# GEMAUT (2006–2026): A Brief History of a Robust and Open-Source Tool for the Automatic Generation of High-Resolution Digital Terrain Models from Satellite-Based Surface Models

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**Abstract**

This contribution presents GEMAUT, a robust and open-source tool for the automatic generation of Digital Terrain Models (DTM) from high-resolution satellite-based Digital Surface Models (DSM). The paper provides a historical overview of the methods used for DTM extraction over the past twenty years, from early morphology-based filters to physically based optimization models and recent deep learning approaches. This retrospective is complemented by an analysis of the evolution of Earth-observation sensors, whose increasing spatial resolution now enables the application of LiDAR-oriented ground-filtering techniques directly to satellite DSM. The latest version of GEMAUT removes one of the main limitations of earlier implementations by eliminating the need for an external ground mask. Ground points are automatically extracted from the DSM using either the slope-based filter implemented in SAGA or the Cloth Simulation Filter available in PDAL. The terrain is then reconstructed through an energy-based surface optimization approach that combines robust data fidelity terms with curvature-based regularization. A second major contribution is the introduction of an automatic quality assessment module. By analysing DSM–DTM elevation differences, GEMAUT produces a spatialized precision mask that estimates the relative vertical accuracy at pixel level. This capability supports reliable quality control in operational and industrial workflows. The tool has been fully refactored, relies exclusively on open-source libraries, and is publicly released on GitHub to encourage transparency, reproducibility, and collaboration within the ISPRS community.

## 1. Introduction

Digital Surface Models (DSM) derived from high-resolution satellite imagery provide detailed three-dimensional representations of the Earth's surface, including buildings, vegetation, and other above-ground structures. In contrast, Digital Terrain Models (DTM) represent the bare-earth topography and are essential for a wide range of applications such as image orthorectification, height normalization, change detection, and 3D urban modelling.

While DSM can be generated automatically from stereo or tri-stereo satellite imagery using photogrammetric pipelines such as MicMac (Rupnik et al., 2017), the extraction of accurate DTM from DSM remains a challenging task. The presence of above-ground objects, noise, and matching errors introduces significant difficulties in isolating ground points and reconstructing a reliable terrain surface.

Over the past two decades, numerous approaches have been proposed to address this problem, including morphological filtering, physical simulation methods, and more recently deep learning techniques. Despite these advances, many methods still rely on external data, supervised learning, or complex parameter tuning, which can limit their operational usability and generalization across different landscapes.

In this context, GEMAUT (Génération de Modèles Automatiques de Terrain, Automatic Terrain Model Generation) was initially introduced as a robust method for estimating DTM from DSM in urban environments (Champion and Boldo, 2006). The early versions of the method relied on external ground/non-ground masks derived from geographic databases. Subsequent developments explored automatic ground extraction using machine learning and deep learning approaches. However, these approaches revealed significant limitations, particularly due to their dependence on training data and external inputs.

Recent improvements in satellite imagery, such as the availability of submetric DSM from sensors like Pléiades Neo (30 cm) and CO3D (Lebègue et al., 2020), have enabled a paradigm shift. The latest version of GEMAUT no longer requires any external mask and performs fully automatic ground extraction directly from the DSM. This evolution led to the development of a fully automated, open-source pipeline that improves robustness, scalability, and ease of use.

The objective of this paper is to present this new version of GEMAUT and to demonstrate its ability to automatically generate high-resolution DTM from satellite DSM. The proposed pipeline combines state-of-the-art ground extraction methods with a robust energy-based optimization framework and introduces an original automatic quality assessment module. The performance of the method is evaluated on high-resolution satellite data over an urban area, with both qualitative and quantitative analyses.

## 2. Related Works

Numerous methods have been proposed over the past two decades to derive Digital Terrain Models (DTM) from Digital Surface Models (DSM), particularly in the context of airborne LiDAR and, more recently, high-resolution satellite imagery.

Early approaches are largely based on mathematical morphology and local geometric criteria. Among them, the slope-based filtering method introduced by Vosselman (2000) remains a widely used reference. This approach classifies ground points based on local elevation differences and distance relationships and is implemented in several open-source GIS tools such as SAGA. While simple and effective, it may struggle in complex urban or vegetated environments.

A second family of methods relies on physical modelling or surface optimization. The Cloth Simulation Filter (CSF) proposed by Zhang et al. (2016) simulates a virtual cloth draping over the inverted DSM to approximate the terrain


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surface. This approach has been widely adopted due to its intuitive formulation and relatively good performance across various landscapes. More recently, tools such as Bulldozer (Lallement et al., 2023) (Brunet et al., 2020) have extended this concept into scalable and operational software frameworks.

In parallel, several works have explored hybrid and adaptive filtering strategies. For instance, Krauß et al. (2011) highlighted that no single method performs optimally across all environments and suggested combining multiple approaches depending on local terrain characteristics. Similarly, Pijl et al. (2020) proposed the TERRA algorithm, which applies anisotropic filtering to better preserve terrain discontinuities such as embankments or terraces.

More recently, deep learning approaches have been introduced to directly learn the transformation from DSM to DTM. DSM2DTM (Bittner et al., 2023) uses a convolutional neural network to perform end-to-end terrain reconstruction, showing promising results. However, such approaches require large amounts of high-quality training data and may suffer from limited generalization and reduced interpretability.

The method proposed in this paper builds upon these different families of approaches. It combines automatic ground extraction based on both slope-based filtering (SAGA) and cloth simulation (PDAL/CSF), with a robust energy-based surface reconstruction inherited from earlier works on GEMAUT. In contrast to many existing methods, the proposed pipeline operates without any external data or supervised learning, enabling fully automatic and scalable DTM generation from satellite DSM.

## 3. Methodology

The proposed GEMAUT pipeline aims at automatically generating a Digital Terrain Model (DTM) from a Digital Surface Model (DSM) without requiring any external data. The method is composed of three main steps: (1) automatic ground point extraction, (2) terrain surface reconstruction through energy-based optimization, and (3) automatic quality assessment of the resulting DTM.

### 3.1 Ground Point Extraction

The first step consists in identifying ground points directly from the input DSM. Two alternative methods are implemented in GEMAUT.

The first approach relies on a slope-based filtering method (Vosselman, 2000), implemented in the SAGA GIS library. This method classifies points as ground based on local elevation differences constrained by a maximum slope threshold. It is simple, robust, and does not require training data, but may be sensitive to parameter settings and complex urban structures.

The second approach is based on the Cloth Simulation Filter (CSF) (Zhang et al., 2016), implemented through the PDAL library. In this method, the DSM is inverted, and a virtual cloth is simulated to drape over the terrain. Points located below the cloth are classified as ground, while others are considered non-ground. This approach is generally more permissive and better suited to complex environments, although it may retain some above-ground artifacts.

Both methods operate directly on the DSM and do not require any external mask or supervised learning, enabling a fully automatic ground extraction process.

### 3.2 Terrain Reconstruction by Energy Minimization

Once ground points are extracted, the DTM is reconstructed through an energy-based optimization framework. The terrain surface is modelled as a continuous function that minimizes a global energy composed of two terms: a data attachment term and a regularization term.

$$E(z) = K(z) + \lambda G_{\alpha,k}(z,\sigma)$$

The data attachment term enforces consistency between the reconstructed surface and the observed ground points. To ensure robustness against outliers (e.g., residual non-ground points), a robust M-estimator is used (Zhang et al., 2003) combining asymmetric norms adapted to the error distribution, as detailed in (Champion, 2026).

$$G_{\alpha,k}(z,\sigma) = \sum_{\substack{(c,l)\in[1,M]x[1,N] \\ p_{c,l}\in Sursol}} \rho_{\alpha,k}\left(\frac{z_{c,l} - obs_{c,l}}{\sigma}\right)$$

The regularization term constrains the smoothness of the surface by penalizing high curvature, ensuring a stable and physically plausible terrain model.

$$K(z) = \sum_{(c,l)\in[1,M]x[1,N]} \left(\frac{\partial^2 z}{\partial^2 x_c}\right)^2 + \left(\frac{\partial^2 z}{\partial^2 y_l}\right)^2$$

The resulting optimization problem is solved using a conjugate gradient descent algorithm (Fletcher–Reeves), providing a good trade-off between computational efficiency and convergence stability. The DSM itself is used as an initial solution, which helps guide the optimization toward a realistic terrain surface.

To handle large datasets, the computation is performed tile-wise, followed by a mosaicking step to ensure continuity between adjacent tiles.

### 3.3 Automatic Quality Assessment

A key contribution of this work is the introduction of an automatic quality assessment module, which provides a spatialized estimation of the relative vertical accuracy of the generated DTM.

The method is based on the analysis of elevation differences between the DSM and the DTM (ΔZ = Z_DSM − Z_DTM). Only the negative part of the distribution, corresponding mainly to ground points, is considered. This distribution is then symmetrized to approximate a normal error model.

A local confidence interval is estimated, typically using the 90th percentile, within sliding windows (e.g., 50 × 50 m). This results in a spatialized uncertainty map, indicating areas of high and low confidence in the reconstructed terrain.

This approach does not require any external reference data and enables automatic self-qualification of the DTM, which is particularly useful in operational contexts.

# 4. Experiments

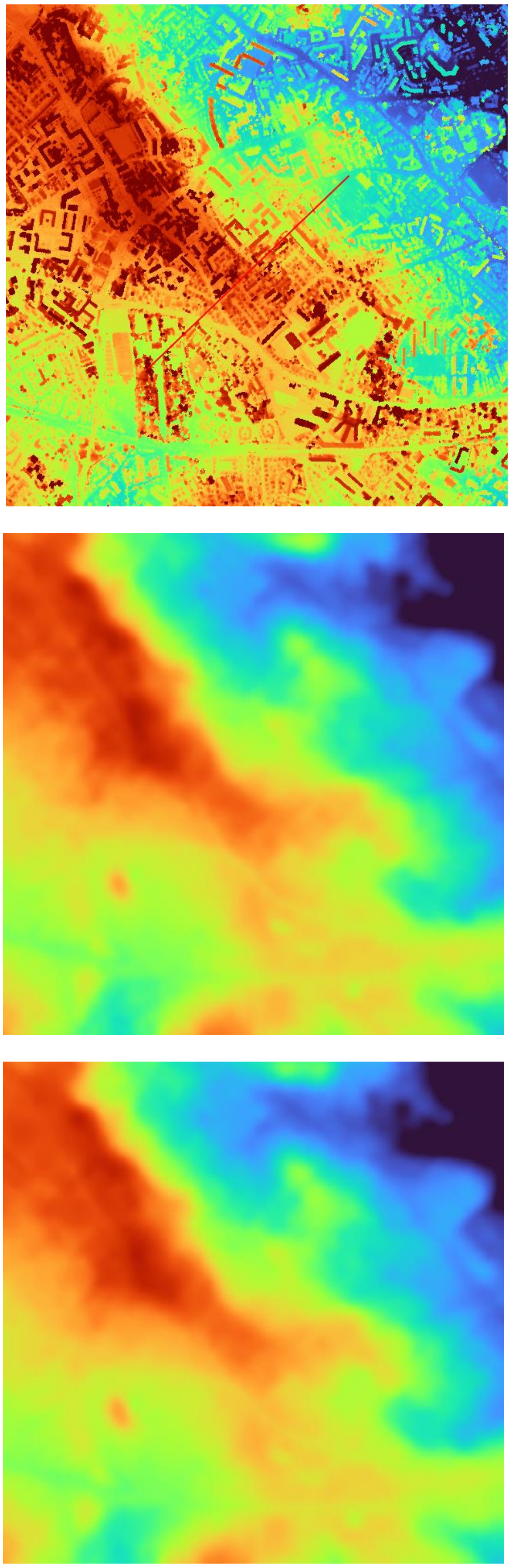

Figure 1: Digital Surface Model (DSM) generated with MicMac (top). Digital Terrain Model (DTM) reconstructed from the ground/non-ground mask obtained with PDAL (middle) and SAGA (bottom). Elevation is represented using a hypsometric colour scale (blue: low elevations, red: high elevations), ranging from 40 m to 85 m.

## 4.1 Study Area and Data

The experiments were conducted over an urban area located in Montpellier, France, covering approximately 2.5 × 2.5 km². The dataset consists of two Pléiades Neo stereo triplets acquired during winter 2021–2022.

A Digital Surface Model (DSM) was generated from these images using the open-source photogrammetric pipeline MicMac (Rupnik et al., 2017). The resulting DSM has a submetric spatial resolution, enabling detailed representation of urban structures and terrain features (Figure 1 – Top).

## 4.2 Experimental Setup

Two DTM were generated from the input DSM using the GEMAUT pipeline, corresponding to the two available ground extraction methods: SAGA (slope-based filtering approach) and PDAL (Cloth Simulation Filter / CSF). All processing steps were performed using the same DSM and identical reconstruction parameters, allowing a direct comparison between the two extraction strategies.

The experiments were conducted on a standard workstation equipped with an Intel Xeon CPU (2.4 GHz). For the study area, the processing time was approximately 3 minutes using the PDAL-based method and 16 minutes using the SAGA-based method.

# 5. Evaluation and Discussion

The evaluation of the generated DTM was carried out using both qualitative and quantitative analyses.

## 5.1 Qualitative Analysis

First, a visual inspection was performed to assess the ability of the method to remove above-ground objects such as buildings and vegetation while preserving terrain structures. As illustrated in the elevation profiles (Figure 2), the reconstructed DTM closely follow the expected terrain surface, with a significant reduction of noise and artifacts present in the input DSM. Both ground extraction methods (SAGA and PDAL) produce consistent results, although some local differences can be observed.

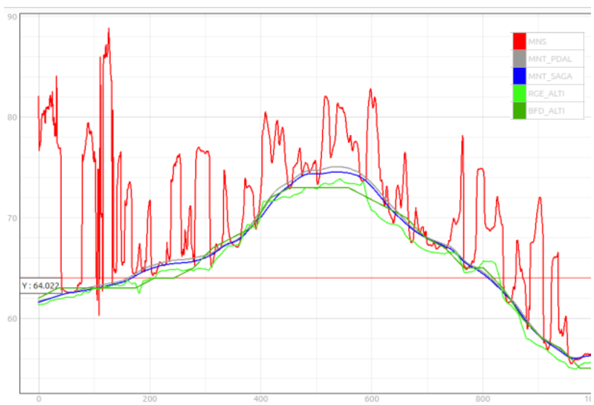


Figure 2: Elevation profile extracted along the red line shown in Figure 1. DSM (red); DTM generated with GEMAUT using PDAL (grey) and SAGA (blue); Reference DTM (Description below) from RGE Alti® (light green) and BD Alti® (dark green). The profile illustrates the ability of the method to remove above-ground objects while preserving terrain structure.


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### 5.2 Quantitative Analysis

Second, a quantitative comparison was conducted using external reference DTM from the French national mapping agency (RGE Alti® and BD Alti®). Elevation differences between the GEMAUT DTM and these reference datasets were computed to evaluate the vertical accuracy of the method (Figure 3).

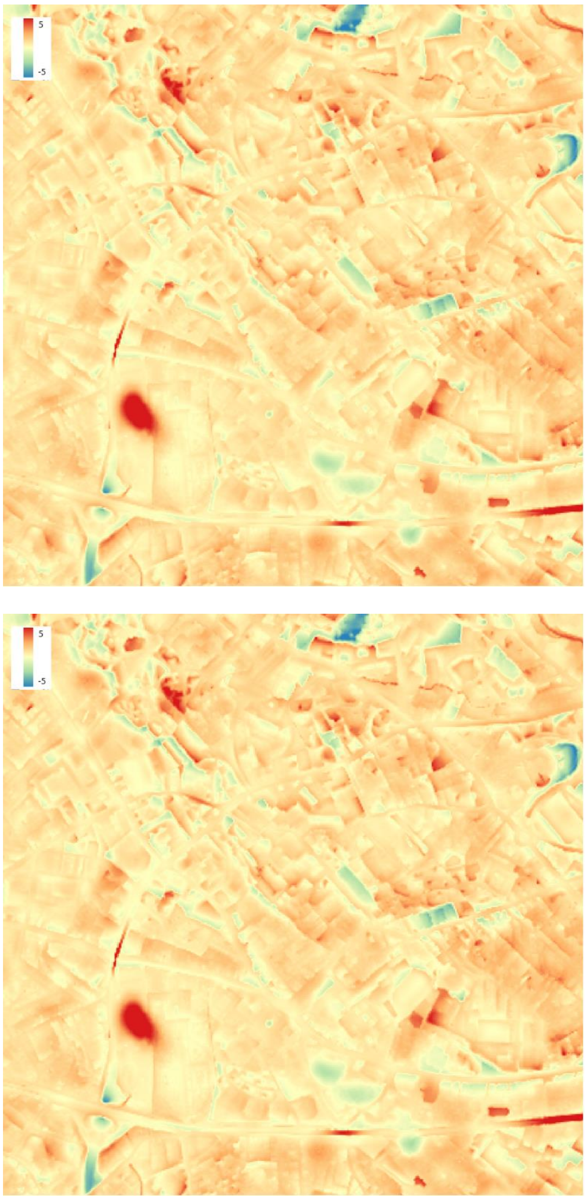


Figure 3: Elevation difference maps between the GEMAUT DTM (PDAL mode) and two reference datasets. (Top) Difference between GEMAUT DTM and RGE Alti®. (Bottom) Difference between GEMAUT DTM and BD Alti®. Colours represent elevation differences ranging from –5 m (blue) to +5 m (red). These maps highlight areas of local over- and under-estimation and provide a spatial assessment of the vertical accuracy of the proposed method.

The elevation differences depicted in Figure 3 show a mean error of 0.89 m, a standard deviation of 0.93 m, and a root mean square error (RMSE) of 1.28 m when compared to RGE Alti®. When compared to BD Alti®, the mean error is 0.46 m, the standard deviation is 1.11 m, and the RMSE is 1.20 m.

These results demonstrate the robustness of the proposed method and its ability to generate accurate DTM from satellite DSM, with an overall vertical accuracy consistent with the expected performance of Pléiades Neo stereo imagery.

### 5.3 Evaluation of the Quality Assessment Module

In addition, the relevance of the proposed automatic quality assessment module was analysed by visually comparing the estimated uncertainty map with observed local reconstruction errors.

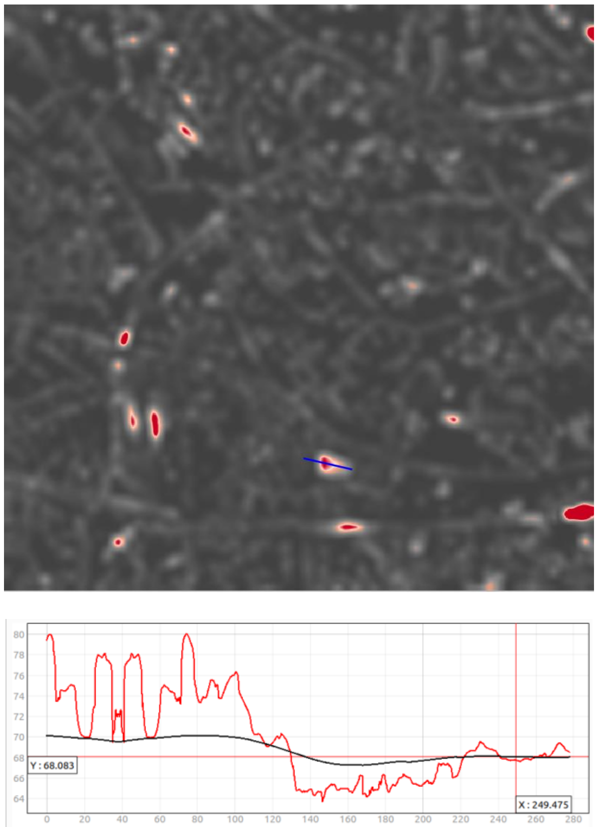


Figure 4: Automatic quality assessment. (Top) Uncertainty map (black: low error ~0 m; red: high error, up to ~ 3.5 m). (Bottom) Elevation profile across an alert area (blue arrow on the top), showing a discrepancy between the DSM (red) and the DTM (black), confirming the relevance of the detected uncertainty.

The automatic quality assessment map highlights areas of lower confidence (in red), which generally correspond to complex regions such as dense urban structures or steep slopes. In these areas, as shown in Figure 4, local discrepancies in the reconstructed terrain are effectively detected, confirming the relevance of the proposed self-qualification approach.

### 5.4 Comparison of Ground Extraction Methods

The comparison between the two ground extraction strategies reveals complementary behaviours.

Figure 5: Comparison of ground masks derived using PDAL/CSF (top) and SAGA (middle), and their impact on the DTM. Bottom: elevation difference (DTM_SAGA – DTM_PDAL), ranging from –1 m (light blue) to +3 m (dark blue). The figure illustrates the different behaviours of the two filters and their influence on terrain reconstruction.

As shown n Figure 5 (Top), the PDAL/CSF approach tends to be more permissive, retaining more points that may belong to above-ground objects. As a result, the corresponding DTM may locally overestimate the terrain elevation.

In contrast, the SAGA slope-based method (Middle) is more restrictive, removing a larger number of points, including some actual ground points. This leads to slightly lower terrain elevations, with a systematic difference of approximately 10 cm compared to the PDAL-based DTM. However, as depicted in Figure 5 (bottom), this difference remains negligible with respect to the overall vertical accuracy of the system and does not significantly impact the quality of the reconstructed terrain.

### 5.5 Limitations

Despite the overall good performance of our system, some limitations remain. Residual artifacts can still be observed in complex areas, particularly due to misclassified points during the ground extraction phase.

In addition, the tile-based processing strategy may introduce minor edge effects, which can locally affect the continuity of the reconstructed surface.

Finally, the proposed quality assessment provides a relative estimation of uncertainty, as it relies solely on the DSM and does not account for absolute errors present in the input data.

## 6. Conclusions

This paper presented a new version of the GEMAUT pipeline for the automatic generation of Digital Terrain Models (DTM) from high-resolution satellite Digital Surface Models (DSM). The proposed approach removes the need for any external ground mask and relies solely on the input DSM, enabling a fully automated and scalable processing chain.

The method combines automatic ground extraction techniques with a robust energy-based optimization framework to reconstruct the terrain surface. In addition, an automatic quality assessment module was introduced, providing a spatialized estimation of the relative vertical accuracy of the output DTM.

Experiments conducted on Pléiades Neo data over an urban area demonstrated the ability of the method to produce accurate and consistent DTM. Both qualitative and quantitative analyses confirmed the robustness of the approach, with performance levels consistent with the expected accuracy of satellite stereo reconstruction.

Despite these promising results, some limitations remain, particularly in complex environments where residual artifacts may persist due to imperfect ground point classification or tiling effects. Further investigations are required to improve the robustness of the method in such cases and to extend the validation to a wider range of landscapes.

Finally, a major contribution of this work lies in the open-source release of the proposed tools. The GEMAUT pipeline for terrain reconstruction and the automatic quality assessment module are publicly available under open-source licenses, promoting transparency, reproducibility and collaboration within the geospatial community. The source code is available on GitHub: https://github.com/IGNF/GEMAUT-pipeline and https://github.com/IGNF/make-quality-great-again

## References

Bittner, K., Zorzi, S., Krauss, T., & d’Angelo, P. (2023). DSM2DTM: An end-to-end deep learning approach for digital terrain model generation. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-1/W2-2023, 67–74.

Brunet, P.-M., Lassalle, P., Baillarin, S., Vallet, B., Le Bris, A., et al. (2020). AI4GEO: A data intelligence platform for 3D geospatial mapping. *ISPRS Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.*

Champion, N., & Boldo, D. (2006). A robust algorithm for estimating digital terrain model from digital surface models in dense urban areas. *ISPRS Commission III Symposium on Photogrammetric Computer Vision.*

Champion, N. (2026) GEMAUT: Un Outil pour Générer Automatiquement des Modèles Numériques de Terrain Haute Résolution. *Revue Française de Photogrammétrie et de Télédétection*. In French. To appear.

Lallement, D., Lassalle, P., & Ott, Y. (2023). BULLDOZER: An open and scalable software for DTM extraction. *ISPRS Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-4/W7-2023, 89–96.

Krauß, T., Arefi, H. and Reinartz, P. (2011) Evaluation of selected methods for extracting digital terrain models from satellite born digital surface models in urban areas. *ISPRS Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.*

Lebègue, L., Cazala-Hourcade, E., Languille, F., Artigues, S., and Melet, O.: CO3D, A WORLDWIDE ONE ONE-METER ACCURACY DEM FOR 2025, *ISPRS Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIII-B1-2020, 299–304.

Pijl, A., Bailly, J.-S., Feurer, D., El Maaoui, M. A., Boussema, M. R., & Tarolli, P. (2020). TERRA: Terrain Extraction from elevation Rasters through Repetitive Anisotropic filtering. *International Journal of Applied Earth Observation and Geoinformation*, 84, 101977.

Rupnik, E., Daakir, M., & Pierrot-Deseilligny, M. (2017). *MicMac – a free, open-source solution for photogrammetry. Open Geospatial Data, Software and Standards, 2(3).*

Vosselman, G. (2000). Slope based filtering of laser altimetry data. *International Archives of Photogrammetry and Remote Sensing (IAPRS)*, XXXIII, Part B3, 935–942.

Zhang, K., Chen, S.-C., Whitman, D., Shyu, M., Yan, J., & Zhang, C. (2003). *A progressive morphological filter for removing non-ground measurements from airborne LiDAR data. IEEE Transactions on Geoscience and Remote Sensing*, 41(4), 872–882.

Zhang, W., Qi, J., Wan, P., Wang, H., Xie, D., Wang, X., & Yan, G. (2016). An easy-to-use airborne LiDAR data filtering method based on cloth simulation. *Remote Sensing*, 8(6), 501.