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3 DSM AND DTM GENERATION FROM VHR SATELLITE STEREO IMAGERY OVER PLASTIC
4 COVERED GREENHOUSE AREAS

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6 Abderrahim Nemmaoui*^a, Fernando J. Aguilar ^a, Manuel A. Aguilar ^a, Rongjun Qin ^{b,c}

7
8 * Corresponding author: an932@ual.es

9 ^a Department of Engineering, University of Almería, Ctra. de Sacramento s/n, La Cañada de San Urbano, Almería
10 04120, Spain (an932@ual.es, faguilar@ual.es, maguilar@ual.es)

11 ^b Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, 218B Bolz Hall,
12 2036 Neil Avenue, Columbus, OH 43210, USA (qin.324@osu.edu)

13 ^c Department of Electrical and Computer Engineering, The Ohio State University, Dresse Lab 205, 2015 Neil
14 Avenue, Columbus, OH 43210, USA

15 **Abstract**

16 Agriculture under Plastic Covered Greenhouses (PCG) has represented a step
17 forward in the evolution from traditional to industrial farming. However, PCG-
18 based agricultural model has been also criticized for its associated environmental
19 impact such as plastic waste, visual impact, soil pollution, biodiversity degradation
20 and local runoff alteration. In this sense, timely and effective PCG mapping is the
21 only way to help policy-makers in the definition of plans dealing with the trade-off
22 between farmers' profit and environmental impact for the remaining inhabitants.

23 This work proposes a methodological pipeline for producing high added value
24 3D geospatial products (Digital Surface Models (DSM) and Digital Terrain Models
25 (DTM)) from VHR satellite imagery over PCG areas. The 3D information layer
26 provided through the devised approach could be very valuable as a complement to
27 the traditional 2D spectral information offered by VHR satellite imagery to improve
28 PCG mapping over large areas.

29 This methodological approach has been tested in Almeria (Southern Spain)
30 from a WorldView-2 VHR satellite stereo-pair. Once grid spacing format DSM and
31 DTM were built, their vertical accuracy was assessed by means of lidar data
32 provided by the Spanish Government (PNOA Programme).

33 Regarding DSM completeness results, the image matching method based on
34 hierarchical semi-global matching yielded much better scores (98.87%) than the
35 traditional image matching method based on area-based matching and cross-
36 correlation threshold (86.65%) when they were tested on the study area with the
37 highest concentration of PCG (around 85.65% of PCG land cover). However, both
38 image matching methods yielded similar vertical accuracy results in relation to the
39 finally interpolated DSM, with mean errors ranging from 0.01 to 0.35m and random
40 errors (standard deviation) between 0.56 and 0.82 m. The DTM error figures also
41 showed no significant differences between both image matching methods, although
42 being highly dependent on DSM-to- DTM filtering error, in turn closely related to
43 greenhouse density and terrain complexity.

44 *KEYWORDS: Digital Elevation Model, Digital Surface Model, Greenhouse land cover,*

45 *VHR satellite stereo imagery, Stereo image matching.*

46 **1. Introduction**

47 Since the first use of plastic film in agriculture in 1948 (Garnaud, 2000), plastic
48 covering has been used extensively in the cultivation of vegetables around the world.
49 Particularly, plastic covered greenhouses (PCG) can be considered a step forward in the
50 evolution from traditional to industrial farming (i.e. from extensive to intensive farming).
51 PCG present a cover made of transparent plastic film to control the environmental
52 conditions and growth of the crops growing inside. This leads to a significant crop yield
53 increasing under highly controlled growing conditions. For these reasons, greenhouse
54 farming plays an increasing role in modern agriculture, becoming one of the most important
55 agricultural activities in arid and semi-arid regions. Crops under PCG accounted for a total
56 coverage of about 3019 million hectares worldwide in 2016, mainly located in Europe
57 (Mediterranean areas), North Africa, the Middle East and China (Wu et al., 2016). In these
58 areas, PCG increase day by day, thus obtaining timely and accurate information regarding
59 their spatial distribution could make an important contribution to local agricultural
60 management, environmental protection and land use/land cover (LULC) policy.

61 LULC changes can directly affect the status and integrity of ecosystems. For instance,
62 natural and multifunctional landscapes can be converted into areas of intensive farming,
63 altering the main land-use type and natural character of a region. This is the case of Almeria,
64 south-eastern Spain, a region that is currently hosting the largest concentration of
65 greenhouses in the world, spread across more than 30000 hectares, and being locally known
66 as “The Plastic Sea of Almeria” (Aguilar et al., 2015). The region has undergone major
67 LULC changes over the preceding decades due to the expansion of intensive greenhouse
68 horticulture, making the area one of the most economically prosperous in the country.

69 Furthermore, ecosystems in south-eastern Spain are high in biodiversity and are, because
70 of their location in the driest region in continental Europe, vulnerable to global change
71 impacts. In this sense, management decisions should promote a transition towards
72 sustainable landscape strategies which result in human needs being satisfied while
73 simultaneously maintaining important ecological processes responsible for the delivery of
74 ecosystem services (Quintas-Soriano et al., 2016). This transition requires a thorough
75 knowledge of PCG spatio-temporal distribution where remote sensing seems to be the only
76 feasible approach for understanding its impacts on climate and eco-environment in a large
77 geographic area. In fact, remote sensing can efficiently provide quantitative and qualitative
78 information of great interest for the study of planning, land organization and sustainable
79 development of this kind of extremely complex agro-systems (Aguilar et al., 2007).

80 However, PCG spectral-based mapping from remote sensing turns out to be
81 challenging because the spectral signature of the plastic-covered greenhouse can change
82 drastically (Aguilar et al., 2015, 2014a; Tarantino and Figorito, 2012). In fact, different
83 plastic materials with varying thickness, transparency, ultraviolet and infrared reflection
84 and transmission properties, additives, age and colours are used in greenhouse coverings
85 (M. A. Aguilar et al., 2016). Moreover, as plastic sheets are semi-transparent, the changing
86 reflectance of the crops underneath them affects the greenhouse spectral signal reaching the
87 sensor (Levin et al., 2007). Finally, such plastic materials occasionally yield specular
88 reflections that create shiny spots that are particularly challenging for the extraction of their
89 corresponding 3D surface geometry from overlapping digital images acquired from
90 multiple views, a widely known computer vision approach named digital image matching.

91 Regarding PCG mapping from remote sensing approaches, an increasing scientific
92 literature has emerged during the last decade. A comprehensive literature review can be

93 found in Aguilar et al. (2015), M. A. Aguilar et al. (2016), Celik and Koc-San (2018),
94 Lanorte et al. (2017), Novelli et al. (2016) and Yang et al. (2017), showing that many
95 researchers have tried to improve the accuracy of PCG mapping by applying both pixel-
96 based and object-based supervised image classification algorithms to high and medium
97 resolution satellite imagery and by means of both static and multi-temporal approaches,
98 reporting overall accuracies ranging between 85% and 94%. Nowadays it is difficult to
99 overcome those scores without adding new information (i.e. in addition to spectral and
100 texture features) to the features vector employed to feed the classifier.

101 On the other hand, nowadays geospatial analysis headed up to mapping complex
102 above-ground features (e.g. built-up areas) are emerging, usually requiring digital surface
103 and terrain modelling to produce Digital Surface Models (DSM), which capture the natural
104 and built-up features on the Earth's surface, and Digital Elevation Models (DEM), which
105 are able to characterize the topography or bare-earth elevation (Li et al., 2005). Both
106 geospatial products have proven to be relevant in several agricultural applications (Celik
107 and Koc-San, 2018; Mokarram and Hojati, 2017; Seeruttun and Crossley, 1997) .

108 The so-called normalized digital surface model (nDSM) is generated by computing
109 the difference between the DSM and the DEM. Since the nDSM excludes the influence of
110 topography, it represents the height of all overlying objects on the terrain, such as buildings,
111 trees and greenhouses. In this way, several researchers have proposed to incorporate this
112 3D information as a raster layer to improve the overall accuracy classification and
113 extraction of man-made features on built-up areas (Aguilar et al., 2014b; Luethje et al.,
114 2017; Weidner and Förstner, 1995; Zhang et al., 2015). Recently nDSM have been also
115 used to derive the 3D properties of urban buildings, which represent the three-dimensional
116 nature of living spaces and are needed in population estimation or urban planning (Tomas

117 et al., 2016).

118 At the same time, the launching of many Very High Resolution (VHR) satellites
119 capable of capturing panchromatic imagery with Ground Sample Distance (GSD) lower
120 than 1 m has opened the greatest possibilities for cartographic applications based on the
121 extraction of DSM and DEM. These products are generated by image matching strategies
122 from VHR satellite imagery stereo pairs or stereo triplets. Current stereo capabilities of
123 VHR satellites, together with their agile pointing ability, enable the generation of
124 geometrically robust (in terms of base-to-height ratio) and radiometrically consistent along-
125 track stereo images which can be acquired for any place on Earth (Zhang and Gruen, 2006;
126 Büyüksalih and Jacobsen, 2007a.; D'angelo et al., 2008; Dowman et al., 2012; Poli and
127 Caravaggi, 2012; Aguilar et al., 2014b). In this sense, space-borne images provide a cost-
128 efficient alternative to aerial images and can be obtained regardless of various national
129 over-flight restrictions. Furthermore, their appropriate stereo geometry and radiometric
130 similarity allow obtaining high resolution DSM by i) carrying out an aerotriangulation and
131 bundle adjustment process based on object-to-image geometry provided by the well-known
132 rational polynomial coefficients (RPC) (Grodecki and Dial, 2003), and ii) generating a
133 DSM from applying automatic stereo matching procedures over previously epipolarly
134 rectified stereo images (e.g. Alobeid et al., 2010). Since RPC are generated without ground
135 data, it is necessary to improve satellite imagery orientation for high accuracy applications
136 by measuring ground control points (GCP) and computing bias-corrected RPC (Aguilar et
137 al., 2013; Tong et al., 2010). Aguilar et al. (2017) have recently developed an approach for
138 improving the initial direct geolocation accuracy of VHR satellite imagery based on the
139 extraction of 3D GCP from freely available ancillary data at global coverage such as multi-
140 temporal information of Google Earth and the Shuttle Radar Topography Mission 30 m

141 digital elevation model. This approach can be very useful when ground surveyed control
142 points are not available.

143 There is available an abundant literature about the use of VHR satellite or aerial
144 imagery for DSM generation. For instance, the reader can find a complete and
145 comprehensive overview of the characteristics and use of VHR satellite and aerial images
146 in (Dowman et al., 2012). Concerning the radiometric and geometric quality of VHR
147 satellite imagery, while the earlier studies were based on slightly coarser spatial resolution
148 (>0.5 m Ground Sample Distance (GSD)) (e.g. Büyüksalih and Jacobsen, 2007a; D'angelo
149 et al., 2008; Toutin, 2006a; Toutin et al., 2001; Zhang and Gruen, 2006), the last
150 investigations have been mainly focused on VHR satellites with GSD even lower than 0.5
151 m, such as GeoEye-1 and WorldView-1/2/3/4 (Åstrand et al., 2012; Barbarella et al., 2017;
152 Capaldo et al., 2012b; Reinartz et al., 2014), and the capabilities of the PAN triplet product
153 from Pléiades-1 to generate DSMs (Fratarcangeli et al., 2016; Poli et al., 2015; Tack et al.,
154 2009). Other works were more focused on testing image matching algorithms (Alobeid et
155 al., 2010; Capaldo et al., 2012a; de Franchis et al., 2014; Di Rita et al., 2017; Ghuffar, 2016;
156 Noh and Howat, 2015; Qin, 2016; Shean et al., 2016; Wenzel et al., 2013). There are also
157 several works about DSM generation from VHR satellite imagery over different types of
158 land cover, including urban areas (Arefi and Reinartz, 2013; Büyüksalih and Jacobsen,
159 2007b; Dowman, 2000; Jacobsen, 2006; Muller et al., 1997; Sohn and Dowman, 2007; Tian
160 et al., 2014), mountainous areas (Toutin, 2002), densely vegetated deciduous forest (DeWitt
161 et al., 2017), glaciated regions (Noh and Howat, 2015) or over herb and grass land cover
162 (Hobi and Ginzler, 2012). However, to the best of our knowledge, few works have been
163 specifically focused on plastic covered greenhouse areas (Aguilar et al., 2014a; Celik and
164 Koc-San, 2018; Aguilar et al., 2018).

165 The procedure for assessing digital elevation model (DEM) or DSM quality involves
166 examination of the vertical accuracy and completeness (Butler et al., 1998; Höhle and
167 Potuckova, 2006). Most of the current research uses highly accurate lidar information as
168 ground truth to check the accuracy of DSMs generated from VHR satellite images (Capaldo
169 et al., 2012a; Noh and Howat, 2017, 2015, Toutin, 2006b, 2006a). Considering that the
170 automatic DSM cannot be obtained in all areas due to matching errors provoked by
171 insufficient texture, occlusions or radiometric artifacts, DSM vertical accuracy should be
172 complemented by DSM completeness, a DSM quality indicator defined as the percentage
173 of correctly matched points over the working area (Höhle and Potuckova, 2006)

174 The main goal of this study is to develop and test a methodological approach to
175 produce high quality DSM and DEM from WorldView-2 along-track stereo pair headed up
176 to obtain 3D geospatial features. These 3D features could complement 2D spectral features
177 in PCG mapping over large areas, as it has been already reported by Aguilar et al. (2014a)
178 and Celik and Koc-San (2018). In this sense two software packages, based on two clearly
179 different stereo image matching approaches, were tested with respect to their ability to
180 produce photogrammetrically derived DSM/DEM over dense greenhouse covered areas.

181 The rest of this paper is organized as follows. The study area and datasets are
182 described in the section 2. The third section outlines a detailed explanation of the
183 methodological approach devised to produce high quality DSM and DEM from VHR
184 satellite imagery and the pipeline used to assess the performance of the two stereo image
185 matching approaches. The results corresponding to the completeness and characteristics of
186 the residual populations for the stereo-photogrammetrically derived DSM and DEM are
187 presented and discussed in the section 4. Conclusions are provided in the last section.

188 2. Study Site and Datasets

189 2.1. Study area

190 The study area is located in the province of Almeria (Southern Spain), housing the
191 greatest concentration of greenhouses in the world. It comprised a rectangle area of about
192 8000 ha centred on the WGS84 geographic coordinates of 36.7824°N and 2.6867°W (Fig.
193 1).

194 This pilot area presents an elevation ranging between 152.6 m and 214.8 m above
195 mean sea level (Spanish orthometric heights EGM08-REDNAP), with a moderate north-
196 south mean slope of around 4.3%.

197 **Fig. 1.** Location of the study site in the province of Almeria (Spain) and the four selected subareas as red
198 rectangles. These subareas are characterized, in addition to PCG, by features such as dry ravines (1), vegetation
199 (2) urban areas (3) and very high concentration of PCG (4). Coordinate System: WGS84 UTM Zone 30.

200 Within the study area, four representative rectangular test areas of 920 m x 620 m
201 were selected, including different land covers and features such as dry ravines and bare soil
202 (test area 1), vegetation and bare soil (test area 2), urban areas (test area 3) and a variable
203 density of PCG land cover which reaches the highest density in the fourth test area (test
204 area 4) (Fig. 1).

205 2.2. WorldView-2 stereo pair

206 A WorldView-2 (WV-2) along-track stereo pair taken on July 5, 2015, was used. It
207 consisted of 2 Level-2A images (ORS2A) format, dynamic range of 11-bit (without
208 dynamic range adjustment) and 0.5 m GSD (PAN). The off-nadir angle for the two stereo
209 pair images turned out to be 12.6° and 24.6° (Table 1).

210 **Table 1** Characteristics of the panchromatic band for the WV-2 stereo pair.

211 **2.3. Ground truth lidar data**

212 The lidar data used as ground truth in this study were provided by the PNOA (National
213 Plan of Aerial Orthophotography of Spain) as RGB coloured point cloud in LAS binary
214 file, format v. 1.2, containing easting and northing coordinates (UTM ETRS89 30N) and
215 orthometric elevations (geoid EGM08-REDNAP). It was taken on September 23, 2015, by
216 means of a Leica ALS60 discrete return sensor with up to four returns measured per pulse
217 and an average flight height of 2700 m. The nominal average point density of the lidar
218 campaign was 0.7 points/m², although the finally registered point density of the test area,
219 considering overlapping, turned out to be 0.97 points/m² (all returns). The nominal nadiral
220 horizontal accuracy (RMSE_{xy}) and nominal vertical accuracy (RMSE_z) after processing
221 took values lower than 0.3 m and 0.2 m, respectively (Ministerio de Fomento de España,
222 2015). The 131 GPS-RTK surveyed GCP were employed to check the nominal vertical
223 accuracy of lidar data. The standard deviation of the computed lidar vertical error, only
224 including open terrain GCP (Aguilar et al., 2008), took a value of 0.14 m, which mean a
225 vertical accuracy higher than the 0.2 m nominal vertical error of PNOA lidar data.

226 A local maxima filter algorithm with 2 m neighbourhood size to search for maximum
227 height was applied to the lidar point cloud to obtain the corresponding lidar-derived point
228 cloud DSM. Additionally, a lidar-derived point cloud DEM was produced by automatically
229 filtering ground points using the Improved Progressive TIN Densification (IPTD) filtering
230 algorithm proposed by Zhao et al. (2016). The corresponding IPTD set of parameters was
231 optimized for each test area. The automatically classified ground points were manually
232 edited to achieve a final high-quality point cloud DEM.

233 The lidar-derived point cloud DSM and DEM were finally interpolated to 1 m grid
234 spacing by using the Gaussian Markov Random Field (GMRF) algorithm, following the
235 procedure and the mathematical framework described and tested by F. J. Aguilar et al.
236 (2016). (The cited paper and the GMRF interpolation method code are freely available at
237 <https://github.com/3DLAB-UAL/dem-gmrf> [Link to code](#)). In this work the GMRF
238 interpolation method was tested in the same study area providing good results. As an
239 advantage, the GMRF mathematical framework makes possible to both retrieve the
240 estimated uncertainty for every interpolated elevation point and include break lines or
241 terrain discontinuities between adjacent cells to produce high-quality DEMs.

242 The lidar-derived grid format DSM and DEM depicted in Fig. 2 were employed as
243 ground truth for the vertical accuracy assessment of the stereo-photogrammetrically
244 extracted DSM and DEM corresponding to the four test areas.

245 Fig. 2. Lidar-derived grid format DSM and DEM for the four test areas. Left column: Lidar-derived DSM. Right
246 column: Lidar-derived DEM. The red line (DEM test area 1 in the first row on the right) corresponds to the
247 location of the profile represented in Fig. 7).

248 **3. Methods**

249 The methodological pipeline proposed in this work to provide 3D information
250 potentially useful to improve PCG mapping over large areas from VHR satellite stereo
251 imagery is described in this section. It consisted of the steps shown below.

252 **3.1. Step 1: Stereo photogrammetrically derived DSM**

253 Two different software packages, based on two clearly different types of image
254 matching approaches, were used to stereo-photogrammetrically generate the DSM from

255 WV-2 imagery.

256 PCI Geomatics v. 2016 (PCI Geomatics, Richmond Hill, ON, Canada) was the first
257 software tested. This software has been chosen in several studies and works (i.e. Barbarella
258 et al., 2017; Capaldo et al., 2012a; Di Rita et al., 2017a) as benchmark for others software
259 packages in comparison tests.

260 PCI Geomatics (PCI henceforth) implements a photogrammetric tool called
261 OrthoEngine devised to produce geospatial products. The OrthoEngine matching algorithm
262 is based on cross-correlation where an automated area-based matching procedure is
263 performed on quasi-epipolar images. Specifically, this procedure is based on a hierarchical
264 (seven steps) sub-pixel mean normalized cross correlation matching method that generates
265 correlation coefficients between zero and one for each matched pixel, meaning zero a total
266 mismatch and one a perfect match. When the correlation coefficient of a matched point is
267 lower than 0.5, this point is rejected, and its height is not computed, meaning a gap and
268 reducing the DSM completeness. Finally, a second-order surface is then fitted around the
269 maximum correlation coefficients to find the match position to sub-pixel accuracy (Cheng,
270 2015).

271 The other tested software was RPC Stereo Processor (RSP), initially developed by
272 Qin, (2014) for 3D change detection and land cover classification studies. It was further
273 refined as a standalone software package that performs stereo matching on RPC modelled
274 space-borne images producing mapping products such as DSM and orthophoto (Qin, 2016).
275 RSP implements a hierarchical semi-global matching (SGM) approach based on the widely
276 known algorithm proposed by Hirschmuller, (2008) to generate the disparity maps after
277 applying an epipolar rectification process to the original stereo images. Note that the classic
278 SGM creates a raster file to store the aggregated cost for each disparity value, thus requiring

279 a lot of memory for computation. Hence RSP provides a hierarchical solution based on
280 running the classic SGM algorithm through pyramid image layers. At the same time, RSP
281 restrains the disparity search in the original resolution within a given range (e.g. [-1000,
282 1000]) in order to retain high resolution in the coarsest layer of the pyramids (Qin, 2016).

283 The initial vendor supplied RPC set, derived from satellite ephemeris and star tracker
284 observations, usually contains bias that should be corrected for precise epipolar image
285 generation. A first order affine transformation (six parameters) on the image space was used
286 to obtain bias-corrected RPC at the RPC-based satellite image orientation stage both in the
287 case of PCI and RSP pipelines. Following the recommendations of Åstrand et al., (2012)
288 and Aguilar et al., (2013), 7 GPS-RTK ground points evenly distributed over the working
289 area were selected as GCP. The remaining 124 ground points were used as Independent
290 Check Point (ICP). The planimetric accuracy ($RMSE_{2D}$) of the image orientation phase
291 measured at those ICPs was 0.45 m. It is important to keep in mind that the GCP were only
292 marked once on the image space of the PCI project, being later exported to be automatically
293 marked in the RSP project to assure the same conditions at the satellite image orientation
294 phase.

295 After carrying out the sensor orientation phase, 1 m grid spacing DSM was stereo-
296 photogrammetrically extracted from each one of the two tested approaches. In the case of
297 PCI, hilly terrain and without filling blanks (no interpolation) parameters were chosen. In
298 the case of the RSP software, the DSM was also extracted without filling blanks.

299 **3.2. Step 2: DSM outlier removal**

300 Potential outliers were automatically removed from the original DSM (presenting
301 blank areas) by adapting the parametric statistical method for DEM error detection

302 published by Felicísimo, (1994). This algorithm takes advantage of probabilistic criteria to
303 apply a parametric procedure based on the assumption that differences between the height
304 of every point and its corresponding neighbourhood mean height follows a normal
305 distribution. In our case, the neighbourhood size was set to 1.5 times the DSM grid spacing.

306 Once potential outliers were removed (outlier-corrected DSM), the GMRF
307 interpolation method described in F. J. Aguilar et al. (2016) was employed to fill the blank
308 areas and produce a continuous 1 m grid spacing DSM (GMRF DSM) .

309 ***3.3. Step 3: Automatic DEM extraction from the outlier-corrected DSM***

310 It is beyond the scope of this work to compare the results provided by the various
311 available algorithms focused on 3D data filtering to automatically convert a DSM into a
312 bare-earth DEM because of most of these algorithms have been developed to deal with high
313 vertical accuracy lidar point clouds. Therefore, their performance on photogrammetrically
314 derived 3D point clouds from VHR satellite imagery should be carefully tested. In this way,
315 the easy-to-use algorithm (only two parameters to tune) called DSM2DTM, implemented
316 in PCI Geomatics, was employed to automatically extract the corresponding DEM from the
317 outlier-corrected DSM obtained in the step 2. This algorithm is able to convert a DSM into
318 a bare-earth DEM by obtaining local area minimum/maximum values and then operating a
319 moving polynomial function utilizing the local values in the specified object size parameter
320 (PCI Geomatics, 2016).

321 The DSM2DTM algorithm was launched by using an iterative python code with two
322 varying parameters to search for an optimal output DEM in each test area. Those parameters
323 were the following:

324 i) Object size, with values ranging from 50 m to 200 m depending on the morphology

325 of each test area and the image matching algorithm. It specifies the size of the
326 filters which are used to remove surface features. Typically, the size should be as
327 large as the largest feature (e.g. greenhouse) that should be removed.

328 ii) Gradient percentage threshold (slope), with values ranging from 5% to 35%
329 depending on the morphology of each test area and the image matching algorithm.
330 Features with slopes less than this threshold will be treated as natural features and
331 will not be removed. The type of terrain selected was “Hilly” in all cases.

332 Finally, a 1 m grid spacing DEM was built from the automatically filtered terrain points
333 provided by the DSM2DTM algorithm by applying the GMRF interpolation method (F. J.
334 Aguilar et al., 2016).

335 ***3.4. Quality assessment of the extracted GMRF DSM and DEM***

336 The quality of the extracted GMRF DSM and the derived DEM was assessed by
337 computing their completeness and vertical accuracy. In order to study the influence of the
338 dominant land cover on the aforementioned quality indicators, the quality assessment was
339 carried out over the four test areas previously described and depicted in Fig. 1. In each case,
340 the corresponding lidar-derived DSM and DEM were used as ground truth, computing
341 residuals as photogrammetric height minus lidar height.

342 The completeness of every DSM was computed for every test area as the ratio between
343 the blank areas (number of missing image matching points) and all the DSM 1 m grid
344 spacing points which should have been potentially extracted.

345 The vertical accuracy statistics of each GMRF DSM and DEM were separately
346 computed for each test area after applying the widely known 3σ rule (Daniel and Tennant,
347 2001) to remove blunder errors from the residuals populations (z-residuals). In this way,

348 several statistics such as mean value, standard deviation and 90th (*LE90*) and 95th (*LE95*)
349 percentile linear error were computed.

350 4. Results and discussion

351 4.1. DSM Completeness

352 The completeness scores of the DSM produced from PCI and RSP methods were
353 significantly different. In fact, Fig. 3 depicts that the RSP-derived DSM showed a less
354 number of missing image matching points than the one obtained from PCI, especially in
355 those test areas where urban and PCG land cover were more abundant (test areas 3 and 4,
356 respectively. See Fig. 1 and Fig. 3).

357 Fig. 3. Stereo photogrammetrically derived DSM corresponding to the four test areas generated from PCI (left
358 column) and RSP (right column).

359 In the test area 1 (Fig. 3), containing bare soil and dry ravines as the more
360 representative features, the RSP software reached a completeness higher than 99%
361 compared to around 93% achieved by PCI (Table 2). In the case of the test area 2, which
362 mainly presents bare soil and vegetation land covers, the completeness took values of
363 99.57% and 94.42% for the RSP and PCI methods, respectively. Regarding the test area 3,
364 predominantly covered by PCG, urban areas and bare soil, the completeness reached a
365 value of 99.25% in the case of the RSP method, offering a significantly lower value of
366 88.13% in the case of the PCI approach. In the very dense greenhouse covered area labelled
367 as the test area 4, the completeness score of 98.87% provided by the RSP method clearly
368 exceeded the value of 86.65% performed by the PCI method.

369 **Table 2** PCG landcover density and completeness values for the DSM extracted from applying the RSP and PCI
370 stereo-matching approaches.

371 From comparing the completeness results obtained in the four test areas, it can be
372 stated that the higher the PCG landcover density, the lower the completeness score,
373 especially in the case of PCI results. Indeed, the RSP method provided better results than
374 the PCI one for the four test areas. The difference in completeness scores between RSP and
375 PCI DSM reached the highest value (around 12%) in the test area 4, which had the biggest
376 concentration of greenhouse landcover.

377 It is worth nothing that there is a clear relationship between missing matching points
378 (low local DSM completeness) and the local radiometric dissimilarity over greenhouse
379 plastic cover between the two overlapping satellite images. This finding can be made out
380 in Fig. 4, where the DSM produced in the test area 4 from using PCI and RSP software
381 packages are depicted together with the two VHR WV-2 PAN satellite images. The blue
382 ellipses highlight greenhouses presenting important radiometric changes due to glint effect
383 in one of the stereo pair images, thus causing matching problems in DSM production (red
384 colour). However, when greenhouses presented extreme values of digital number because
385 of they are painted white in summer to protect crops from excessive radiation and reduce
386 the heat inside, the matching algorithm worked usually well. These painted greenhouses
387 are marked by mean of yellow ellipses in Fig. 4, not presenting visible radiometric changes
388 between the two stereo pair images.

389 Fig. 4. Influence of local radiometric dissimilarity on greenhouse plastic cover in relation to DSM completeness
390 over the test area 4. The PAN images from WV2 stereo pair are shown above. DSM produced by PCI and RSP
391 software packages are shown below. Blue ellipses highlight greenhouses presenting glint changes while yellow
392 ellipses mark two greenhouses painted white. Matching problems in both DSM are presented in red colour.

393 4.2. Vertical accuracy

394 4.2.1. GMRF DSM vertical accuracy assessment

395 Table 3 shows the results for the GMRF DSM vertical accuracy assessment
396 corresponding to each test area. In general, and regarding random errors assessment, the
397 two tested satellite image matching methods performed quite similar, providing standard
398 deviation and $L95$ values ranging from 0.56 to 0.82 m and 1.34 to 2.10 m, respectively. The
399 poorest vertical accuracies in terms of DSM random errors were obtained in the case of the
400 test area 4, which presented the highest concentration of PCG.

401 In relation to systematic errors, the RSP approach showed a higher positive bias than
402 the PCI one, thus slightly overestimating the reference z-values given by the lidar-derived
403 DSM in all the test areas, but especially in the test areas 3 and 4 which housed the highest
404 density of PCG (Table 2). In terms of linear error computed at 90% and 95% percentiles
405 ($L90$ and $L95$), the results provided by both RSP and PCI approaches can be considered as
406 significantly similar, also rising with the increase of greenhouse land cover density.

407 Provided that RSP presented a higher completeness in DSM generation than PCI, their
408 similar results from the vertical accuracy assessment in terms of random errors and a
409 slightly higher bias in the case of RSP seem to point to the fact that RSP is incurring a
410 commission error when working on difficult to match image areas (e.g. glint effect
411 mentioned above). In other words, PCI matching method turns out to be more reluctant to
412 accept pairs of matching points with weak similarity (measured through cross-correlation
413 coefficient), therefore tending to leave more blank areas and so reducing completeness. On
414 the contrary, RSP can compute the 3D position of those weak matching points, so
415 improving the visual appearance of the compiled DSM but also increasing the probability

416 of incurring vertical error. It is important to highlight that the GMRF interpolation
 417 algorithm was able to properly fill the DSM gaps left by PCI method, especially in
 418 greenhouse land cover areas, without significantly affecting the final vertical accuracy
 419 results, a finding already reported by F. J. Aguilar et al. (2016).

420 The spatial distribution of GMRF DSM errors is depicted in Fig. 5. The error
 421 distribution of RSP and PCI compiled GMRF DSM presented a similar pattern, with the
 422 highest vertical error mainly localized along manmade features edges. Most of errors are
 423 positive, i.e. stereo-photogrammetrically derived DSM slightly overestimated the true z-
 424 values provided by the lidar reference DSM. This was expected since photogrammetric
 425 points could be considered as the features visual envelope. Finally, most of the working
 426 area presented absolute errors lower than 1 m, which can be deemed an adequate result.

427 **Table 3** Vertical accuracy assessment results for the GMRF DSM produced by the PCI and RSP stereo
 428 matching methods. Units expressed in meters.

429 **Fig. 5.** Spatial distribution of residuals for the GMRF DSM corresponding to the four test areas generated from
 430 PCI (left column) and RSP (right column).

431 4.2.2. *DEM vertical accuracy assessment*

432 With regards to the automatically filtered and GMRF interpolated DEM, the random
 433 errors, measured in terms of standard deviation, were similar for all the test areas and
 434 between the two image matching methods tested for DSM production (Table 4). As
 435 expected, the computed DEM standard deviation was consistently higher than that
 436 estimated in the case of GMRF DSM, ranging from 1.16 to 2.28 m. Indeed, now there are
 437 two concomitants sources of error, DSM original error and DSM-to-DEM error (DSM
 438 filtering error). However, the test area 1 showed the highest random error value, mainly due

439 to the presence of two relatively deep dry ravines running from North to South.

440 Also note that the systematic errors depicted a different behaviour in the test area 1
441 compared to those observed in the other test areas. In fact, the mean error in the test area 1
442 presented a negative bias, thus underestimating the true elevation provided by the lidar
443 derived DEM data. Just the opposite happened in the other test areas. This bias effect was
444 again more pronounced in those DEM filtered from the DSM produced by RSP method,
445 probably because RSP assumes more risk in image matching over cumbersome areas. In
446 the vertical profile shown in Fig. 7, it can be appreciated that the filtered DEM extracted
447 from the corresponding PCI generated DSM (similar behaviour was observed in the case
448 of the RSP derived DEM) resulted in an excessively smooth surface along the dry ravine,
449 producing a noticeable decrease in slope on its originally steep flanks and a subsequent
450 underestimation of the elevations provided by the lidar-derived DEM. This undesirable
451 effect was due to the way in which the algorithm DSM2DTM, implemented in PCI
452 Geomatics, automatically converts a DSM into a bare-earth DEM by applying a series of
453 filtering steps that remove features such as buildings, greenhouses and vegetation stands
454 and, at the same time, maintain natural terrain features under a previously set slope
455 threshold. Likely, the slope threshold parameter selected for the test area 1 (35%) should
456 be increased to avoid filtering out the steep gully flanks. In any case, it is beyond the scope
457 of this article to conduct an in-depth study about the optimization of the available DSM-to-
458 DEM filtering algorithms. Only note that the use of spatially adapted parameters could
459 notably improve the results regarding DEM accuracy.

460 **Table 4** Vertical accuracy assessment results for the DEM extracted from the DSM produced by the PCI and
461 RSP stereo matching methods. Units expressed in meters.

462 The spatial distribution of DEM residuals is shown in Fig. 6. As explained above, the
463 test area 1 depicts a general underestimation of the true elevation values mainly located
464 along the two steep flanks of the dry ravines. An opposite situation can be seen in the other
465 test areas, where the general tendency would be more prone to overestimate DEM
466 elevations, especially in greenhouse built-up areas. In fact, the higher the greenhouse
467 density, the higher the positive bias in signed DEM residuals (Table 4). In the main, the
468 DSM-to-DEM algorithm produced an insufficient removal of built-up features, especially
469 greenhouses, as compared to the lidar derived DEM which may even register some last
470 laser returns onto the greenhouse floor, thus contributing to a better definition of the bare-
471 earth DEM.

472 **Fig. 6.** Spatial distribution of residuals for the DEM corresponding to the four test areas derived from PCI DSM
473 (left column) and RSP DSMs (right column).

474 **Fig. 7.** Vertical profile crossing one of the dry ravines located at the test area 1 (the red line in Fig. 2 indicates the
475 location of this profile). The points represented in magenta correspond to the lidar-derived DEM (see section 2.3),
476 while the red points take part of the DEM filtered from the PCI DSM (see section 3.3).

477 **Conclusions**

478 In this work it is proposed a methodological pipeline to automatically produce
479 valuable 3D information (DSM and bare-earth DEM geospatial products) from VHR stereo
480 imagery in order to potentially improve PCG mapping over large areas. Lidar derived DSM
481 and DEM were used to carry out the vertical accuracy assessment of the stereo
482 photogrammetrically generated products. Note that, to the best of our knowledge, this is the
483 first work that addresses the challenge of the generation of DSM and DEM products in
484 dense PCG areas from VHR satellite imagery. The way to merge this 3D geospatial

485 information and the traditional 2D spectral-based information will be faced in further
486 works.

487 With regards to DSM completeness, the RSP approach yielded significantly better
488 scores than PCI, above all in high dense PCG areas, demonstrating that semi-global
489 matching can extract image matching points even over radiometrically difficult-to-match
490 image patches (e.g. some greenhouse roofs with a pronounced glint effect). This advantage
491 turns out to be very relevant when dealing with generating DSM in very dense PCG areas.

492 Concerning vertical accuracy of the GMRF DSM, both PCI and RSP methods yielded
493 similar vertical accuracy results in terms of random errors, with standard deviations ranging
494 from 0.56 to 0.82 m. It must be underlined that a slightly higher positive bias (height
495 overestimation) was detected in the case of RSP as compared to PCI, likely because RSP
496 can incur a commission error when working on difficult to match image patches to achieve
497 higher completeness scores than PCI.

498 The DEM error figures also showed no significant differences between the two tested
499 approaches regarding random errors, presenting standard deviations ranging from 1.16 to
500 2.28 m. In relation to the systematic errors, they were much higher than those obtained in
501 the case of GMRF DSM production, again RSP method showing a slightly higher bias than
502 PCI. Summing up, the computed DEM error figures were highly dependent on DSM-to-
503 DEM filtering error, in turn closely related to greenhouse density and terrain complexity.
504 Concerning DSM-to-DEM automatic filtering, the PCI algorithm DEM2DTM usually
505 yielded reasonable results, especially considering that only two parameters were tuned
506 during a trial and error process. However, more spatially adapted parameters would be
507 required to improve the final DSM-to-DEM filtering results. In this sense, it can be
508 concluded that more research should be devoted to improving the filtering tools available

509 to automatically convert a stereo photogrammetrically derived DSM into a bare-earth DEM
510 in the case of PCG areas.

511 The 3D information provided through the methodological pipeline described in this
512 work could be very valuable as a complement to the traditional 2D spectral information
513 offered by VHR satellite imagery to improve PCG mapping and monitoring over large
514 areas. This might be accomplished, for example, by computing the normalized digital
515 surface model from the difference between the GMRF DSM and the corresponding DEM
516 to obtain a georeferenced raster layer containing the height of all overlying objects on the
517 terrain, such as buildings, trees and greenhouses.

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738 **LIST OF TABLES**

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751 Table 1 Characteristics of the panchromatic band for the WV-2 stereo pair.

<i>Product</i>	<i>WV-2 Stereo Pair</i>	
<i>Images</i>	<i>WV-2 Image 1</i>	<i>WV-2 Image 2</i>
Acquisition Date	July 5, 2015	July 5, 2015
Acquisition Time (GTM)	11:02	11:03
Off-nadir View Angle	12.6°	24.6°
Collection Azimuth	59.2°	172.7°
Collected Col GSD (m)	0.488	0.519
Collected Row GSD (m)	0.480	0.584
Product Pixel Size (m)	0.5	0.5

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Table 2 PCG landcover density and completeness scores for the DSM extracted from applying the RSP and PCI stereo-matching approaches.

	PCG landcover (%)	Completeness (%) RSP stereo-matching	Completeness (%) PCI stereo-matching
Test area 1	16.43	99.42	93.19
Test area 2	27.51	99.57	94.42
Test area 3	49.32	99.25	88.13
Test area 4	85.65	98.87	86.65

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Table 3 Vertical accuracy assessment results for the GMRF DSM produced by the PCI and RSP stereo matching methods. Units expressed in meters.

Test areas Method	Test area 1		Test area 2		Test area 3		Test area 4	
	RSP	PCI	RSP	PCI	RSP	PCI	RSP	PCI
Mean error	0.15	0.05	0.19	0.06	0.28	0.01	0.32	0.35
Standard deviation	0.62	0.65	0.59	0.56	0.78	0.72	0.80	0.82
Maximum error	3.43	3.68	3.15	2.92	3.68	3.13	3.53	4.11
Minimum error	-3.15	-3.58	-2.64	-2.68	-3.10	-3.04	-2.92	-3.38
L95	1.35	1.55	1.35	1.34	1.97	1.86	1.96	2.10
L90	0.88	0.84	0.90	0.79	1.26	1.16	1.34	1.37

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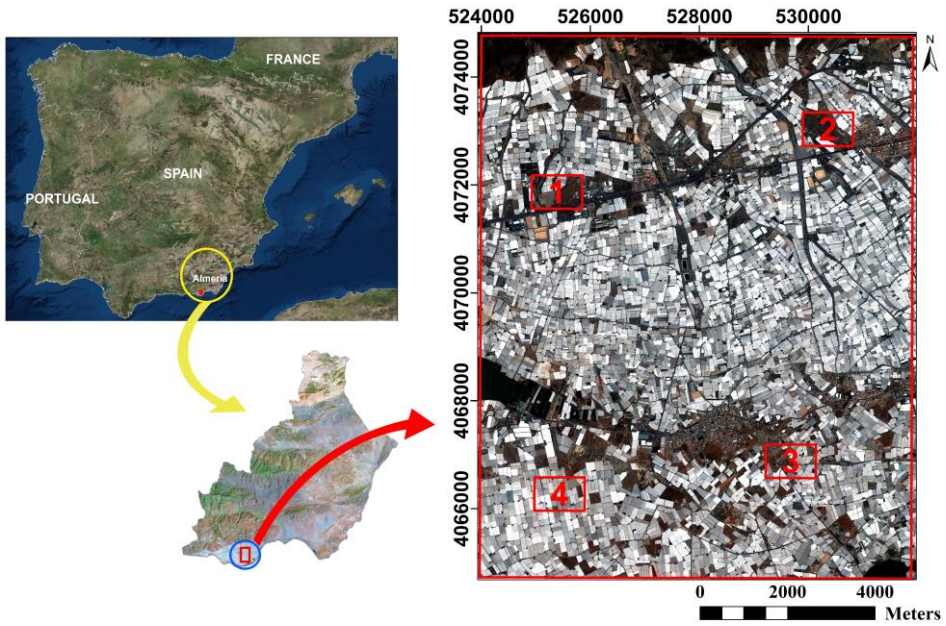
Table 4 Vertical accuracy assessment results for the DEM extracted from the DSM produced by the PCI and RSP stereo matching methods. Units expressed in meters.

Test area DEM derived from	Test area 1		Test area 2		Test area 3		Test area 4	
	RSP	PCI	RSP	PCI	RSP	PCI	RSP	PCI
Mean error	-1.28	-1.26	0.46	0.27	0.97	0.61	1.78	1.60
Standard deviation	2.28	2.00	1.41	1.36	1.16	1.21	1.35	1.44
Maximum error	6.20	5.61	5.22	4.72	4.73	4.57	5.84	5.95
Minimum error	-8.62	-8.08	-4.34	-4.16	-2.30	-3.28	-2.30	-3.74
L95	5.81	5.10	3.59	3.19	3.27	3.01	3.83	3.92
L90	4.90	4.13	2.90	2.72	2.83	2.54	3.51	3.46

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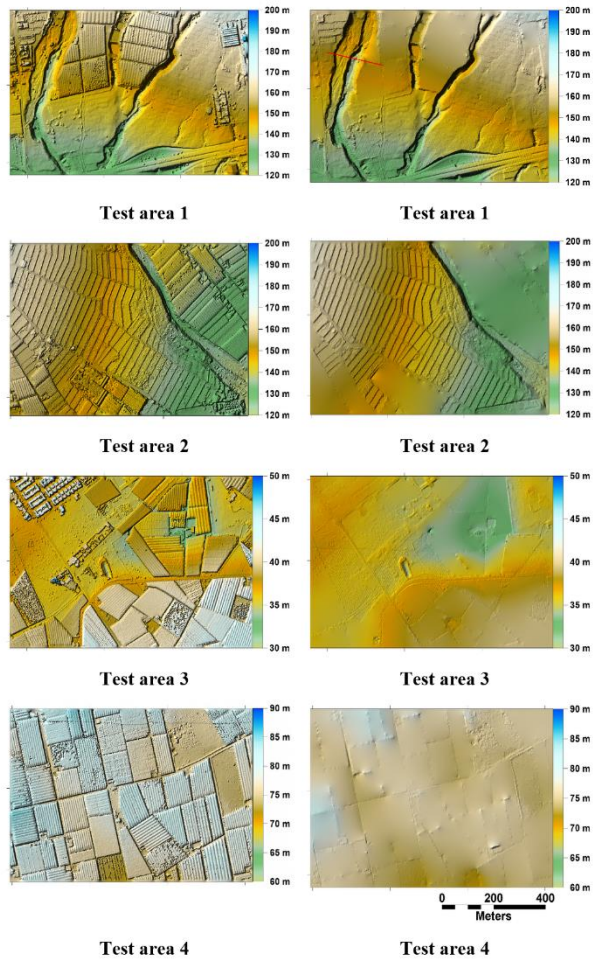
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768 These subareas are characterized, in addition to PCG and bare soil, by dry ravines (1), vegetation (2) urban areas
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790 location of this profile). The points represented in magenta correspond to the lidar-derived DEM (see section
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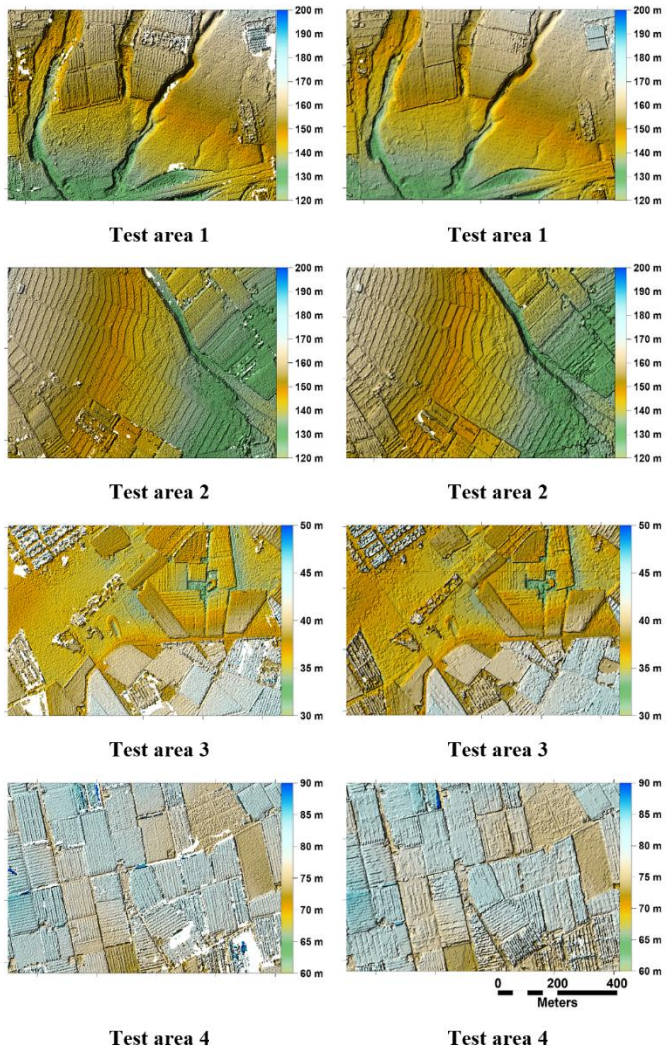
Fig. 1. Location of the study site in the province of Almeria (Spain) and the four selected subareas as red rectangles. These subareas are characterized, in addition to PCG and bare soil, by dry ravines (1), vegetation (2) urban areas (3) and very high concentration of PCG (4). Coordinate System: WGS84 UTM Zone 30.



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Fig. 2. Lidar-derived grid format DSM and DEM for the four test areas. Left column: Lidar-derived DSM. Right column: Lidar-derived DEM. The red line (DEM test area 1 in the first row on the right) corresponds to the location of the profile represented in Fig. 7).

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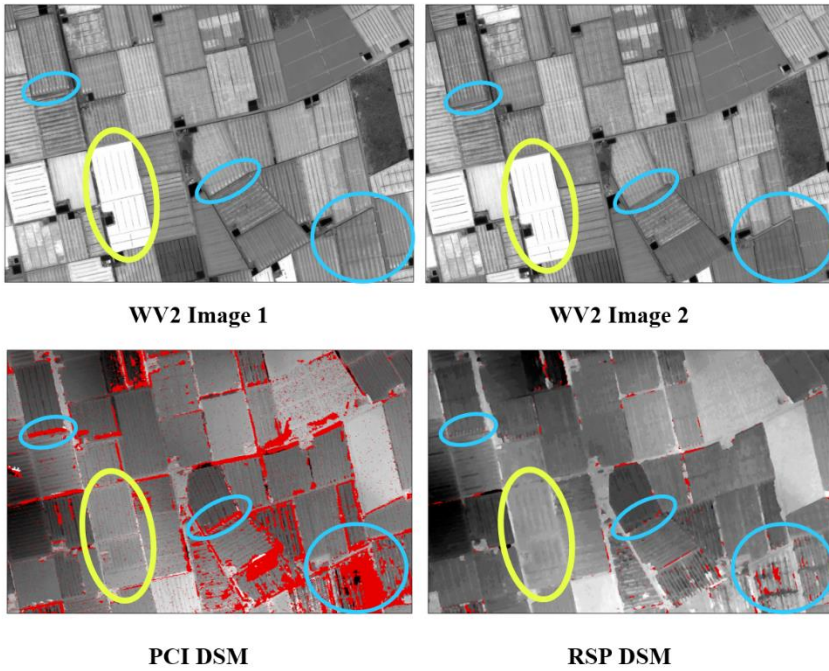
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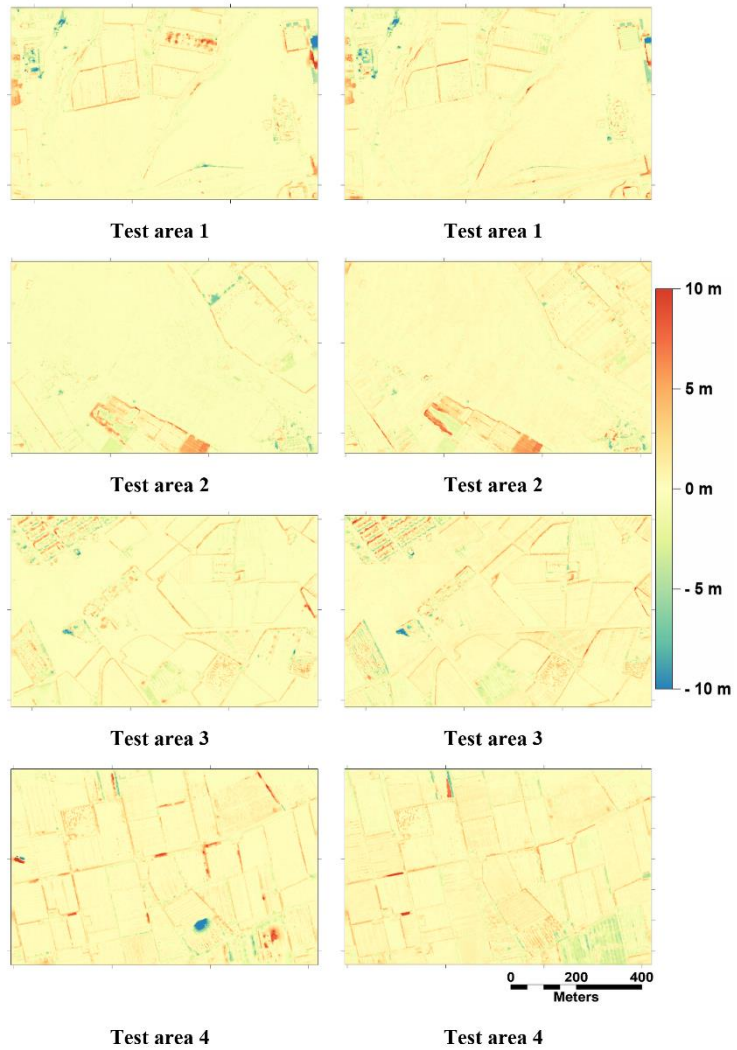
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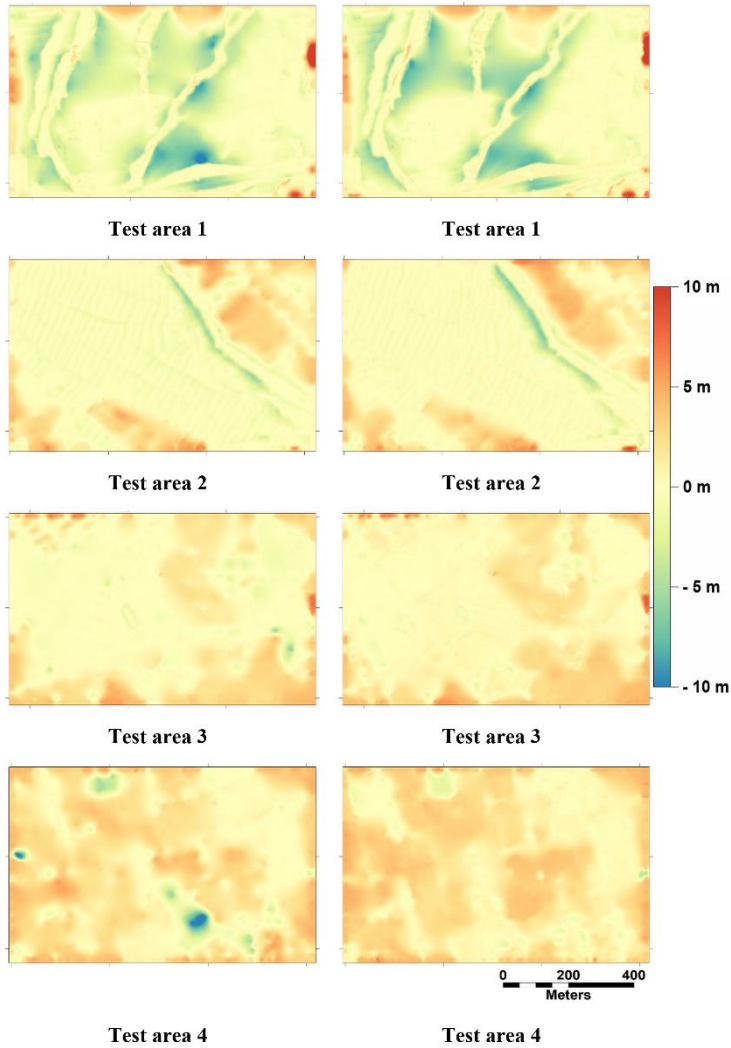
Fig. 4. Influence of local radiometric dissimilarity on greenhouse plastic cover in relation to DSM completeness over the test area 4. The PAN images from WV2 stereo pair are shown above. DSM produced by PCI and RSP software packages are shown below. Blue ellipses highlight greenhouses presenting glint changes while yellow ellipses mark two greenhouses painted white. Matching problems in both DSM are presented in red colour.



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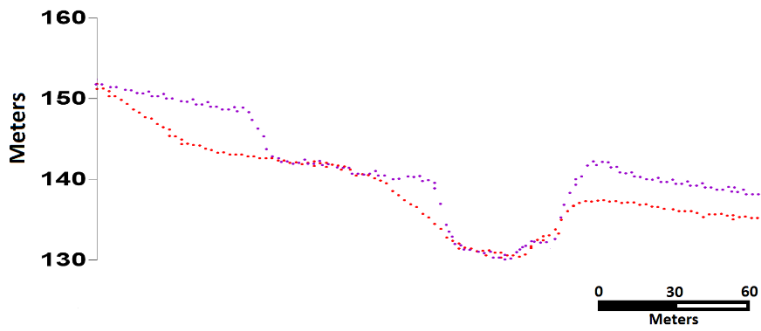
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Fig. 6. Spatial distribution of residuals for the GMRF DEM corresponding to the four test areas derived from PCI DSM (left column) and RSP DSM (right column).



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Fig. 7. Vertical profile crossing one of the dry ravines located at the test area 1 (the red line in Fig. 2 indicates the location of this profile). The points represented in magenta correspond to the lidar-derived DEM (see section 2.3), while the red points take part of the DEM filtered from the PCI DSM (see section 3.3).