



HAL
open science

TERRA: Terrain Extraction from elevation Rasters 6 through Repetitive Anisotropic filtering 7 8 9

Anton Pijl, Jean-Stéphane Bailly, Denis Feurer, Mohamed Amine El Maaoui,
Mohamed Rached Boussema, Paolo Tarolli

► **To cite this version:**

Anton Pijl, Jean-Stéphane Bailly, Denis Feurer, Mohamed Amine El Maaoui, Mohamed Rached Boussema, et al.. TERRA: Terrain Extraction from elevation Rasters 6 through Repetitive Anisotropic filtering 7 8 9. *International Journal of Applied Earth Observation and Geoinformation*, 2020, 84, pp.101977. 10.1016/j.jag.2019.101977 . hal-02316912

HAL Id: hal-02316912

<https://hal.science/hal-02316912>

Submitted on 15 Oct 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18

TERRA: Terrain Extraction from elevation Rasters through Repetitive Anisotropic filtering

Anton Pijl* ^a; Jean-Stéphane Bailly ^{b, c}; Denis Feurer ^b; Mohamed Amine El Maaoui ^d; Mohamed Rached Boussema ^d; Paolo Tarolli ^a

^aDept. of Land, Environment, Agriculture and Forestry, University of Padova, 35020 Legnaro (PD), Italy (* anton.pijl@phd.unipd.it; paolo.tarolli@unipd.it)

^bLISAH, University of Montpellier, INRA, IRD, Montpellier SupAgro, Montpellier, France (denis.feurer@ird.fr)

^cAgroParisTech, 75231 Paris, France (bailly@agroparistech.fr)

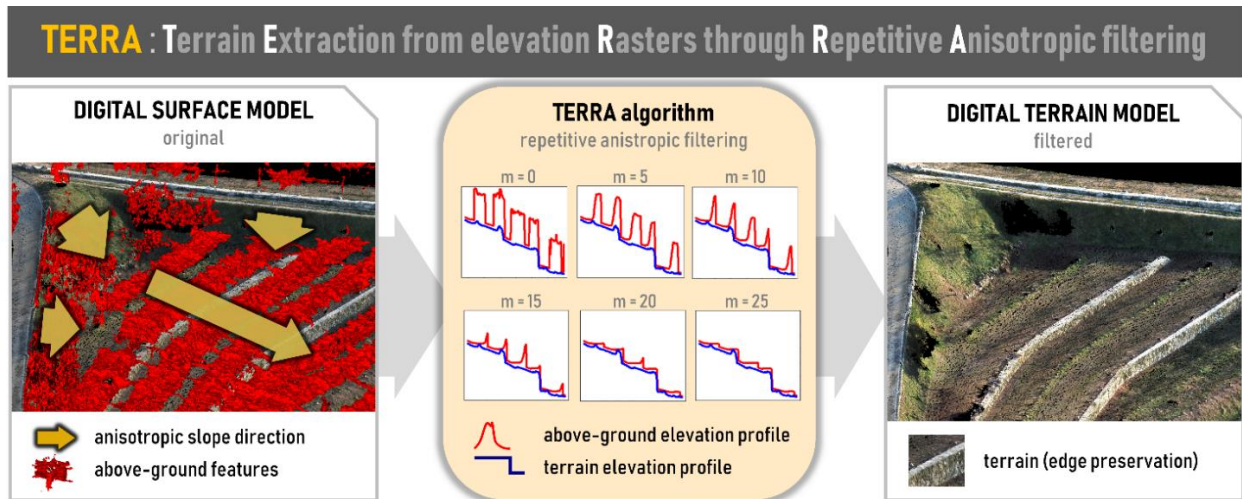
^dENIT, 1002 Tunis, Tunisia (maaouiamine@yahoo.fr; rached.boussema@enit.rnu.tn)

19 **ABSTRACT**

20 Over the past decades, several filters have been developed to derive a Digital Terrain Model (DTM) from a Digital Surface
21 Model (DSM), by means of filtering out aboveground objects such as vegetation. In this filtering process, however, one
22 of the major challenges remains to precisely distinguish sharp terrain features, e.g. ridges, agricultural terraces or other
23 anthropogenic geomorphology such as open-pit mines, riverbanks or road ramps. Hence, loss of elevation data around
24 terrain edges (and consequent smoothing) is very common with existing algorithms. In terraced landscapes, the
25 preservation of precise geomorphology is of key importance in digital terrain analyses, such as hydrologic and erosion
26 modelling, or automatic feature recognition and inventorying. In this work, we propose a new filtering method called
27 TERRA (Terrain Extraction from elevation Rasters through Repetitive Anisotropic filtering). The novelty of the algorithm
28 lies within its usage of terrain aspect to guide the anisotropic filtering direction, therefore maximising the preservation of
29 terrain edges. We derived six DTMs from DSMs using UAV Structure from Motion (SfM) photogrammetry, laser
30 altimetry and satellite sources (grid resolutions ranging from 0.1–1.0 m). The results indicated a close agreement of DTMs
31 filtered using the TERRA algorithm and reference DTMs, while terrace risers were well preserved even under thick
32 canopies of vines and trees. Compared to existing filtering approaches, TERRA performed well in minimising Type I
33 errors (false ground removal), while Type II errors occurred locally where vegetation was covering the terrace edges.
34 Given the promising filtering performance, and supported by the minimal requirements of parameterisation and
35 computation, the TERRA algorithm could be a useful tool in DTM preparation for digital terrain analysis of agricultural
36 terraces and similar hillslopes characterised by a complex mosaic of sharp terrain and non-terrain features.

37 *Keywords:* Digital Terrain Model (DTM) extraction; terraces; anisotropic filtering; vegetation removal; edge preservation

38 *Graphical abstract*



39
40

41 **1. INTRODUCTION**

42 Topographic data are widely used as powerful supportive information in various fields of research and in civil
43 applications, such as environmental management or landscape planning. With modern advances in remote sensing
44 techniques, such data are increasingly accessible with improving level of detail (Passalacqua et al., 2015; Tarolli, 2014),
45 often organised as regular-grid Digital Elevation Models (DEMs). Remotely sensed elevation data, however, typically
46 contains both bare-earth and aboveground information such as vegetation cover (Digital Surface Model, DSM). Many

47 applications require either purely ground information (Digital Terrain Model, DTM), e.g. in hydrology, or the height
48 difference of a DTM and DSM, e.g. as a Canopy Height Model (CHM). Therefore, differentiation between ground and
49 non-ground elevation data is of wide interest. A range of systematic filtering methods have thus emerged, which however
50 have a common issue with the preservation of sharp terrain features (Liu, 2008; Meng et al., 2010). This limits reliable
51 digital terrain analysis in landscapes characterised by terrain ridges, or sharp anthropogenic features such as open-pit
52 mines, riverbanks, urban ramps or agricultural terraces. Terraced landscapes represent one of the most widespread
53 examples of complex anthropogenic geomorphology (Tarolli et al., 2014; Wei et al., 2016), of which the culture-historical
54 and economic values are widely recognised, e.g. by the United Nations Educational, Scientific and Cultural Organization
55 (UNESCO) and the Food and Agriculture Organization (FAO) (Dela-Cruz and Koohafkan, 2009). Precise information
56 on terrain morphology is of key importance in several types of terrace terrain analysis, e.g. (semi-)automatic terrace
57 recognition and inventories (Bailly and Levvasseur, 2012; Sofia et al., 2016, 2014), high-precision soil erosion
58 simulations (Pijl et al., 2019a; Tarolli et al., 2015) or digital designs of terrace drainage systems (Pijl et al., 2019b).

59 Various approaches exist for identifying terrain from regular-grid DSM, that are typically based on geometrical
60 characteristics such as slope (Roggero, 2001; Sithole, 2001; Vosselman, 2000), mathematical morphology (Chen et al.,
61 2007; Zhang et al., 2003), or alternatively on linear prediction or interpolation-based methods (Kraus and Pfeifer, 1998).
62 In order to provide a systematic comparison of ground-filtering algorithms, the ISPRS Working Group III/3 evaluated the
63 performance of eight established methods (Sithole and Vosselman, 2004). These algorithms (developed by Axelsson,
64 1999; Brovelli et al., 2002; Elmqvist et al., 2001; Pfeifer et al., 1998; Roggero, 2001; Sithole, 2001; Sohn and Dowman,
65 2002; Wack and Wimmer, 2002) represented the different filtering approaches and were tested for different landscape
66 types and elements. Three terrain types were found to be particularly challenging: steep slopes, vegetated slopes, and
67 discontinuous terrain features. Interestingly, all three characteristics are typical descriptors of terraced landscapes, making
68 it one of the most challenging environments for automatic DTM-from-DSM generation. Under these circumstances,
69 typically, ground features are falsely removed as aboveground features (Type I error). In particular, sharp ridges were
70 shown to be very poorly preserved, with 7 of 8 algorithms removing these elements in >50 % of all cases, and 1 algorithm
71 in 10–50 % of cases (Sithole and Vosselman, 2004).

72 The difficulties of filtering discontinuous terrain are pointed out by Meng et al. (2010) as well, who relate it to the
73 conventional assumptions about (non-)terrain geometry that underlie the algorithms. Sharp geomorphological features
74 share 3 out of 4 typical properties of non-ground features, i.e. steep slopes, large elevation differences, and local
75 heterogeneity of elevations. The edge-preservation challenge is widely reported in diverse filtering approaches, e.g. multi-
76 directional ground filtering (Meng et al., 2009), one-dimensional and bi-directional labelling (Shan and Aparajithan,
77 2005), or Simple Morphological Filter aided by novel image-processing techniques (Pingel et al., 2013). The two-step
78 adaptive extraction method by Yang et al. (2016), specifically designed to preserve terrain breaklines, also produces Type
79 I errors (false ground-point removal) around terrace edges, underlining the persisting challenges of this terrain type. An
80 increasingly common approach is segmentation-based filtering based on supervised training (Grilli et al., 2017). Famous
81 examples include graph-cut methods (He et al., 2018; Ural and Shan, 2016) or the CANUPO algorithm (Brodu and Lague,
82 2012), which group data points based on multi-scale homogeneity in geometric characteristics. Despite their powerful
83 potential in many applications, such approaches rely on active supervised learning and are known to be computationally
84 very heavy, both limiting their adoption and suitability for large-scale analyses (Grilli et al., 2017; Lermé and Malgouyres,
85 2017). Also non-geomorphologic filters reportedly have limited applicability in these terraced landscapes, e.g. NDVI-

86 based segmentation in vineyard terraces that is typically hampered by grass cover (Burgos et al., 2015; Santesteban et al.,
87 2013).

88 Interesting opportunities, however, lie in the regular geometry of hillslope terrain, particularly in engineered terraces.
89 Anisotropic filtering holds potential for terrain edge-preservation in the filtering process (Passalacqua et al., 2015). Given
90 that slope aspect is often not entirely mono-directional across hillslopes, its local anisotropy could dictate the filtering
91 direction. While anisotropy or non-linear filters has been successfully applied for edge-preserving terrain smoothing from
92 noise (Passalacqua et al., 2015; Perona and Malik, 1990), a filter driven from terrain slope anisotropy has not been
93 developed before, to the best of our knowledge. If one can assume that ground elevation changes are locally homogeneous
94 in sign (i.e. consistently up- or downhill), a simple iterative erosive operation could progressively remove objects with
95 opposite elevation change.

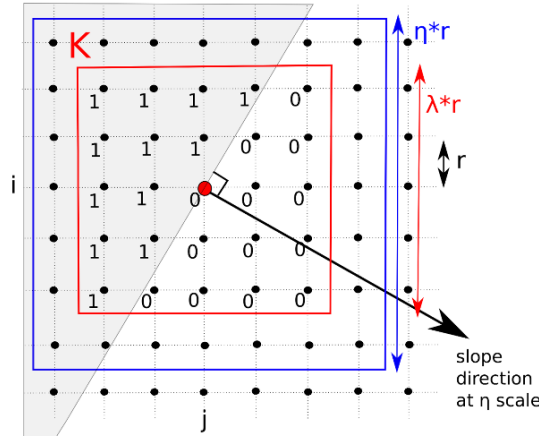
96 This paper proposes a novel DTM-from-DSM filtering algorithm called TERRA (Terrain Extraction from elevation
97 Rasters through Repetitive Anisotropic filtering). The filter has a primary focus on the preservation of sharp terrain
98 features on complex vegetated hillslopes, by acting as an anisotropic erosive terrain “scraper” whilst maintaining larger
99 perpendicular objects such as contour terraces. The regular-grid approach of the TERRA algorithm favours its time-
100 efficiency (Grilli et al., 2017; Shan and Aparajithan, 2005; Wack and Wimmer, 2002) and allows generic applicability,
101 i.e. it could be applied independently of data source and surveying platform. Thus, the algorithm could be a powerful tool
102 in DTM creation e.g. in support of high-resolution analysis on field scale (e.g. LiDAR- or photogrammetry-based) or
103 large-scale geomorphologic inventories (e.g. satellite-based). Filtering performance is evaluated in terms of non-ground
104 removal and ground preservation compared to ground-truth elevation data, as tested on six different topographic datasets
105 of challenging vegetated terrace landscapes.

106 Section 2 of this article elaborates on the technical details of the TERRA algorithm (2.1), the background of the several
107 test sites (2.2), the diverse origin of topographic data (2.3), the parameterisation of the algorithm (2.4), and the
108 experimental design for performance assessment of TERRA (2.5). Filtering results by TERRA and its performance are
109 then presented in Section 3, while Section 4 furthermore touches on its limitations and further potential.

110 **2. MATERIALS AND METHODS**

111 **2.1 TERRA: a new digital elevation model filtering algorithm**

112 The TERRA algorithm virtually acts as a “scraper” removing topsoil elements in the slope direction at each DSM grid
113 node. It works as a smoothing operation but locally directed along the slope while only considering downhill neighbouring
114 values. Firstly, it computes the slope direction (aspect) at coarser spatial resolution as a multiplication of aggregation
115 factor η and grid resolution r , thus avoiding slope noising resulting from vegetation and preventing interruption by non-
116 terrain features. This slope direction is secondly resampled at each initial DSM grid node (Figure 1, note that the
117 aggregation window for determining slope direction is kept relatively small in this figure for visual understanding).
118 TERRA then operates as an iterative focal anisotropic filter. For each grid node (i,j) of the DSM at a given iteration m ,
119 anisotropy results from null weights given by kernel function K to downstream nodes within the focal window, i.e. in
120 front of the semi-circular sector of the slope aspect at (i,j) node (Figure 1).



121

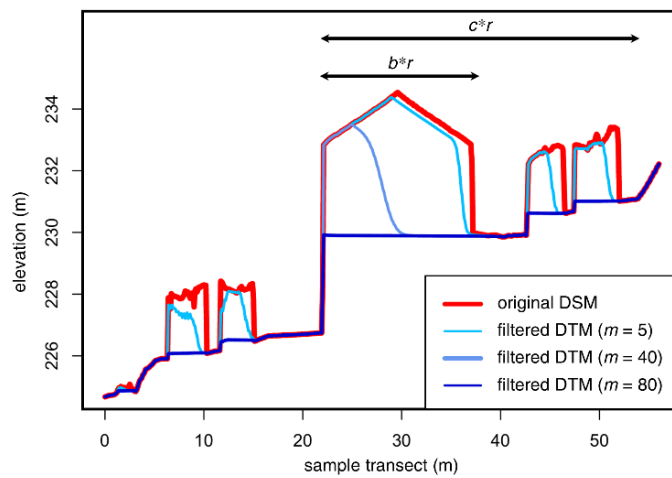
122 *Figure 1 – Schematic top-view of the TERRA filtering algorithm, showing the determination of hillslope aspect (coarser resolution*
 123 *with η cells) and subsequent attribution of null weights to all downstream grid nodes within kernel K (finer resolution with λ cells).*

124 At each iteration m over the grid, elevation value Z_m on grid node (i, j) is computed as:

125

$$Z_m(i, j) = \operatorname{argmin}(Z_{m-1}(i, j), K_{i, j}(\lambda, \eta)) \quad (\text{Eq.1})$$

126 With $K_{i, j}(\lambda, \eta)$ as the chosen kernel averaging function (e.g. median). The processes is repeated from m equal to 1 up to M ,
 127 the total number of iterations. The three algorithm parameters η , M and λ can be linked to physical properties of the
 128 studied surface. Let us consider the terrain features of interest are of maximum size $c*r$ and topsoil elements to remove
 129 are of maximum length $b*r$ along slope direction (illustrated in Figure 2, corresponding to the study case in Figure 3,
 130 bottom-right). According to the Nyquist-Shannon theorem of sampling, the η parameter should be chosen in order to
 131 preserve terrain contour curvature at least two times coarser than c ($\eta \geq 2c$). The M parameter should be initiated with
 132 the value of b , given that the iterative filtering will “scrap” a given non-terrain object cell by cell, with a maximum number
 133 of b (this iterative filtering is illustrated in Figure 2). The latter λ parameter is less sensitive and controls the desired level
 134 of smoothing on terrain data related to the used kernel averaging function. The TERRA algorithm is freely available as R
 135 script under GNU GPL licence at: <https://www.umr-lisah.fr/?q=fr/scriptsr/terra-script-r> (see Supplementary Material A).

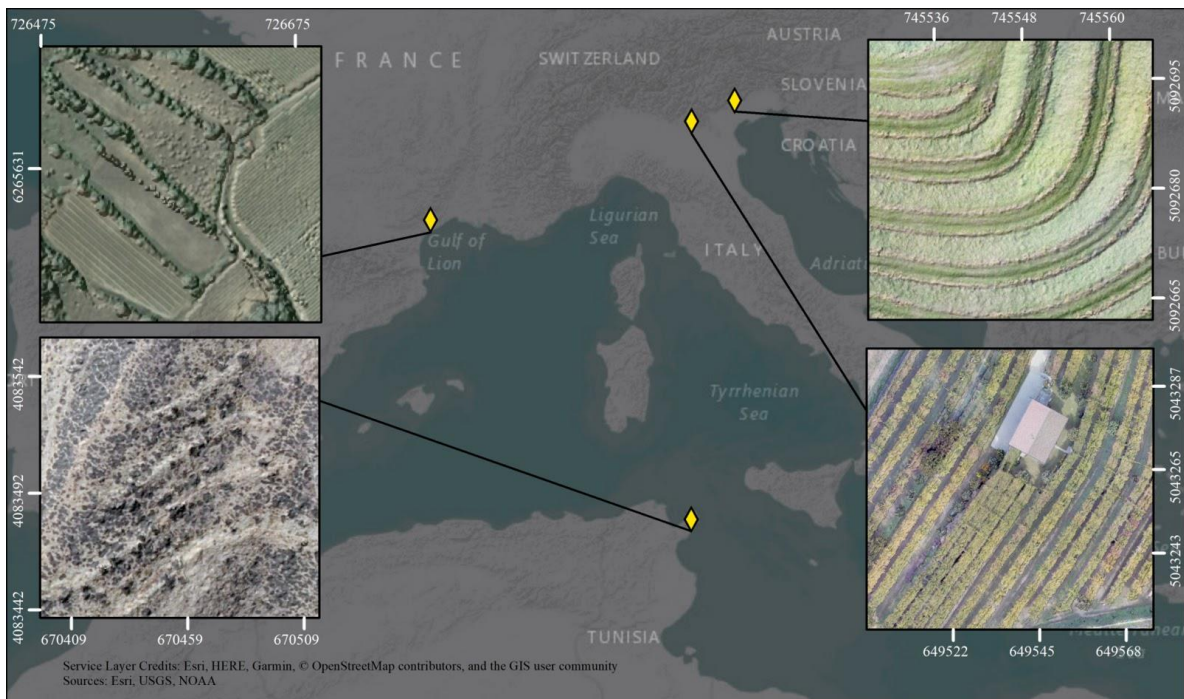


136

137 *Figure 2 – Schematic side-view transect elevation profile of a DSM and several DTMs filtered with given iterations m , illustrating*
 138 *also the physical meaning of $b*r$ (maximum downslope length of non-terrain object) and $c*r$ (dimension of typical terrain features,*
 139 *here a terrace bank). The determination of slope direction at η -scale (i.e. right-to-left direction) is not affected by local interruptions*
 140 *such as the building or vegetation, considering that $\eta \geq 2c$.*

141 **2.2 Test sites**

142 A total of four test sites across three Mediterranean countries were used for testing the TERRA algorithm (Figure 3).
143 These locations provided six distinct application scenarios due to multiple topographic data sources in some of the sites
144 (Table 1). A common characteristic of all sites is the presence of agricultural terraces that are to some extent covered by
145 vegetation. In Italy, two terraced vineyards are selected that are characterised by dry-stone walls (vertical) and earth banks
146 (typically inclined to about 45°), respectively located in the Verona province (45°31'36.80"N; 10°54'54.32"E) and Treviso
147 province (45°56'43.26"N; 12°10'4.49"E). The Roujan site is part of an observatory in Mediterranean France
148 (43°28'56.01"N; 3°20'55.69"E) that has been monitored since 1992 (ORE OMERE: <http://www.obs-omere.org/>; Molénat
149 et al., 2018), containing wider vineyard terraces with intermittent dry-stone walls that are partly covered in natural shrubs.
150 The Cap Bon test site in Tunisia (36°52'55.68"N; 10°54'45.25"E) is located on the steep slopes of a hill where a mixed
151 soil conservation system was settled. This soil conservation system consists in small shrubs associated to contour lines
152 benches. This test site is located just near to Kamech, the second site of the OMERE observatory mentioned above.



153
154 *Figure 3 – Location of the four test sites of this study: Roujan, France (top-left); Kamech, Tunisia (bottom-left); Treviso, Italy (top-*
155 *right); and Verona, Italy (bottom-right). For each site, orthomosaics are displayed with geographical extent in the WGS 84-UTM 32*
156 *coordinate system (EPSG:32632).*

157 **2.3 Topographic data sources**

158 The various sites offer an interesting set of test cases, given their diversity in topographic data source. In Treviso (TRE)
159 and Verona sites (VER-O and VER-D), very high-resolution elevation data (0.1 m) was obtained using Unmanned Aerial
160 Vehicles (UAVs) and photogrammetric processing. An independent source of ground elevation data was provided through
161 accurate field-measurements of DGPS reference points. In Roujan, high-resolution surface topography data (1 m) was
162 obtained from Pleiades optical satellite imagery (ROU-P) and LiDAR laser altimetry (ROU-L), with the latter also
163 providing a reference terrain model without vegetation. The Kamech dataset (KAM), high-resolution elevation data (0.3
164 m) was obtained by photogrammetric processing of digital aerial imagery acquired by the Tunisian office of topography
165 and cadastre.

167 In Treviso and Verona, UAV surveys were carried out during October 2017 (TRE and VER-O datasets) using a *DJI*
 168 *Phantom 4 Pro* (20 MP optical camera with 8.8 mm focal length). In the latter site, a repeated UAV survey was carried
 169 out during December 2017 (VER-D dataset), when no leaves were present on the grape vines, using a *DJI Mavic Pro*
 170 (12.3 MP optical camera with 4.7 mm focal length). Nadir images were taken from a 50-m altitude with >75 % front- and
 171 side-overlap, and oblique images were sparsely captured to better cover hidden parts (e.g. terrace fronts or vegetation
 172 blind spots), with a total number of 316, 146 and 254 images for TRE, VER-O and VER-D, respectively. Reference
 173 terrain elevation points were measured using a *TopCon HyperV* DGPS device for calibration of the photogrammetric
 174 analysis (resp. 18, 19 and 17 ground control points) and as an independent validation dataset for the vegetation filtering
 175 process (dense transects of 60 and 200 points for the two locations, resp.).

176 UAV imagery was processed using Structure-from-Motion (SfM) photogrammetry software *Agisoft Photoscan*, in order
 177 to derive a 3D model from the overlapping 2D images and additional ground control points. The resulting dense point
 178 clouds had a point density of 694, 1545 and 2023 pt/m² and a recommended DEM resolution of 0.03, 0.02 and 0.02 m/pix,
 179 which was harmonised to 0.1 m for the TRE, VER-O and VER-D datasets. In addition to the DSMs, reference DTMs
 180 were derived by manual point cloud filtering (further elaborated in Section 2.5), with vertical errors to DGPS points of
 181 0.09±0.06 m, 0.02±0.06 m and 0.02±0.10 m, respectively for the three datasets.

182 *Table 1 – Study sites and their main characteristics, used in this study for testing the filtering algorithm.*

DATASET ACRONYM	LOCATION	TERRACE TYPE	VEGETATION TYPE	DATA SOURCE	REFERENCE DTM	RESOLUTION (m)
TRE	Treviso (IT)	earth banks, relatively steep	vineyards (rows)	UAV SfM	manual filtering + DGPS	0.1
VER-O	Verona (IT)	earth banks & dry- stone walls	vineyards (pergola cultivation), leaves-on	UAV SfM	manual filtering (VER-D) + DGPS	0.1
VER-D	"	"	vineyards (pergola cultivation), no leaves	UAV SfM	manual filtering + DGPS	0.1
ROU-L	Roujan (FR)	dry-stone walls, partly vegetated	vineyards (rows), lines of trees and bushes	LiDAR	LiDAR DTM	1.0
ROU-P	"	"	"	Pleiades (stereoscopic)	LiDAR DTM (ROU-L)	1.0
KAM	Kamech (TN)	contour bunds	sparse trees and low bush	aircraft SfM	manual filtering	0.3

185 *Multi-echo LiDAR*

186 In Roujan, Aerial Laser Scanning (ALS) was carried out during June 2002. A helicopter mounted with a *Falcon II Toposys*
187 LiDAR system covered the area from a 900-m altitude, with a 83 MHz laser pulse emission rate and a 10 pt/m² 3D points
188 spatial sampling rate. Multi-echo information was used to create a 1-m DSM (from first pulse points) and DTM (from
189 last pulse points, followed by a multi-step filtering process). For more details about this particular ALS survey and data
190 processing, the authors refer to [Bailly et al. \(2008\)](#). DGPS validation points taken in the field showed a vertical error
191 standard deviation of the 1-m DTM of 0.06 m in flat areas and 0.15 m on the steepest slopes.

192 *Pleiades satellite*

193 In Roujan, Pleiades satellite imagery was recorded during the leaves-off period of January 2013 (ROU-P). A stereo pair
194 of images was taken with a high incident angle of 30° (base-to-height ratio of about 1/1.6). A 1-m DSM was constructed
195 using *MICMAC* software ([Pierrot-Deseilligny et al., 2011](#); [Pierrot-Deseilligny and Paparoditis, 2006](#)). For more technical
196 details on the photogrammetric analysis of this particular dataset, the authors refer to [Sofia et al. \(2016\)](#). Validation with
197 ground-measured DGPS points showed a vertical error standard deviation of 0.51 m.

198 *Airborne SfM photogrammetry*

199 For Kamech (KAM), aerial imagery was available from airborne survey performed by the Tunisian office of topography
200 and cadastre during June 2010. The whole set of images was acquired with a *Vexcel UltraCamXp* at an average altitude
201 of 5200 m. From this set, four images covering the area of interest were extracted. Each image has 11310*17310 pixels
202 with an average ground sampling distance of 0.3 m. Four GCPs picked on Google Earth imagery were used to obtain an
203 absolute geographic reference (estimated vertical accuracy <10 m). SfM photogrammetric processing was carried out
204 using *Agisoft Photoscan* software and a DEM at 0.3 m resolution was exported. For this test site, no validation data is
205 available.

206 **2.4 Parameterisation**

207 The TERRA algorithm was tested for the six test datasets with the parameters given in Table 2. Aspect aggregation factor
208 η and number of iterations M were determined from the physical dimensions of area-specific objects. Both parameters
209 should be at least the downslope length of non-terrain objects: for η to correctly determine terrain aspect, and for M to
210 allow enough “scrapping” iterations to remove the object (as described in Section 2.1). Parameter values could be
211 translated into metric equivalents by considering raster resolutions (see Table 1), e.g. if the *pergola* canopy found in VER-
212 D has a maximum downhill length of 8 m, the η and M parameters could be set to 100 (10 m equivalent * 0.1 m resolution).
213 Finally, kernel size (λ) was set to 7 for all datasets, based on an arbitrary assumption of allowed semi-circular (downhill)
214 smoothing. Initial tests suggested limited sensitivity of the produced results by varying kernel sizes, although no elaborate
215 sensitivity analysis was carried out for this parameter in the presented study.

216

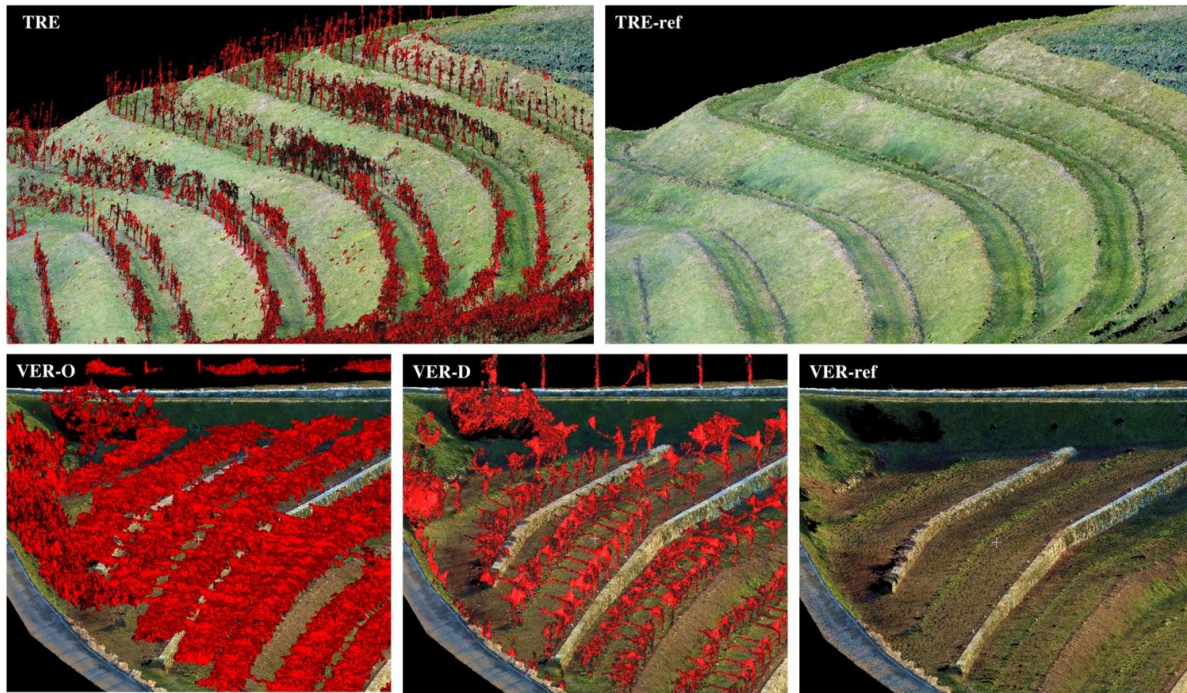
Table 2 – TERRA parameter values used in this study.

DATASET	ASPECT AGGREGATION FACTOR (η)	TOTAL NUMBER ITERATIONS (M)	KERNEL SIZE (λ)
TRE	30 (equiv. 3 m)	30 (equiv. 3 m)	7
VER-O	100 (equiv. 10 m)	100 (equiv. 10 m)	7
VER-D	100 (equiv. 10 m)	100 (equiv. 10 m)	7
ROU-L	30 (equiv. 30 m)	30 (equiv. 30 m)	7
ROU-P	30 (equiv. 30 m)	30 (equiv. 30 m)	7
KAM	30 (equiv. 9 m)	30 (equiv. 9 m)	7

2.5 Reference DTMs and filtering performance assessment

Reference DTMs were available from different sources varying among datasets (Table 1). For the SfM-photogrammetric datasets (i.e. TRE, VER-O, VER-D, KAM), a reference terrain model was obtained by manual filtering based on the original point cloud, which is an established approach for relatively small datasets (Meng et al., 2010; Sithole and Vosselman, 2004). The manual filtering was done using *CloudCompare v2.9.1* software, based on the vertical distance of any point to surrounding points while paying close attention to the preservation of complex landscape features (examples in Figure 4). An exceptional case was the VER-O dataset, in which ground points were insufficient to provide a complete reference DTM, hence the VER-D reference DTM was used (thus implying an uncertainty due to shifts). For the LiDAR-based dataset ROU-L, a reference DTM was readily available. The same reference DTM was also used for comparison with the filtered ROU-P DTM, after a vertical shift was performed corresponding to the average distance of their DSMs (3.64 m, which relatively homogeneous throughout the study site, with a standard deviation of 0.27 m). Such comparison can further be justified as no changes in terrace morphology were detected between the timing of the ROU-L (2002) and ROU-P (2013) datasets (Sofia et al., 2016), and erosion rates in Roujan are relatively low with a reported 0.695 mm/year (Paroissien et al., 2010).

The filtering performance of TERRA was done in several steps. Firstly, the filtered DTMs were compared to dense DGPS transect available from the field surveys of TRE and VER-O, based on Root Mean Square Error (RSME) values (Section 3.1). Secondly, the filtered DTMs were compared to the original DSMs, based on a visual interpretation of the difference maps (Section 3.2). Lastly, the filtered DTMs were compared to the reference DTMs based on difference maps and transect elevation profiles (Section 3.3). The maps were classified according to Type I and II errors in order to allow a quantitative comparison with literature. For this particular purpose, a threshold was introduced to distinguish between appropriate filtering and terrain underestimation (i.e. false ground removal or Type I error) or overestimation (i.e. false non-ground preservation or Type II error). This threshold was set variable for the different datasets, as twice the raster resolution in case of SfM-derived datasets as empirically estimated in many previous studies (e.g. Lane et al., 2000), thus 0.2 m for TRE, VER-O, VER-D; and 0.6 m for KAM), and as 0.3 m for the ROU-L and ROU-P datasets, corresponding for the former to the 95% confidence band for random altimetric errors in LiDAR measurements.



243

244

245

246

Figure 4 – Snapshot of manual aboveground filtering (red) in preparation of reference DTMs for the VER-O, VER-D and TRE datasets. Various vineyard cultivation types can be distinguished, e.g. the typical pergola in Verona (second row), with a reduction of canopy cover between the UAV flights of October and December, 2017.

247

3. RESULTS

248

3.1 Comparison of filtered DTMs and DGPS

249

250

251

252

253

254

255

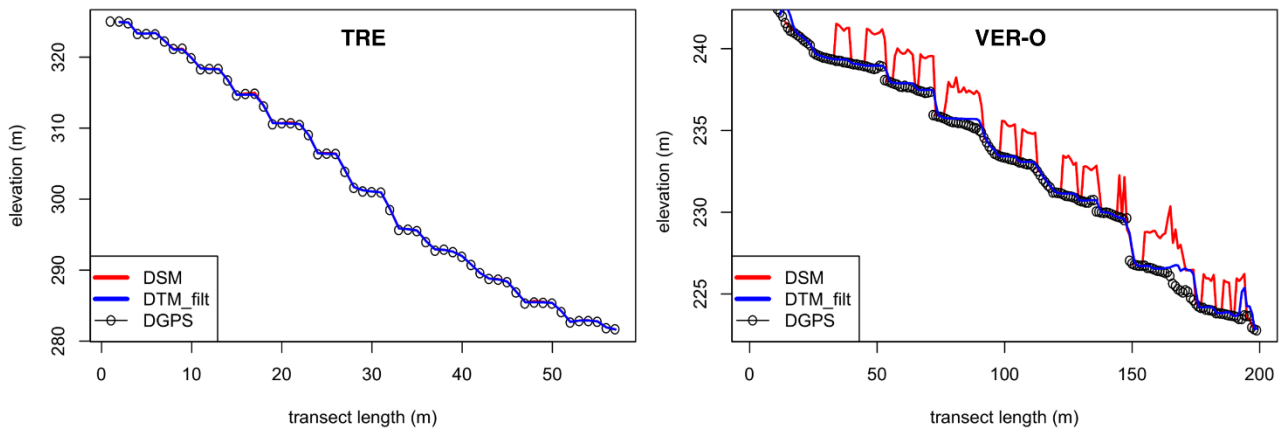
256

257

258

259

Figure 5 illustrates the generally strong agreement between field-measured DGPS points (black circles) and the filtered DTM elevation profile across these points (blue lines) alongside with the original DSM elevations (red lines). RMSE values between the measured points and filtered DTM are respectively 0.121 m and 0.256 m for the TRE and VER-O datasets. In the former, additional comparison of the reference DTM with the DGPS points reveals a RMSE of 0.110 m, indicating that almost the entire error of the filtered DTM can instead be explained by a photogrammetric error (considering also that vegetation is not abundant, see Figure 5). The remaining errors are limited (roughly 0.011 m) and indicate promising filtering performance. This is underlined by the case of VER-O, where thick vegetation coverage is present, and the RMSE of the DSM and DGPS was originally 1.744 m. The remaining error can be attributed to situations where terrace edges are covered in overhanging vegetation, e.g. around VER-O transect lengths 90 m and 170 m in Figure 5. A further comparison of filtered and reference DTMs is given Section 3.3, following a comparison with the original DSMs in Section 3.2.



260

261

262

Figure 4 – DGPS transect elevation values (black circles) and corresponding extracts of DSM (red lines) and filtered DTM (blue lines; DTM_filt) in TRE and VER-O datasets.

263

3.2 Comparison of filtered DTMs and original DSMs

264

265

266

267

268

269

270

271

272

DTMs derived from the original DSMs by the TERRA algorithm are shown in Figure 6 (left and centre columns). The difference maps show clear patterns of aboveground features (right column, reddish colours), such as vine rows (TRE, VER-O, VER-D), the building (VER-O, VER-D), and trees and bushes (VER-D, ROU-L, ROU-P, KAM). Even in VER-O, originally significantly covered in *pergola* type vines, a DTM is derived that is visually very close to VER-D (while the latter has much more ground information). Terrace edges are still evident in VER-O, although additional sharp micro ‘ridges’ are detectable where the canopy ends on the banks of some terraces (e.g. eastern segment of VER-O, filtered DTM). Some remainders of vegetation can be detected under terrace edges (e.g. middle segments of VER-O and VER-D), which is further explored in the following section. Instead, vegetation located slightly further from ridges are removed well (e.g. visible just north and south of the house in VER-O and VER-D).

273

3.3 Comparison of filtered and reference DTMs

274

275

276

277

278

Difference maps and transect profiles show that there is generally a good agreement between filtered and reference DTMs across the study sites (Figure 7). Sharp terrain edges such as terrace fronts are well preserved throughout the study areas, even in the case of near-vertical stone walls of VER-O and VER-D (Figure 7, e.g. between transect length 90–100 m). Some deviations exist, which are predominantly negative and result from remaining vegetation in the filtered DTM (cyan colours). Two recurring situations of such errors can be recognised:

279

280

281

282

(i) Dense vegetation is present at the foot of a terrace wall, with elevation values similar to the upslope terrace elevation. In this case, a continuous surface is produced, consisting of terrace terrain elevations and remainders of canopy elevations. Some examples can be found throughout the difference map of VER-D (Figure 7, dashed circles), and related transect at lengths 17 m and 35 m (see dashed arrows).

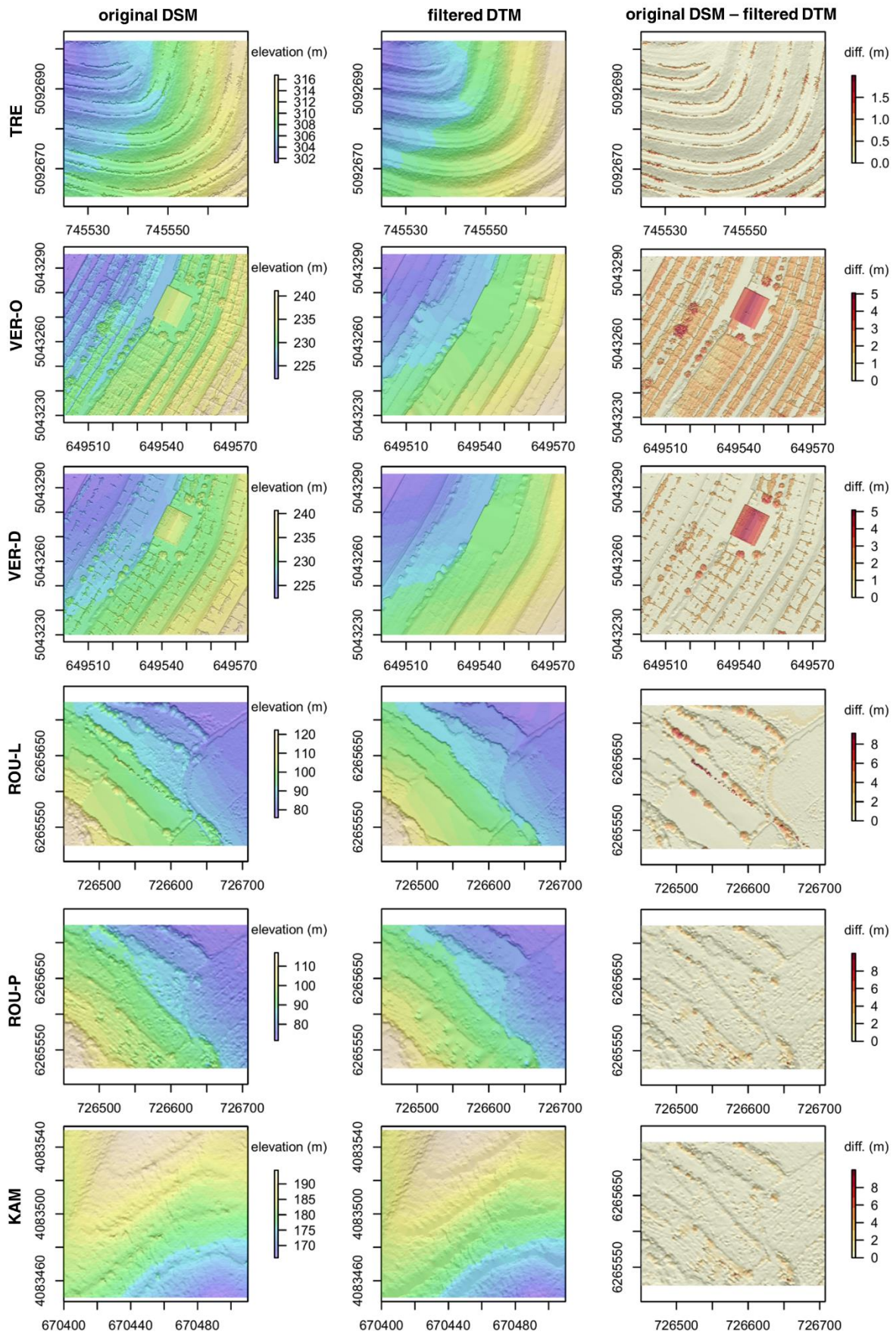
283

284

285

286

(ii) Dense vegetation is located on top the terrace and ‘overshadowing’ the terrace edge. In this case, terrace fronts are estimated to be located at the vegetation edge, which is often too wide compared to the actual bench width. Examples are visible in the transect profiles of VER-O (around 40 m, see dashed arrow), ROU-L and ROU-P (around 25 m and 30 m, see dashed arrows), and throughout the respective difference maps (see dashed circles).



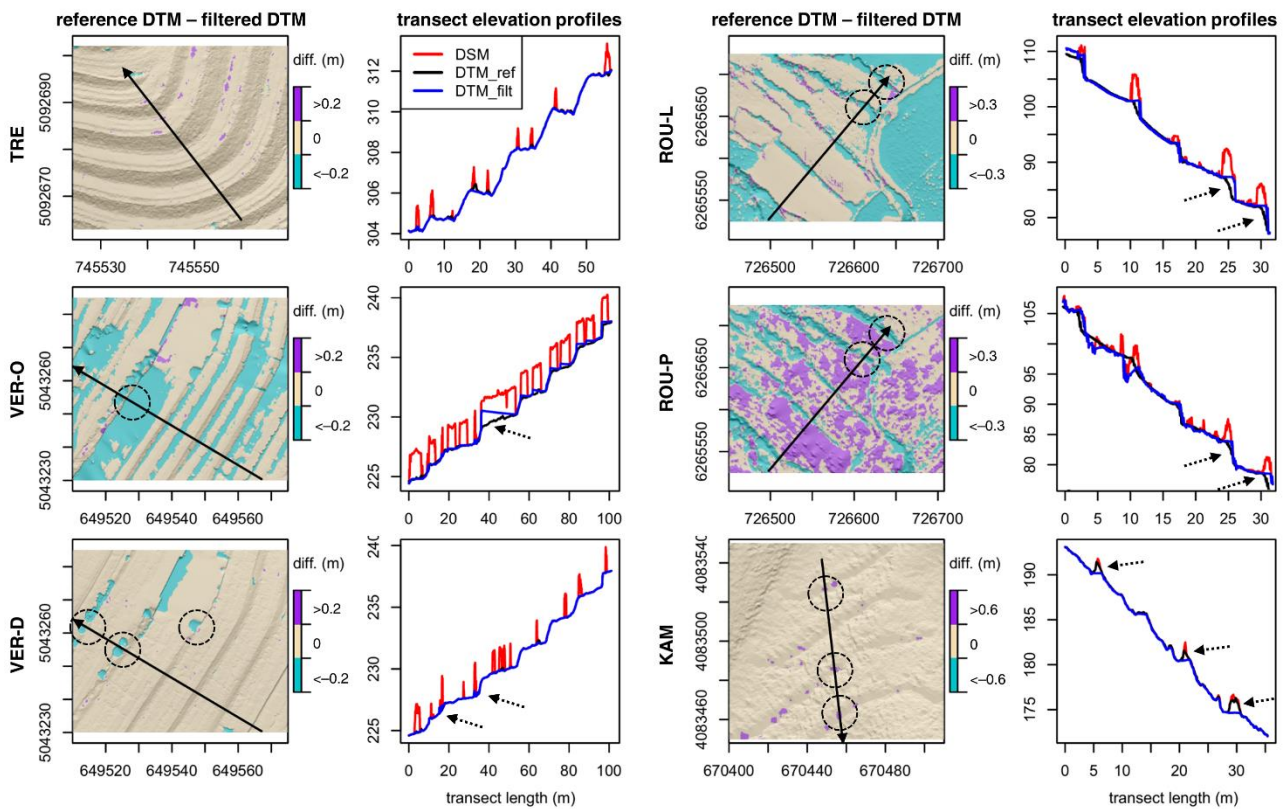
287

288

289

Figure 6 – Digital elevation models for each dataset: the original DSM (left), the DTM filtered using the TERRA algorithm (centre), and the difference map (right); all displayed in coordinate system WGS 84-UTM 32 (EPSG:32632)

290 A quantification of the spatial distribution of Type I and II errors is provided in Table 3. In general, the TERRA algorithm
 291 performs very well in avoiding Type I errors (i.e. ground is preserved), and is more prone to Type II errors (i.e. non-
 292 ground is falsely preserved). On average, Type I errors are relatively sparse with 5.1%, which indicates an improved
 293 performance compared to the 8 filtering approaches evaluated by [Sithole and Vosselman \(2004\)](#), of which 7 show Type
 294 I errors in more than 50% of cases. Type II errors here are generally more frequent with an average of 19.9%, but
 295 performance according to [Sithole and Vosselman \(2004\)](#) would be classified as *Fair* (10–50%) or *Good* (<10%) for the
 296 individual datasets (Table 3, third column), which is comparable with the 8 considered filters under vegetated slopes.
 297 Two datasets show notably high errors: (i) ROU-P in Type I errors occurring on the horizontal terrace banks (Figure 7,
 298 ROU-P, purple colours), which can be related to general quality of the dataset combined with the usage of an external
 299 reference DTM (from ROU-L); (ii) ROU-L in Type II errors, which are mostly related to a large flat vineyard canopy
 300 covering the eastern segment of the study site (Figure 7, ROU-L, cyan colours). Additionally, Type II errors are indeed
 301 relatively high in the zones where terrace edges are covered in vegetation (situation –ii– in the previous paragraph), i.e.
 302 VER-O (41.2%), ROU-L (18.1%) and ROU-P (50.9%, combined with the effect of the flat vineyard).



303
 304 *Figure 7 – Distance comparison of terrain elevations: difference maps of reference and filtered DTMs considering a specific*
 305 *threshold for Type I and II errors (resp. purple and cyan colours), and transect elevation values extracted along the black solid*
 306 *arrows depicted on the maps in downhill direction (DSM as red lines; reference DTM as black; filtered DTM as blue); all displayed*
 307 *in coordinate system WGS 84-UTM 32 (EPSG:32632).*

308 Furthermore, the derived DTMs have mean elevations relatively close to the reference DTMs (Table 3), i.e. <10 cm for
 309 high-resolution datasets TRE, VER-D and KAM, and <70 cm for the LiDAR-based and Pleiades-based datasets ROU-L
 310 and ROU-P. The mean distance between the filtered and reference DTMs of VER-O is slightly higher, which is biased
 311 by the different origin of the reference (i.e. deriving from the VER-D survey). Pearson’s correlation coefficients of

312 reference and filtered DTMs range between 0.995 and 0.999 for all datasets, emphasising the expected overall agreement
 313 of derived elevation values with the reference on steep slope test sites. Only in the case of KAM the reference DTM is
 314 generally higher than the filtered DTM (Table 3), which is related to the slight “scrapping” of the top of the contour bunds
 315 (Figure 7, dashed circles and arrows).

316 *Table 3 – Statistics on terrain elevations: mean and standard deviation of the reference DTMs, filtered DTMs, and difference maps;*
 317 *the Pearson correlation coefficient of reference and filtered DTMs; and the Root Mean Square Error (RMSE) of ground-measured*
 318 *DGPS values vs. their extracts from the filtered DTMs.*

DATASET	TYPE I errors	TYPE II errors	REFERENCE DTM <i>mean ± std. (m)</i>	FILTERED DTM <i>mean ± std. (m)</i>	REFERENCE DTM – FILTERED DTM <i>mean ± std. (m)</i>	CORRELATION COEFFICIENT <i>(reference and filtered)</i>
TRE	1.5%	6.1%	309.21 ± 5.88	309.30 ± 5.83	-0.09 ± 0.59	0.996
VER-O	0.8%	41.2%	229.66 ± 3.73	229.86 ± 3.83	-0.20 ± 0.35	0.995
VER-D	0.8%	3.0%	229.65 ± 3.72	229.65 ± 3.72	0.00 ± 0.11	0.999
ROU-L	3.5%	50.9%	94.2 ± 14.10	94.7 ± 14.20	-0.51 ± 0.81	0.998
ROU-P	23.3%	18.1%	90.6 ± 14.10	91.2 ± 14.20	-0.63 ± 1.07	0.997
KAM	0.9%	0.0%	182.68 ± 6.14	182.68 ± 6.15	0.07 ± 0.11	0.999
<i>average:</i>	<i>5.1 %</i>	<i>19.9 %</i>	-	-	-	-

319 4. DISCUSSION

320 4.1 Performance and novelty of TERRA algorithm

321 This study presented TERRA, a novel filtering algorithm for deriving a DTM from a DSM. Its development was motivated
 322 by the general difficulties that existing filters commonly have with the preservation of sharp terrain features, due to their
 323 similarities with non-ground features (Meng et al., 2010, 2009; Pingel et al., 2013; Shan and Aparajithan, 2005). To the
 324 best knowledge of the authors, TERRA is the first filter to make use of anisotropy in terrain aspect to guide the filtering
 325 direction, and as such, minimise the loss of valuable terrain information (Type I errors).

326 The studied topographic datasets represent a typical challenge for existing methods, i.e. steep, vegetated and discontinuous
 327 slopes (Sithole and Vosselman, 2004), which are all common features of the agricultural terraces considered here. Results
 328 show that the TERRA algorithm is able to derive a DTM from a given DSM with terrain elevations very close to the
 329 reference ($r > 0.995$), with minimal parameterisation requirements that can easily be estimated *a priori* from the
 330 dimensions of known physical objects. The largest deviations from the reference terrain is found where dense vegetation
 331 is present around terrace walls, resulting in false preservation of above-ground remainders (Type II errors on 19.9% of
 332 surface). However, the TERRA algorithm performs particularly well in preserving terrain features such as terrace edges
 333 under diverse conditions of canopy type and the origin of topographic data (Type I errors on 5.1% of surface). The
 334 performance is further characterised by relatively fast computations, thanks to the regular-grid data structure, e.g. when
 335 compared to 3D point cloud-based filters (Grilli et al., 2017; Lermé and Malgouyres, 2017).

336 4.2 Limitations of methodology

337 Limitations to the presented methodologic set-up affect the results due to various reasons, including the algorithm
338 structure and the data origin and comparison. Tests of the TERRA algorithm in various conditions give a good initial
339 confidence of wider application and further testing of the method. The major source of errors in this study is the presence
340 of vegetation around the terrace front, covering the edge either from above or from the side (Section 3.3). Additionally,
341 certain specific topographic conditions could hypothetically to be more difficult in terms of vegetation filtering and terrain
342 preservation:

343 (i) The presence of contour-structures with risers such as contour bunds or stone walls, that are actually considered
344 part of the terrain but are likely to be “scrapped” (as suggested by the results from the KAM dataset here);

345 (ii) Highly sinuous hillslopes with strong contour curvature, e.g. in a strongly concave or convex hill segment, will
346 impede the determination of hillside aspect, while the aspect aggregation factor η has a lower limit dictated by the
347 dimensions of non-terrain objects.

348 Uncertainties in the presented material also result from topographic data sources. Examples include photogrammetric
349 errors or the inherent noise related to satellite stereography, creating artefacts in the DSM. On the one hand, the TERRA
350 filter can cope with this issue, or even improve it by filtering it out. On the other hand, final results will be affected
351 negatively when artefacts are in the dimensional order of magnitude of features of interest (e.g. terrace wall height). Other
352 data-related uncertainties derive from the set-up of this study, where reference DTMs of VER-D and ROU-L were used
353 for VER-O and ROU-P as well (in order to provide a more precise or complete reference). In this case, comparisons
354 between produced and reference DTMs have a systematic error due to different data origins (two distinct photogrammetric
355 analyses for VER-datasets, or laser altimetry vs. satellite stereography for ROU-datasets).

356 4.3 Potential applications

357 With the development of a robust, reliable and rapid tool for DTM generation from the DSM, studies related to feature
358 detection and inventories can be facilitated. Particularly considering that (semi-)automatic feature extraction is typically
359 sensitive for sharp terrain features and curvature (Bailly and Levavasseur, 2012; Sofia et al., 2016, 2014; Tarolli et al.,
360 2014), the preservative performance TERRA algorithm is very suitable for this analysis, and carries strong potential for
361 large-scale application. Apart from the focus on terraced landscapes, the algorithm might also perform well in landscapes
362 with similar features, such as open-pit mines, riparian zones in anthropogenic lowlands (polders), or urban ramps (Sithole
363 and Vosselman, 2004), provided that a sloping surface is present. Similarly, in such applications, it may become a
364 powerful DTM preparation tool to aid feature extraction analyses, such as in the mapping of drainage networks (Bailly et
365 al., 2008), landslide crowns (Tarolli et al., 2012), open-pit mines (Xiang et al., 2018), or for the geomorphometric
366 characterisation of anthropogenic features (Tarolli et al., 2019). Finally, due to its ability to erase small obstacles along
367 slopes, the proposed filter may also be beneficial for pre-processing noisy DEMs before hydrological analyses based on
368 flow direction computing. Further research is needed and encouraged to explore the potential of the TERRA algorithm,
369 and to test it as a pre-processing link in a longer chain of topographic analyses.

370

371 5. CONCLUSIONS

372 The proposed TERRA filtering algorithm is shown to have a convincing performance in first tests. Filtered DTMs
373 produced from DSMs are relatively close to the reference DTMs in the six datasets, under various conditions of
374 topography, presence of aboveground features, and data source and resolution. Sharp terrain features such as terrace edges
375 are very well preserved (low Type I errors), which distinguishes the TERRA algorithm from most existing filters. Minor
376 Type II errors occur where terrace edges are covered by vegetation on top of the terrace, or form a continuous surface
377 with downslope vegetation located at the foot of the terrace wall.

378 Presented results create confidence for further application of the algorithm, based on its filtering skill and supported by
379 minimal parameterisation requirements and computational efficiency due to the raster-based approach (as compared to a
380 3D-cloud-based approach). Further applications and analyses are encouraged for DTM creation and testing purposes. The
381 algorithm may also play a key role in (semi-)automatic mapping of terrace structures, allowing a rapid DTM preparation
382 step while maintaining typical terrain features (e.g. sharp edges) often critical for such analyses. Testing for DSM filtering
383 in other environments such as anthropogenic landscapes with sloping terrain (e.g. hydraulic engineered lowlands, open-
384 pit mines) is also encouraged in future exploration. The TERRA algorithm is freely available as R script under GNU GPL
385 licence at: <https://www.umr-lisah.fr/?q=fr/scriptsr/terra-script-r> (see Supplementary Material A).

386 ACKNOWLEDGEMENTS

387 This work is part of the HighLandDEM project funded by the MISTRALS EnviMed IV program. It was partly supported
388 by project ViTE “Vineyard Terraced landscapes: understanding the Environmental constraints to improve sustainable
389 managements”, funded by the Linda Scattolin research program at TESAF department of the University of Padova (Italy).
390 The authors would further like to thank data providers French Space Agency CNES and Airbus Defense and Space for
391 Pleiades images, the Tunisian office of topography and cadastre for aerial images, the French National Program for
392 Remote Sensing PTNS and the CNES R&T program for LiDAR data acquisition, and UAV-services *Zenith Aerial*
393 *Solutions s.r.l* (October 2017 mission) and *Cambisol B.V.* (December 2017 mission) for drone-imagery.

394 REFERENCES

- 395
396 Axelsson, P., 1999. Processing of laser scanner data—algorithms and applications. *ISPRS J. Photogramm. Remote Sens.*
397 54, 138–147.
- 398 Bailly, J.S., Lagacherie, P., Millier, C., Puech, C., Kosuth, P., 2008. Agrarian landscapes linear features detection from
399 LiDAR: Application to artificial drainage networks. *Int. J. Remote Sens.* 29, 3489–3508.
- 400 Bailly, J.S., Levavasseur, F., 2012. Potential of linear features detection in a Mediterranean landscape from 3D VHR
401 optical data: application to terrace walls. In: *Geoscience and Remote Sensing Symposium (IGARSS)*. pp. 7110–
402 7113.
- 403 Brodu, N., Lague, D., 2012. 3D terrestrial lidar data classification of complex natural scenes using a multi-scale
404 dimensionality criterion: Applications in geomorphology. *ISPRS J. Photogramm. Remote Sens.* 68, 121–134.
- 405 Brovelli, M.A., Cannata, M., Longoni, U.M., 2002. Managing and processing LIDAR data within GRASS. In: *Proc.*
406 *GRASS Users Conference*. University of Trento, Italy, Trento, Italy, p. 29.

407 Burgos, S., Mota, M., Noll, D., Cannelle, B., 2015. Use of very high-resolution airborne images to analyse 3D canopy
408 architecture of a vineyard. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch.* 40, 399–403.

409 Chen, Q., Gong, P., Baldocchi, D., Xie, G., 2007. Filtering Airborne Laser Scanning Data with Morphological Methods.
410 *Photogramm. Eng. Remote Sens.* 73, 175–185.

411 Dela-Cruz, M.J., Koohafkan, P., 2009. Globally important agricultural heritage systems: a shared vision of agricultural,
412 ecological and traditional societal sustainability. *Resour. Sci.* 31, 905–913.

413 Elmqvist, M., Jungert, E., Lantz, F., Persson, Å., U.Söderman, 2001. Terrain modelling and analysis using laser scanning
414 data. *Int. Arch. Photogramm. Remote Sens.* XXXIV, 219–226.

415 Grilli, E., Menna, F., Remondino, F., 2017. A review of point clouds segmentation and classification algorithms. *Int.*
416 *Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch.* 42, 339–344.

417 He, Y., Zhang, C., Fraser, C.S., 2018. Progressive Filtering of Airborne LiDAR Point Clouds Using Graph Cuts. *IEEE J.*
418 *Sel. Top. Appl. Earth Obs. Remote Sens.* 11, 2933–2944.

419 Kraus, K., Pfeifer, N., 1998. Determination of terrain models in wooded areas with airborne laser scanner data. *ISPRS J.*
420 *Photogramm. Remote Sens.* 53, 193–203.

421 Lane, S.N., James, T.D., Crowell, M.D., 2000. Application of digital photogrammetry to complex topography for
422 geomorphological research. *Photogramm. Rec.* 16, 793–821.

423 Lermé, N., Malgouyres, F., 2017. A Reduction Method For Graph Cut Optimization. *Pattern Anal. Appl.* 17, 361–378.

424 Liu, X., 2008. Airborne LiDAR for DEM generation: Some critical issues. *Prog. Phys. Geogr.* 32, 31–49.

425 Meng, X., Currit, N., Zhao, K., 2010. Ground filtering algorithms for airborne LiDAR data: A review of critical issues.
426 *Remote Sens.* 2, 833–860.

427 Meng, X., Wang, L., Silván-Cárdenas, J.L., Currit, N., 2009. A multi-directional ground filtering algorithm for airborne
428 LIDAR. *ISPRS J. Photogramm. Remote Sens.* 64, 117–124.

429 Molénat, J., Raclot, D., Zitouna, R., Andrieux, P., Coulouma, G., Feurer, D., Grunberger, O., Lamachère, J.M., Bailly,
430 J.S., Belotti, J.L., Ben Azzez, K., Ben Mechlia, N., Ben Younès Louati, M., Biarnès, A., Blanca, Y., Carrière, D.,
431 Chaabane, H., Dagès, C., Debabria, A., Dubreuil, A., Fabre, J.C., Fages, D., Floure, C., Garnier, F., Geniez, C.,
432 Gomez, C., Hamdi, R., Huttel, O., Jacob, F., Jenhaoui, Z., Lagacherie, P., Le Bissonnais, Y., Louati, R., Louchart,
433 X., Mekki, I., Moussa, R., Negro, S., Pépin, Y., Prévot, L., Samouelian, A., Seidel, J.L., Trotoux, G., Troiano, S.,
434 Vinatier, F., Zante, P., Zrelli, J., Albergel, J., Voltz, M., 2018. OMERE: A Long-Term Observatory of Soil and
435 Water Resources, in Interaction with Agricultural and Land Management in Mediterranean Hilly Catchments.
436 *Vadose Zo. J.* 17, 0.

437 Paroissien, J.-B., Lagacherie, P., Le Bissonnais, Y., 2010. A regional-scale study of multi-decennial erosion of vineyard
438 fields using vine-stock unearthing–burying measurements. *Catena* 82, 159–168.

439 Passalacqua, P., Belmont, P., Staley, D.M., Simley, J.D., Arrowsmith, J.R., Bode, C.A., Crosby, C., DeLong, S.B., Glenn,
440 N.F., Kelly, S.A., Lague, D., Sangireddy, H., Schaffrath, K., Tarboton, D.G., Wasklewicz, T., Wheaton, J.M., 2015.
441 Analyzing high resolution topography for advancing the understanding of mass and energy transfer through
442 landscapes: A review. *Earth-Science Rev.* 148, 174–193.

- 443 Perona, P., Malik, J., 1990. Scale-Space and Edge Detection Using Anisotropic Diffusion. *IEEE Trans. Pattern Anal.*
444 *Mach. Intell.* 12, 629–639.
- 445 Pfeifer, N., Kostli, A., Kraus, K., 1998. Interpolation and filtering of laser scanner data—implementation and first results.
446 *Interpolat. Filter. laser scanner data—implementation first results XXXII*, 153–159.
- 447 Pierrot-Deseilligny, M., De Luca, L., Remondino, F., 2011. Automated image-based procedures for accurate artifacts 3D
448 modeling and orthoimage generation. *Geoinf. FCE CTU 6*, 291–299.
- 449 Pierrot-Deseilligny, M., Paparoditis, N., 2006. A multiresolution and optimization-based image matching approach: An
450 application to surface reconstruction from spot5-hrs stereo imagery. In: *Proceedings IAPRS*. Ankara, Turkey,
451 Turkey.
- 452 Pijl, A., Barneveld, P., Mauri, L., Borsato, E., Grigolato, S., Tarolli, P., 2019a. Impact of mechanisation on soil loss in
453 terraced vineyard landscapes. *Cuad. Investig. Geográfica 45*, 287–308.
- 454 Pijl, A., Tosoni, M., Roder, G., Sofia, G., Tarolli, P., 2019b. Design of terrace drainage networks using UAV-based high-
455 resolution topographic data. *Water 11* (4), 814.
- 456 Pingel, T.J., Clarke, K.C., McBride, W.A., 2013. An improved simple morphological filter for the terrain classification
457 of airborne LIDAR data. *ISPRS J. Photogramm. Remote Sens.* 77, 21–30.
- 458 Roggero, M., 2001. Airborne Laser Scanning: Clustering in Raw Data. *ISPRS J. Photogramm. Remote Sens.* XXXIV,
459 227–232.
- 460 Santesteban, L.G., Guillaume, S., Royo, J.B., Tisseyre, B., 2013. Are precision agriculture tools and methods relevant at
461 the whole-vineyard scale? *Precis. Agric.* 14, 2–17.
- 462 Shan, J., Aparajithan, S., 2005. Urban DEM Generation from Raw Lidar Data. *Photogramm. Eng. Remote Sens.* 71, 217–
463 226.
- 464 Sithole, G., 2001. Filtering of laser altimetry data using a slope adaptive filter. *Int. Arch. Photogramm. Remote Sens.*
465 *Spat. Inf. Sci.* XXXIV, 203–210.
- 466 Sithole, G., Vosselman, G., 2004. Experimental comparison of filter algorithms for bare-Earth extraction from airborne
467 laser scanning point clouds. *ISPRS J. Photogramm. Remote Sens.* 59, 85–101.
- 468 Sofia, G., Bailly, J.S., Chehata, N., Tarolli, P., Levavasseur, F., 2016. Comparison of Pleiades and LiDAR Digital
469 Elevation Models for Terraces Detection in Farmlands. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* 9, 1567–
470 1576.
- 471 Sofia, G., Marinello, F., Tarolli, P., 2014. A new landscape metric for the identification of terraced sites: The Slope Local
472 Length of Auto-Correlation (SLLAC). *ISPRS J. Photogramm. Remote Sens.* 96, 123–133.
- 473 Sohn, G., Dowman, I., 2002. Terrain surface reconstruction by the use of tetrahedron model with the MDL criterion. *Int.*
474 *Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* XXXIV, 336–344.
- 475 Tarolli, P., 2014. High-resolution topography for understanding Earth surface processes: Opportunities and challenges.
476 *Geomorphology 216*, 295–312.
- 477 Tarolli, P., Cao, W., Sofia, G., Evans, D., Ellis, E.C., 2019. From features to fingerprints: A general diagnostic framework
478 for anthropogenic geomorphology. *Prog. Phys. Geogr.* 43, 95–128.

479 Tarolli, P., Preti, F., Romano, N., 2014. Terraced landscapes: From an old best practice to a potential hazard for soil
480 degradation due to land abandonment. *Anthropocene* 6, 10–25.

481 Tarolli, P., Sofia, G., Calligaro, S., Prosdocimi, M., Preti, F., Dalla Fontana, G., 2015. Vineyards in terraced landscapes:
482 new opportunities from lidar data. *L. Degrad. Dev.* 26, 92–102.

483 Tarolli, P., Sofia, G., Dalla Fontana, G., 2012. Geomorphic features extraction from high-resolution topography:
484 Landslide crowns and bank erosion. *Nat. Hazards* 61, 65–83.

485 Ural, S., Shan, J., 2016. A min-cut based filter for airborne Lidar data. *Int. Arch. Photogramm. Remote Sens. Spat. Inf.*
486 *Sci. - ISPRS Arch.* 41, 395–401.

487 Vosselman, G., 2000. Slope based filtering of laser altimetry data. *Int. Arch. Photogramm. Remote Sens.* XXXIII, 935–
488 942.

489 Wack, R., Wimmer, A., 2002. Digital terrain models from airborne laser scanner data – a grid based approach. *Int. Arch.*
490 *Photogramm. Remote Sens. Spat. Inf. Sci.* XXXIV, 293–296.

491 Wei, W., Chen, D., Wang, L., Daryanto, S., Chen, L., Yu, Y., Lu, Y., Sun, G., Feng, T., 2016. Global synthesis of the
492 classifications, distributions, benefits and issues of terracing. *Earth-Science Rev.* 159, 388–403.

493 Xiang, J., Chen, J., Sofia, G., Tian, Y., Tarolli, P., 2018. Open-pit mine geomorphic changes analysis using multi-temporal
494 UAV survey. *Environ. Earth Sci.* 77, 1–18.

495 Yang, B., Huang, R., Dong, Z., Zang, Y., Li, J., 2016. *ISPRS Journal of Photogrammetry and Remote Sensing* Two-step
496 adaptive extraction method for ground points and breaklines from lidar point clouds. *ISPRS J. Photogramm. Remote*
497 *Sens.* 119, 373–389.

498 Zhang, K., Chen, S.-C., Whitman, D., Shyu, M.-L., Yan, J., Zhang, C., 2003. A Progressive Morphological Filter for
499 Removing Nonground Measurements From Airborne LIDAR Data. *IEEE Trans. Geosci. Remote Sens.* 41, 872–
500 882.

501

SUPPLEMENTARY MATERIAL A: R script TERRA

```
#####
## available at https://www.umn-lisah.fr/?q=fr/scriptsr/terra-script-r
#####

#####
# This file is the R code of the TERRA algorithm
# see
# https://doi.org/10.1016/j.jag.2019.101977
# "TERRA: Terrain extraction from elevation rasters through repetitive
# anisotropic filtering#
# Copyright(c) 2019, AgroParisTech
# == GNU General Public License Usage ==
# TERRA.R is a free tool: you can redistribute it and/or modify
# it under the terms of the GNU General Public License as published by
# the Free Software Foundation, either version 3 of the License, or
# (at your option) any later version.
# TERRA.R is distributed in the hope that it will be useful,
# but WITHOUT ANY WARRANTY; without even the implied warranty of
# MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE. See the
# GNU General Public License for more details.
# See <http://www.gnu.org/licenses/>
# == Other Usage ==
# Other Usage means a use of TERRA algorithm that is inconsistent with the GPL
# license, and requires a written agreement between You and AgroParisTech.
# Licensees for Other Usage of TERRA.R may use this file in accordance
# with the terms contained in the written agreement between You and AgroParisTech.
#####

#####
# @author Jean-Stéphane BAILLY <bailly@agroparistech.fr>
#####

#####
# Require to call first the "raster" R package
#####

#####
# Input and parameters
# Input :
# - dsm : dsm name to be filtered in raster R format
# Parameters :
# - lambda : Kernel size
# - eta : spatial aggregation factor
# - M : number of iteration
#####

#####
# Output :
# - filtered dtm in raster R format
#####

#####
# Note that the Kernel statistic used here is the mean but it can be changed
# manually by any other statistics (min, median, etc)
#####

#####
# Execution example including TERRA compilation :
# source('TERRA.R')
# mnt<-TERRA(dsm=mns,lambda=7,eta=10, M=5)
```

```
#####
```

```
TERRA<-function(dsm=mns,lambda=7,eta=10, M=5)
{
#structural element inner aspect
K<-matrix(0,lambda,lambda)
X<-col(K)-(((lambda-1)/2))-1
Y<-(nrow(K)-row(K))-((lambda-1)/2)
azi<-atan(Y/X)
azi[X<0]<-azi[X<0]+pi
azi[X>=0 & Y<0]<-azi[X>=0 & Y<0]+2*pi
azi<-2*pi-azi
azi[azi==(2*pi)]<-0
azi<-azi+(pi/2)
azi[azi>=(2*pi) & !is.nan(azi)]<-azi[azi>=(2*pi) & !is.nan(azi)]-(2*pi)

DSM<-dsm

for(i in 1:M)
{
#low frequency slope calculation
AGG<-aggregate(DSM, fact=eta, expand=TRUE)
ASP<-terrain(AGG, opt='aspect', unit='radians')
asp<-resample(ASP, DSM, method="ngb")
MNS<-as.matrix(DSM)
ASP<-as.matrix(asp)

MNT<-MNS
for (i in (1+(lambda-1)/2):(nrow(MNS)-(lambda-1)/2)) # i: row.index
{
for (j in (1+(lambda-1)/2):(ncol(MNS)-(lambda-1)/2)) # j: col.index
{
if(!is.na(ASP[i,j]))
{
shift<-ASP[i,j]
s1<-azi>=(shift-pi/2) | azi>=(shift+3*pi/2) | azi<=(shift-3*pi/2)
s2<-azi<=(shift+pi/2) | azi>=(shift+3*pi/2) | azi<=(shift-3*pi/2)
W<-(s1 & s2)
W[((lambda-1)/2)+1,((lambda-1)/2)+1]<-TRUE
W<-!(W)
cand<-mean((W*MNS[(i-((lambda-1)/2)):(i+((lambda-1)/2))),(j-((lambda-1)/2)):(j+((lambda-1)/2)))[W==T], na.rm=T)
if(!is.na(cand)){ if(cand<MNT[i,j]) {MNT[i,j]<-cand}}
}
}
}
values(DSM)<-MNT
}
mnt<-dsm
values(mnt)<-MNT
invisible(return(mnt))
}
```