF x OW	WF x OW	WF x OW	
V-W Method	0,045	0,045	0,003	0,022	0,114
Uniform 3D Grids	0,045	0,045	0,000	0,051	0,141
Randomized Algorithms	0,045	0,045	0,000	0,022	0,111
Q-tree Method	0,045	0,045	0,003	0,036	0,129
OptD Method	0,045	0,045	0,003	0,051	0,144
RpA Method	0,045	0,045	0,000	0,048	0,138
SRpC Algorithm	0,004	0,003	0,003	0,019	0,029
ThinData Algorithm	0,004	0,003	0,001	0,019	0,027
PpC Method	0,045	0,045	0,000	0,078	0,168

As demonstrated in Table 10, the majority of the models under consideration yielded consistent outcomes with regard to the initial criterion of conservation of terrain characteristics (0,045), with the exception of the SRpC Algorithm and ThinData Algorithm (0,004). A comparable scenario was observed in the subsequent criterion of density level, wherein most methods yielded analogous results (0,045), with the exception of the SRpC Algorithm and ThinData Algorithm (0,003). Consequently, it is understood that all methods, except the SRpC and ThinData algorithms, show a better final assessment in terms of efficiency or feasibility to conserve terrain features and in data density level.

Likewise, with regard to Reduction conditions, the results reveal that the V-W, Q-tree, OptD and SRpC methods obtained a similar score (0,003), while ThinData had a slightly lower performance (0,001). On the other hand, the PpC, RpA, Uniform 3D Grids and Randomized methods scored the lowest (0,000). Although the Q-tree, OptD and SRpC methods were shown to be more effective in the reduction conditions, it is important to note that the weight assigned to this criterion was lower compared to others. This suggests that the reduction conditions, although relevant, is not the determining factor in the overall analysis. Therefore, the low results obtained by some methods can be attributed to the lower relative importance of the reduction conditions.

When evaluating the criterion of better performance in comparison with other methods, it was found that the PpC method obtained the highest score (0.078), proving to be the most effective. It was followed in performance by OptD and Uniform 3D Grids, with scores of 0.051. RpA scored 0.048, Q-tree 0.036, and V-W and Randomized Algorithms scored 0.022. Finally, SRpC and ThinData scored the lowest (0.019). These results suggest that the PpC method excels the most in terms of the effectiveness of this method over the other algorithms to which it was compared, while SRpC and ThinData showed lower performance compared to the others.

The comparative analysis, considering all four criteria in a final assessment, identified the PpC (Proportional per Cell) method, the OptD (Optimum Dataset) method, the Uniform 3D Grids and the RpA (Random per Area) algorithm as the most efficient techniques for LiDAR data reduction. While the modified Q-tree algorithm met all the established criteria, its comparative analysis was limited to a single, unspecified reduction method. In contrast, the OptD and PpC methods, as relatively novel approaches, have been rigorously evaluated in several studies against several well-known reduction techniques. This extensive evaluation provides strong support for their high performance in reducing LiDAR data.

V. CONCLUSIONS

The improvement in LiDAR data quality has led to a dilemma in DEM generation: the higher the accuracy, the larger the data volume and, therefore, the greater the computational complexity. Although various methods have been proposed to reduce the data, comprehensive studies have not yet been conducted to evaluate their effectiveness. In this regard, the optimization of LiDAR data processing is an urgent challenge that requires more attention from the scientific community.

The review of the scientific literature on the subject of study of this research provided the necessary information to select the nine LiDAR data reduction methods for DEM generation and to describe, substantiate and evaluate their effectiveness. The selected works cover a variety of methods and algorithms, from traditional ones, such as Visvalingam and Whyatt, to more recent proposals, such as OptD and PcC.

As for the comparison of the methods based on the reduction per cell or applying a reduction criterion, these obtained excellent results in their respective studies, in addition to remaining above the other methods in this study. According to the results obtained, the methods that present the highest feasibility in the reduction of LiDAR data are: the PpC method, the OptD method, the Uniform 3D Grids and the RpA algorithm. These methods obtained a good performance in each of the studies where they were evaluated, meeting most of the established criteria, which translates into greater efficiency in the execution of their task. In relation to the OptD and Ppc methods, these present a high potential in the optimization of DEM because they are new methodologies that intend to provide a solution to the limitations of other algorithms and are developed to improve the reduction process based on the current reality.

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