

Quality assessment of digital surface models extracted from WorldView-2 and WorldView-3 stereo pairs over different land covers.

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1 **Abstract**

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3 Digital surface models (DSMs) extracted from very high resolution (VHR) satellite stereo images
4 are becoming more and more important in a wide range of geoscience applications. The number of
5 software packages available for generating DSMs has been increasing rapidly. The main goal of this
6 work is to explore the capabilities of VHR satellite stereo pairs for DSMs generation over different
7 land-cover objects such as agricultural plastic greenhouses, bare soil and urban areas by using two
8 software packages: (i) OrthoEngine (PCI), based on a hierarchical subpixel mean normalized cross
9 correlation matching method, and (ii) RPC Stereo Processor (RSP), with a modified hierarchical
10 semi-global matching method. Two VHR satellite stereo pairs from WorldView-2 (WV2) and
11 WorldView-3 (WV3) were used to extract the DSMs. A quality assessment on these DSMs on both
12 vertical accuracy and completeness was carried out by considering the following factors: (i) type of
13 sensor (i.e., WV2 or WV3), (ii) software package (i.e., PCI or RSP) and (iii) type of land-cover
14 objects (plastic greenhouses, bare soil and urban areas). A highly accurate light detection and
15 ranging (LiDAR) derived DSM was used as the ground truth for validation. By comparing both
16 software packages, we concluded that regarding DSM completeness, RSP produced significantly
17 ($p < 0.05$) better scores than PCI for all the sensors and type of land-cover objects. The percentage
18 improvement in completeness by using RSP instead of PCI was approximately 2%, 18% and 26%
19 for bare soil, greenhouses and urban areas respectively. Concerning the vertical accuracy in root
20 mean square error (RMSE), the only factor clearly significant ($p < 0.05$) was the land cover. Overall,
21 WV3 DSM showed slightly better (not significant) vertical accuracy values than WV2. Finally,
22 both software packages achieved similar vertical accuracy for the different land-cover objects and
23 tested sensors.

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25 Keywords: DSM, WorldView-2/3, matching, vertical accuracy, completeness, plastic greenhouse.

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1. Introduction

Digital Surface Models (DSMs) are one of the core products of very high resolution (VHR) satellite stereo photogrammetric imagery. Three-dimensional (3D) information plays a crucial role for many geospatial analysis (e.g. [Maune 2007](#)), adding accurate georeferenced datasets into Geographic Information Systems. With the development of spaceborne sensors, it is expected that VHR stereo data can be acquired in a timely and repeated manner for any region of interest, much more affordable than traditional aerial surveys. According to [Noh and Howat \(2015\)](#), the quality of stereoscopic DSMs depends on: (i) the radiometric and geometric quality of the imagery, (ii) the accuracy of the sensor model used to represent the relationship between image and object space, and (iii) the performance of the image matching algorithm.

Regarding radiometric and geometric quality of the imagery, the last investigations about extracting 3D information from VHR satellite stereo pairs are mainly focused on the new breed of DigitalGlobe's VHR satellites such as GeoEye-1 and WorldView-1/2/3/4 ([Aguilar, Saldaña and Aguilar 2014](#); [Noh and Howat 2015](#); [Shean et al. 2016](#); [Barbarella, Fiani and Zollo 2017](#); [DeWitt et al. 2017](#)) which are capable of capturing panchromatic (PAN) imagery of the land surface with ground sample distance (GSD) even lower than 0.5 m. Others recently published works also pay attention to the capabilities of the PAN triplet from Pléiades-1 to generate DSMs ([Poli et al. 2015](#); [Di Rita, Nascetti and Crespi 2017](#); [Qin 2016](#)).

The sensor model used at the stereo pair orientation phase can be particularly important for the DSM accuracy, and most of the state-of-the-art work take either the rigorous linear-array model or parametric rational polynomial function model (RPF) ([Fraser, Baltsavias and Gruen 2002](#); [Toutin 2006](#); [Capaldo et al. 2012](#); [Crespi et al. 2012](#); [Poli and Toutin 2012](#)). As compared to rigorous model, the RPF model is concluded to be capable of achieving similar level of accuracy and being much more compatible across different sensors, thus nowadays is widely used as the standard geometric model for spaceborne optical images. The RPF builds the object-to-image space mapping through 78 parameters called RPC (rational polynomial coefficients). It should be noted that the

1 initial RPC parameters derived from the satellite navigation system usually contain bias, thus the
2 geo-referencing needs a bias-correction phase for generating precise epipolar images for dense
3 image matching, which can be performed either using tie points (relative correction) or accurate
4 ground control points (GCPs, for absolute correction) ([Grodecki and Dial 2003](#); [Fraser and Hanley
5 2003, 2005](#)).

6 With regard to the image matching algorithm, there are many commercial software packages being
7 able to procedure DSM from VHR stereo images such as MATCH-T, supplied by Trimble, LPS
8 eATE, embedded into ERDAS, or Socet Set ATE, by BAE Systems. Among these, OrthoEngine,
9 the photogrammetric module of Geomatica (PCI Geomatics), has been the most used in research
10 works, serving as a benchmark for others packages in comparison tests ([Capaldo et al. 2012](#);
11 [Fratarcangeli et al. 2016](#); [Barbarella, Fiani and Zollo 2017](#); [Di Rita, Nascetti and Crespi 2017](#)). A
12 few open source tools for DSMs generation from VHR satellite have become available such as
13 Satellite Stereo Pipeline (S2P) ([de Franchis et al. 2014](#)), the NASA Ames Stereo Pipeline (ASP)
14 ([Shean et al. 2016](#)), or Digital Automatic Terrain Extractor (DATE) ([Di Rita, Nascetti and Crespi
15 2017](#)). In addition, RPC Stereo Processor (RSP) ([Qin 2016](#)) and the Surface Extraction with TIN-
16 based Search-space Minimization (SETSM) ([Noh and Howat 2017](#)) represent other recently
17 developed tools for DSM extraction. The aforementioned software packages use different image
18 matching algorithms to find the corresponding image points. In that sense, [Alobeid, Jacobsen and
19 Heipke \(2010\)](#) concluded that the matching method for generating DSMs is crucial, especially in
20 urban environments. They found that the area-based least squares matching is not able to generate
21 sharp building outlines and strongly impacted by occlusions. On the other hand, semi-global
22 matching (SGM) ([Hirschmüller 2008](#)) and dynamic programming matching method ([Birchfield and
23 Tomasi 1998](#)) achieve better results working on urban areas.

24 It is important to note that DSM accuracy varies with the terrain surface roughness ([Li 1992](#);
25 [Aguilar et al. 2005](#)) and the target land-cover objects ([Toutin 2006](#); [Hobi and Ginzler 2012](#);
26 [Aguilar, Saldaña and Aguilar 2014](#)). A plethora of literature about DSMs generation from VHR

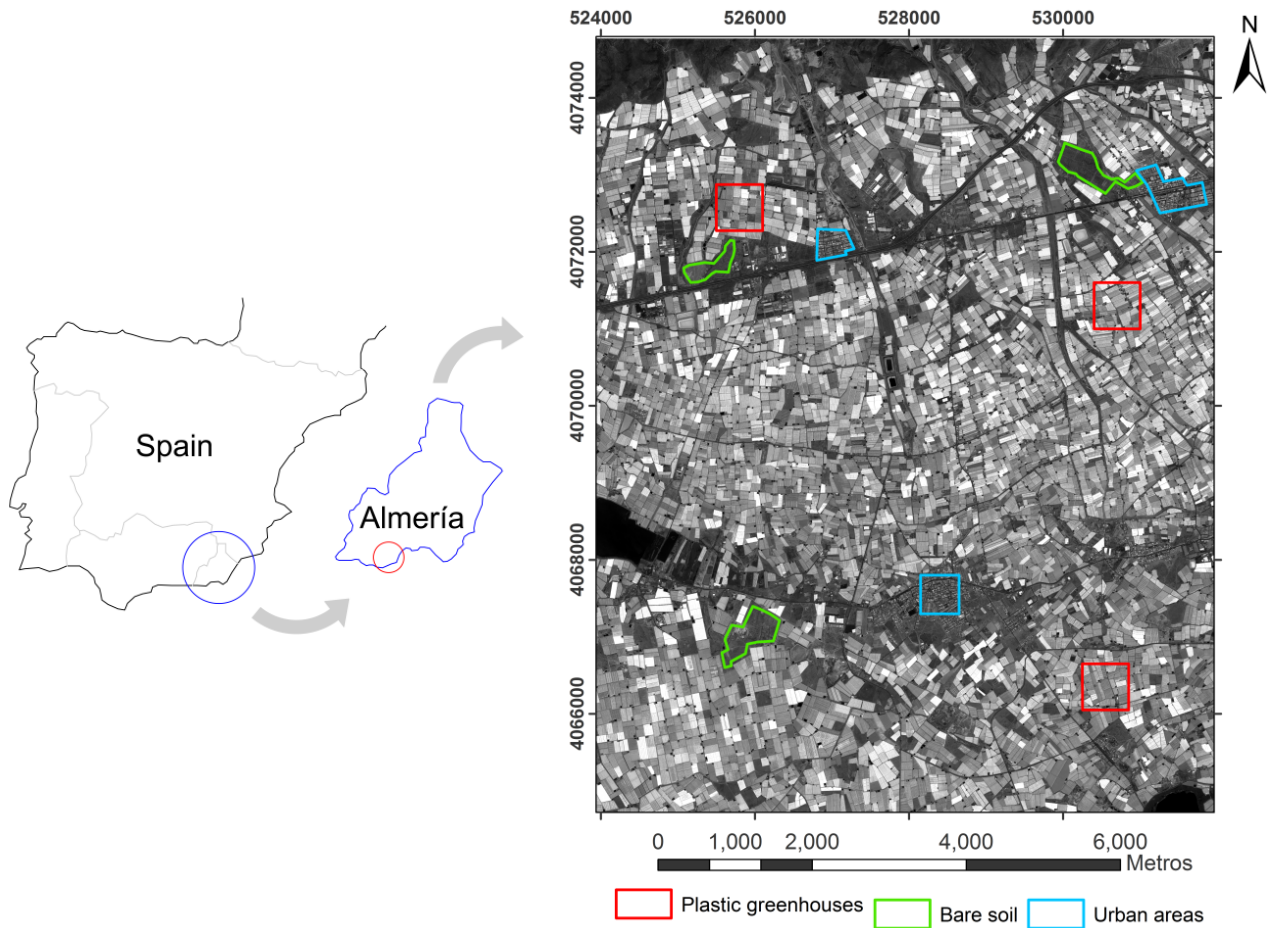
1 satellite imagery over different study sites exists, including urban areas (Di Rita, Nascetti and
2 Crespi 2017), flat bare soil (Aguilar, Saldaña and Aguilar 2014), mountainous areas (Fratarcangeli
3 et al. 2016), densely vegetated deciduous forest (DeWitt et al. 2017), glaciated regions (Noh and
4 Howat 2015) or over herb and grass land cover (Hobi and Ginzler 2012). However, to the best of
5 our knowledge, few works have been specifically focused on greenhouse covered areas (Aguilar et
6 al. 2014), where the different plastic materials with varying thickness, transparency, ultraviolet and
7 infrared reflection and transmission properties, additives, age and colours are challenging for
8 accurate 3D extraction. With such 3D information, the greenhouses mapping accuracy can be
9 greatly improved by incorporating them (e.g., DSM or normalized digital surface model (nDSM))
10 into pixel-based and object-based supervised image classification algorithms (Aguilar et al. 2014;
11 Celik and Koc-San 2018).

12 The vertical accuracy of a DSM generated from VHR satellite images is normally evaluated through
13 highly accurate light detection and ranging (LiDAR) information as ground truth (Toutin 2006;
14 Capaldo et al. 2012; Noh and Howat 2015). However, the generated DSM may not represent height
15 for every single pixel due to matching errors provoked by insufficient texture, occlusions or
16 radiometric artifacts. Therefore, DSM quality should also be evaluated using DSM completeness,
17 defined as the percentage of correctly matched points over the area of interest (Höhle and
18 Potuckova 2011).

19 The main objective of this paper is to evaluate and compare, exactly in the same conditions, the
20 unfilled DSMs extracted from along-track WorldView-2 and WorldView-3 PAN VHR satellite
21 stereo pairs over a very dense greenhouse covered area, also presenting mixed patches of bare soil
22 and urban areas. Two software packages with two clearly different image matching approaches
23 were also tested. In this sense, a DSM quality assessment, including both vertical accuracy and
24 completeness, was performed to statistically analyse the effect of the following factors: (i) type of
25 VHR sensor (i.e., WV2 or WV3), (ii) software package used (i.e., OrthoEngine or RSP) and (iii)
26 type of land cover (plastic greenhouses, bare soil and urban areas).

1 **2. Study sites**

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3 The study area is located in the province of Almeria (Southern Spain). It comprises an area of ca.
4 8000 ha centred on the geographic coordinates (WGS84) 36.7824°N and 2.6867°W (Figure 1). It is
5 just at the core of the greatest concentration of greenhouses in the world, the so-called “Sea of
6 Plastic”. This pilot area presents a smooth relief ranging between 152.6 m and 214.8 m above mean
7 sea level. Within the study area, nine sub-plots (red, green and blue polygons in Figure 1) with areas
8 between 14 ha and 36 ha were selected according to their type of land cover. In fact, three sample
9 areas of each land cover were selected so that they were representatives of plastic greenhouses, bare
10 soil (practically without vegetation) and urban areas respectively.



11 Figure 1. Location of the study area in Almería (Spain). The nine selected subareas over plastic greenhouses, bare soil
12 and urban areas are depicted as red, green and blue polygons respectively. Coordinate system: WGS84 UTM Zone 30N.

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3. Datasets

3.1. WorldView-2 and WorldView-3 stereo pairs

A WorldView-2 (WV2) PAN along-track stereo pair was acquired on 5 July 2015 covering the study site (Table 1). It was collected in Stereo Ortho Ready Level-2A (StereoOR2A) format, presenting both radiometric and geometric corrections. StereoOR2A format is georeferenced to a cartographic projection using a surface of a constant height. It also counts on the corresponding RPC sensor camera model and metadata file. The delivered products were ordered with a dynamic range of 11 bits. The second stereo pair over the study site was collected on 11 July 2016. It was a PAN StereoOR2A product from WorldView-3 (WV3) with a dynamic range of 11 bits. The metadata including viewing geometry, sun positions and other acquisition parameters for both studied stereo pairs are shown in Table 1.

Table 1. Characteristics of panchromatic images from WorldView-2 (WV2) and WorldView-3 (WV3) stereo pairs.

Product	WV2 Stereo Pair		WV3 Stereo Pair	
Images	WV2 Image 1	WV2 Image 2	WV3 Image 1	WV3 Image 2
Acquisition Date (D/M/Y)	5/7/2011	5/7/2011	11/07/2016	11/07/2016
Acquisition Time (GTM)	11:03	11:04	11:31	11:32
Scan direction	Forward	Forward	Forward	Forward
Off-Nadir View Angle	12.6°	24.6°	32.7°	22.2°
In-Track View Angle	8.3 °	-23.5 °	26.2 °	-2.8 °
Cross-Track View Angle	9.6 °	7.7 °	-20.3 °	-22.0 °
Satellite Azimuth	59.2°	172.7°	336.3°	273.6°
Collected GSD	0.484 m	0.550 m	0.422m	0.354 m
Product Pixel Size	0.5 m	0.5 m	0.3 m	0.3 m
Sun Azimuth	126.4°	126.9°	142.9°	143.5°
Sun Elevation	69.1°	69.3°	72.4°	72.5°

3.2. Ground truth LiDAR data

The LiDAR data used as ground truth in this study was provided by the PNOA (National Plan of Aerial Orthophotograph of Spain) as a point cloud in LAS binary file, format v. 1.2 (Montealegre et al. 2015), containing easting and northing coordinates (UTM ETRS89 30N) and orthometric elevations (geoid EGM2008). It was captured on September 23, 2015, by a Leica ALS60 discrete return sensor with up to four returns measured per pulse and an average flight height of 2700 m.

1 The registered point density of the test area, taking into account the overlapping, turned out to be
2 0.97 points/m² (all returns). The estimated vertical accuracy of the LiDAR data was computed on
3 131 GPS-RTK surveyed ground points evenly distributed over the whole study area. The standard
4 deviation of the computed LiDAR vertical error, only including open terrain GCPs (Aguilar and
5 Mills 2008), took a value of 0.14 m, meaning vertical accuracy higher than the 0.2 m nominal
6 vertical error of PNOA LiDAR data (Montealegre et al. 2015).

7 The original density of the LiDAR point cloud was significantly reduced to extract a representative
8 and yet manageable set of LiDAR points. In this sense, only single and first returns LiDAR points
9 were used. Usually, points from single return collect very well bare soil areas, while on plastic
10 greenhouse, the laser beam can capture several returns (on the top of the plastic cover, on the crop
11 inside or on the bare soil) depending mainly on the plastic material. Thus, in order to better
12 represent the DSM ground truth from LiDAR data we selected the first return. After this, LiDAR
13 data from the nine selected subareas were carefully edited by manually removing incorrect points.
14 This task was especially time consuming for the plastic greenhouse subareas where the first return
15 LiDAR points sometimes penetrate the plastic sheet. Finally, a spatially oriented data thinning was
16 carried out by sub-sampling the original point cloud using a minimum distance between points of 2
17 m. Following these steps, an evenly distributed ground truth LiDAR edited data over each study
18 area of around 0.2 points/m² was obtained for validation.

19 **4. Methodology**

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21 **4.1. DSM Extraction from VHR Satellite Imagery**

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23 Two different software packages, based on different image matching approaches, were used to
24 stereo-photogrammetrically generate the DSM from WV2 and WV3 stereo pairs.

25 OrthoEngine, the photogrammetric module of Geomatica v. 2013 software (PCI Geomatics,
26 Richmond Hill, ON, Canada) was the first of the packages tested. OrthoEngine (PCI henceforth)
27 matching algorithm is based on cross-correlation where an automated area-based matching

1 procedure is performed on quasi-epipolar images. Specifically, this procedure utilizes a hierarchical
2 sub-pixel mean normalized cross correlation matching method that generates correlation
3 coefficients between zero and one for each matched pixel, where zero represents a total mismatch
4 and one a perfect match. When the correlation coefficient of a matched point is lower than 0.5, this
5 point is rejected and its height is not computed, meaning a gap and reducing the DSM
6 completeness. Finally, a second-order surface is then fitted around the maximum correlation
7 coefficients to find the match position to sub-pixel accuracy (Chen 2015).

8 RSP (RPC Stereo Processor) was the other software package tested in this work. RSP was initially
9 developed by Qin (2014) for 3D change detection and land cover classification studies and it was
10 further refined as a standalone software package that performs stereo matching on RPC modelled
11 space-borne images producing mapping products such as DSM and orthophoto (Qin 2016). RSP
12 implements a hierarchical SGM approach based on the widely known algorithm proposed by
13 Hirschmüller (2008) to generate the disparity maps after applying an epipolar rectification process
14 to the original stereo images.

15 The sensor orientation phase for both software packages was carried out by the empirical model
16 based on a third-order 3-D rational functions with vendor's RPCs data and refined by a zero-order
17 polynomial adjustment (RPC0), following the block adjustment method published by Grodecki and
18 Dial (2003) for image space. Although RPC0 requires only one GCP, and in order to have a better
19 reliability, seven GPS-RTK surveyed ground points evenly distributed over the working area were
20 used following the recommendations of Aguilar, Saldaña and Aguilar (2013). It is important to keep
21 in mind that the GCPs were only marked once on the image space of the PCI project, being later
22 exported to be automatically marked in the RSP project in order to guarantee the same input.
23 Exactly the same seven GCPs were used to perform the sensor orientation for WV2 and WV3.

24 After carrying out the sensor orientation phase, four grid spacing format DSMs for each subarea
25 were stereo-photogrammetrically extracted by using different combinations of sensor (WV2 and
26 WV3) and software packages (PCI and RSP). The DSMs were always computed in orthometric

1 elevations using the EGM2008 geoid. The resolution of these DSMs was set to 0.6 m and 1 m for
2 WV3 and WV2 respectively (two times of the image GSD). In the case of PCI, “hilly terrain” and
3 “without filling blanks” (no interpolation) parameters were chosen. In the case of the RSP software,
4 the DSM was also extracted without filling blanks. Finally, 36 unfilled DSMs were extracted (9
5 subareas \times 2 software packages \times 2 sensors).

6 **4.2. Quality assessment of the extracted DSMs**

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8 The quality of the extracted DSMs was assessed by computing their completeness and vertical
9 accuracy. As mentioned, the quality assessment was focused on different software packages,
10 sensors and land covers. Thus, three samples of three types of land cover (plastic greenhouses, bare
11 soil and urban areas) were considered within the study area, finally leading to the nine test subareas
12 as shown in Figure 1.

13 The completeness of every DSM was computed for the different studied subareas as the ratio
14 between the number of correctly matched points and the maximum possible number of points for
15 the selected DSM grid spacing. Therefore, the completeness offers a quantitative measure about the
16 influence of the different tested factors on the ability to extract local 3D information over the study
17 area.

18 Regarding the accuracy of the stereo-photogrammetrically extracted DSMs from the WV2 and
19 WV3 stereo pairs in the nine subareas, the 3D points from the manually edited LiDAR DSM were
20 employed as independent check points (ICPs) for assessing the vertical accuracy (LiDAR ICPs),
21 computing vertical residual (z-residual) at each corresponding point as photogrammetric height
22 minus LiDAR height. It is important to note that each ICP will produce a z-residual if the area
23 around the planimetric position of this ICP contains height information in the corresponding DSM.
24 In this case, a bilinear interpolation was used to compute the value of that z-residual. For instance,
25 in the case of the first repetition of plastic greenhouses land cover (area of 36 ha), 58909 LiDAR
26 ICPs were considered as ground truth. However, the total number of successfully extracted z-

1 residuals was fewer in photogrammetrically derived DSMs due to matching algorithm failures (i.e.,
2 the completeness values of the DSMs for each subarea were always lower than 100%). In fact, for
3 this subarea different numbers of total extracted z-residuals (Total z-residuals) were computed from
4 PCI WV2 DSM (38049), RSP WV2 DSM (52084), PCI WV3 DSM (36654) and RSP WV3 DSM
5 (49119). To fully complete the picture, the vertical accuracy assessment for each subarea was also
6 performed only on those ICPs where z-residuals were available for all the sensors and software
7 packages tested in each subarea (i.e., Common ICPs), thus reducing the number of ICPs but
8 ensuring a fair play in the comparison on different factors. In our example corresponding to the first
9 repetition of greenhouse land cover, the final number of ICPs at which z-residuals could be
10 computed in all cases stood at 26109 for PCI WV2 DSM, RSP WV2 DSM, PCI WV3 DSM and
11 RSP WV3 DSM. In that sense, two strategies have been carried out in this work for assessing
12 vertical accuracy from VHR satellite derived DSMs: (i) using all the ICPs from each subarea and
13 combination of software/sensor, and (ii), for ensuring a fair comparison, using only those ICPs
14 where the z-residuals were available for all the sensors and software tested in each subarea. After
15 removing blunders from the z-residuals populations attained from both strategies by applying the
16 widely known three-sigma rule ([Daniel and Tennant 2001](#)), statistics such as Mean, Standard
17 Deviation (SD), vertical Root Mean Squared Error (RMSE) and 95th (LE95) percentile Linear Error
18 were computed for the final vertical accuracy assessment. These statistics are usually adopted for
19 the assessment of DSMs ([Di Rita, Nascetti and Crespi 2017](#)).

20 The number of ICPs from the manually edited LiDAR point cloud, the total number of ICPs which
21 produced z-residuals in each subarea and the number of z-residual attained on common ICPs are
22 depicted in Table 2 for all the studied factors. It is worth noting that the figures depicted in Table 2
23 are the mean values of three samples.

24 In order to study the statistical influence on DSM quality attributed to the three factors studied in
25 this work, an experimental design based on a factorial model with three samples was implemented.
26 Since the residual populations (z-residuals at ICPs) did not always fit a normal distribution, the

1 Kruskal-Wallis H test (Spurrier 2003), a well-known rank-based non-parametric test, was applied to
 2 determine if there were statistically significant differences ($p < 0.05$) between two or more groups of
 3 an independent variable or factor (land cover, software package or sensor) in relation to a
 4 quantitative dependent variable (DSM quality statistics such as Mean, SD, RMSE, LE95 and
 5 Completeness).

6 Table 2. Number of ICPs from the manually edited LiDAR point cloud (LiDAR ICPs), number of all ICPs with z-
 7 residuals (Total z-residuals) and number of common LiDAR ICPs which produce z-residuals from the
 8 photogrammetrically derived DSMs (Common ICPs), for all the studied cases (i.e., land cover, sensor and software).
 9 The depicted figures are given as mean values of three samples or repetitions while the range (Minimum, Maximum)
 10 are presented in brackets and italic font.

Type of land cover	No. ICPs and z-residuals	WV2		WV3	
		PCI	RSP	PCI	RSP
Greenhouse	LiDAR ICPs	55609.7 <i>(51920, 58909)</i>	55609.7 <i>(51920, 58909)</i>	55609.7 <i>(51920, 58909)</i>	55609.7 <i>(51920, 58909)</i>
	Total z-residuals	41824.7 <i>(38049, 45797)</i>	53018.3 <i>(51432, 55539)</i>	36997 <i>(33557, 40780)</i>	49304 <i>(47409, 51384)</i>
	Common ICPs	29457.7 <i>(26109, 33816)</i>	29457.7 <i>(26109, 33816)</i>	29457.7 <i>(26109, 33816)</i>	29457.7 <i>(26109, 33816)</i>
Urban	LiDAR ICPs	41050 <i>(25794, 50679)</i>	41050 <i>(25794, 50679)</i>	41050 <i>(25794, 50679)</i>	41050 <i>(25794, 50679)</i>
	Total z-residuals	22346.3 <i>(14781, 26167)</i>	39090.7 <i>(24798, 47547)</i>	24514.7 <i>(15269, 29955)</i>	35951.7 <i>(22876, 42892)</i>
	Common ICPs	14419 <i>(9246, 18103)</i>	14419 <i>(9246, 18103)</i>	14419 <i>(9246, 18103)</i>	14419 <i>(9246, 18103)</i>
Bare Soil	LiDAR ICPs	36163.3 <i>(20588, 45087)</i>	36163.3 <i>(20588, 45087)</i>	36163.3 <i>(20588, 45087)</i>	36163.3 <i>(20588, 45087)</i>
	Total z-residuals	34654 <i>(19886, 43032)</i>	36113.7 <i>(20560, 45078)</i>	35621 <i>(20195, 44495)</i>	36009.3 <i>(20445, 44968)</i>
	Common ICPs	34082.7 <i>(19622, 42658)</i>	34082.7 <i>(19622, 42658)</i>	34082.7 <i>(19622, 42658)</i>	34082.7 <i>(19622, 42658)</i>

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12 **5. Results and discussion**

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14 **5.1. Visual inspection**

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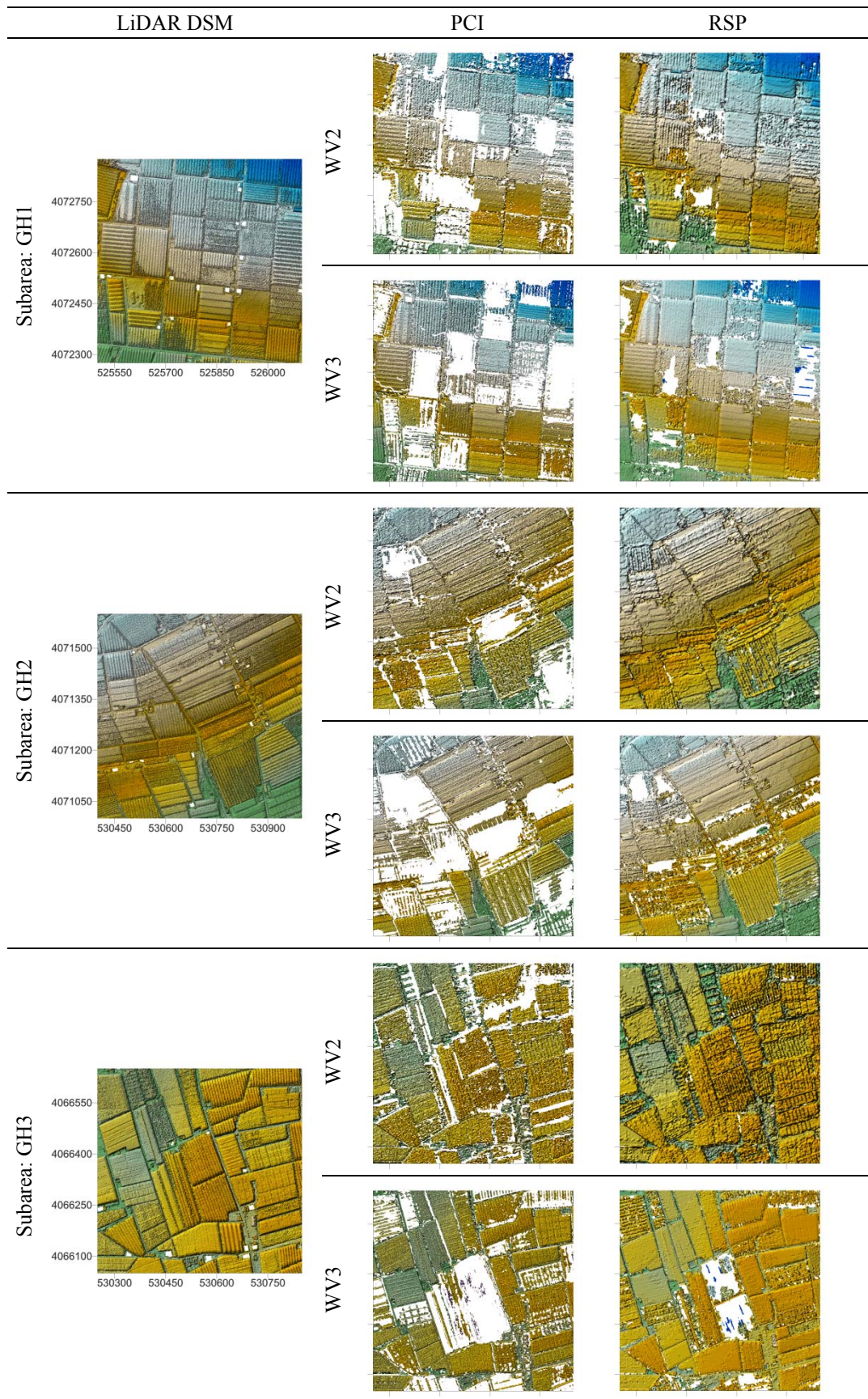
16 Figures 2, 3 and 4 show the three-dimensional shaded relief for the different satellite derived DSMs
 17 produced in this work. Overall, these figures visually show that RSP software package achieved
 18 better results (in terms of completeness) than PCI for both WV2 and WV3 satellites, especially on
 19 urban areas and plastic greenhouses. A more detailed analysis of each figure is presented in below.

1 In Figure 2, the first column shows the original LiDAR data for the three samples of greenhouse
2 land cover (subareas GH1, GH2 and GH3) with a grid spacing of 0.6 m. It is noteworthy that the
3 little water irrigation ponds located at these agricultural areas did not have any first or single
4 LiDAR return. Leica ALS60, as most of the LiDAR systems today, is set up to work over land
5 using an infrared beam which tends to be absorbed by water, so over water bodies there are what
6 are called data voids. These three LiDAR DSMs in Figure 2 can be visually compared to the DSMs
7 derived from the WV2 and WV3 stereo pairs by using both PCI and RSP software packages.
8 Through this visual inspection, the SGM implemented in RSP software achieved much better
9 results than PCI algorithm for both WV2 and WV3 satellites in terms of the completeness. It is
10 important to note that the WV2 DSMs over greenhouses seem to show a smaller number of missing
11 image matching points than WV3 DSMs, although this fact should be statistically confirmed in the
12 next section.

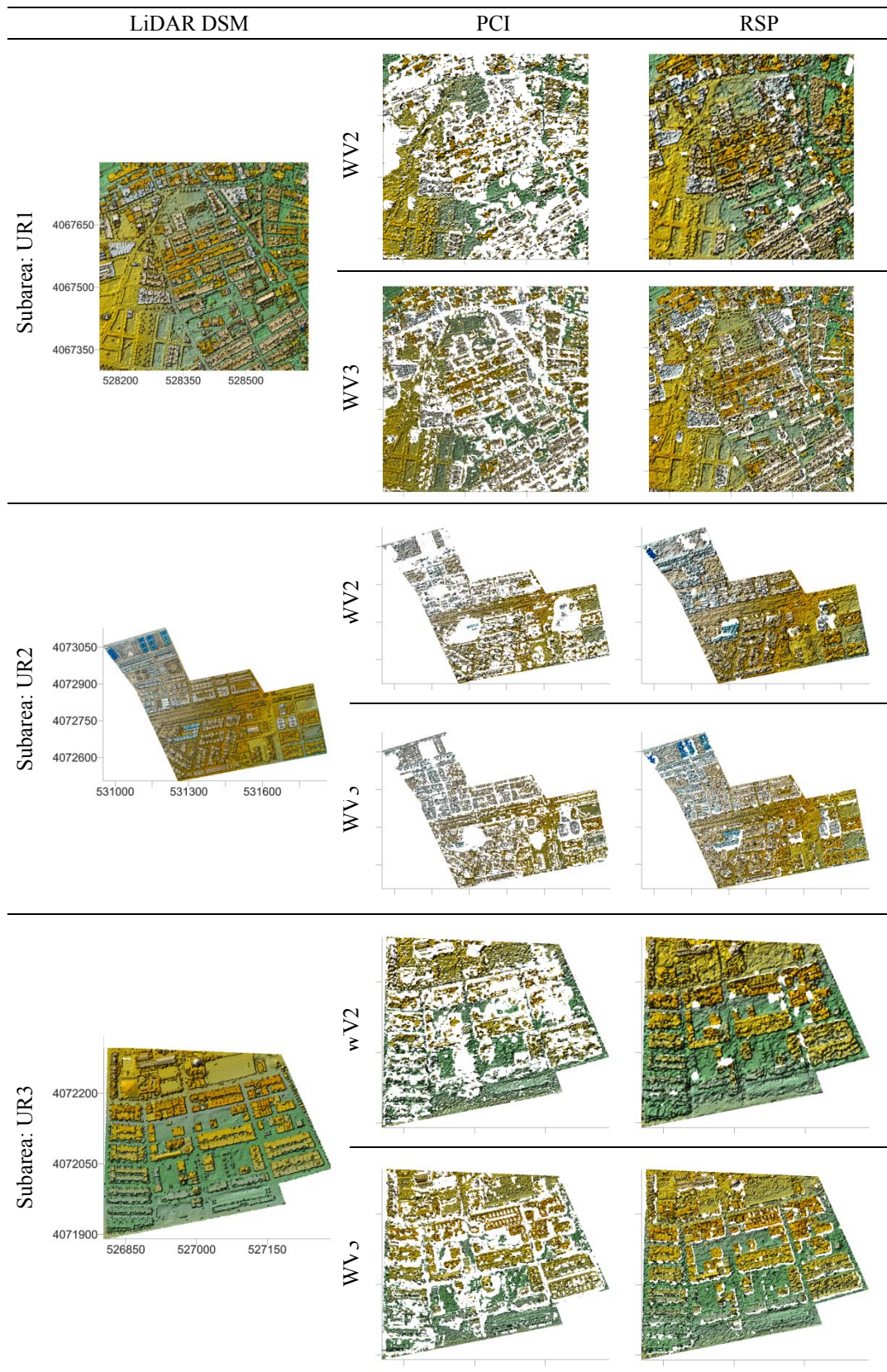
13 The DSMs of the three samples over urban areas (UR1, UR2 and UR3) are shown in Figure 3.
14 Again, the completeness achieved by using RSP yielded much better results than PCI software for
15 both WV2 and WV3 imagery.

16 Concerning the bare soil land cover (Figure 4), the quality of the DSMs derived from WV2 and
17 WV3 stereo pairs appear similar to the quality of the LiDAR derived DSM in the three subareas
18 (BS1, BS2 and BS3). The completeness was close to 100% for all the studied cases in Figure 4,
19 although again RSP presented a slightly better rate of matching points than PCI.

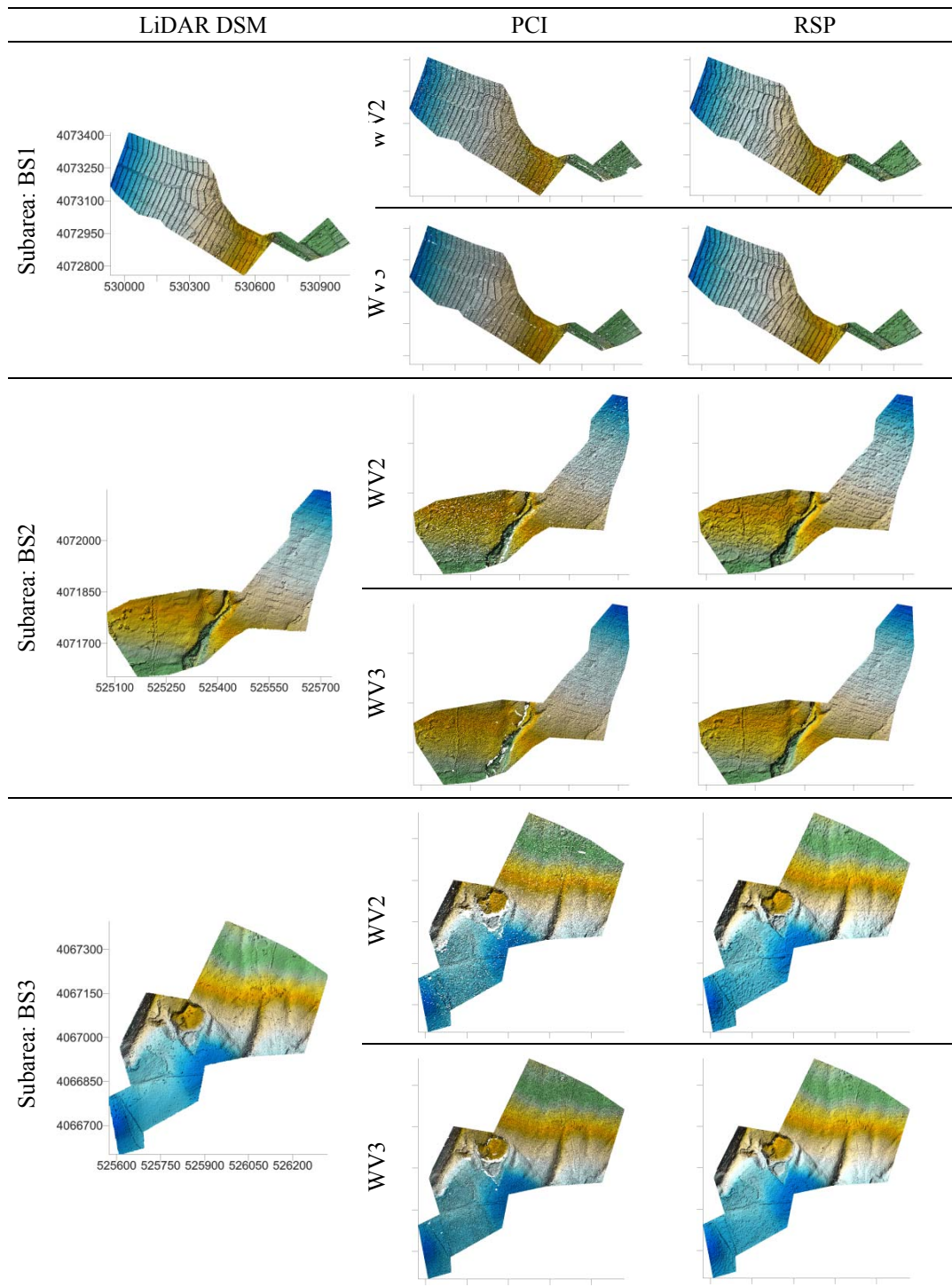
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2 Figure 2. DSMs corresponding to the three subareas (samples) of greenhouse land cover (GH1, GH2 and GH3). First
3 column: Original LiDAR (first and single returns). Second column: PCI derived DSMs from WV2 (1 m grid spacing)
4 and WV3 (0.6 m grid spacing) stereo pairs. Third column: RSP derived DSMs from WV2 (1 m grid spacing) and WV3
5 (0.6 m grid spacing) stereo pairs.



1
2 Figure 3. DSMs corresponding to the three subareas (samples) of urban areas (UR1, UR2 and UR3). First column:
3 Original LiDAR (first and single returns). Second column: PCI derived DSMs from WV2 (1 m grid spacing) and WV3
4 (0.6 m grid spacing) stereo pairs. Third column: RSP derived from WV2 (1 m grid spacing) and WV3 (0.6 m grid
5 spacing) stereo pairs.
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2 Figure 4. DSMs corresponding to the three subareas (samples) of bare soil land cover (BS1, BS2 and BS3). First
3 column: Original LiDAR (first and single returns). Second column: PCI derived DSMs from WV2 (1 m grid spacing)
4 and WV3 (0.6 m grid spacing) stereo pairs. Third column: RSP derived DSMs from WV2 (1 m grid spacing) and WV3
5 (0.6 m grid spacing) stereo pairs.

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1 **5.2.DSM completeness**

2 In this section we analysed the DSM completeness from a statistical point of view. Table 3 shows
3 the completeness scores computed for all the 12 studied cases (i.e., three land covers, two sensors
4 and two software packages). It should be noted that three samples for each case were considered
5 (i.e., 36 VHR satellite derived DSMs). In order to summarize the results, the mean, maximum and
6 minimum values of completeness are shown in Table 3. From the global statistical analysis of the
7 completeness values using Kruskal-Wallis H test, it can be concluded that both land cover and
8 software package factors turned out to be significant ($p < 0.05$).

9 The land cover was the main contributing factor, presenting a partial eta-squared statistic (η_p^2) of
10 64.18%, meaning that 64.18% of the completeness variance is statistically explained by the land
11 cover factor. The best completeness score ($p < 0.05$) was achieved for bare soil with a mean value for
12 the 12 cases shown in Figure 4 of 99.25%. The other two land covers did not present statistical
13 significant differences ($p < 0.05$) with respect to mean values of completeness for the 12 DSMs
14 shown in Figures 2 and 3 (mean completeness value of 85.69% for Greenhouse land cover and
15 79.09% for Urban land cover). [Aguilar, Saldaña and Aguilar \(2014\)](#), in their previous study by
16 using PCI software, reported DSM completeness values over urban areas of 63.23% and 78.83%
17 working from GeoEye-1 and WV2 stereo pairs respectively. In the current study DSM
18 completeness values by applying PCI provided scores of 65.55% and 66.39% from WV2 and WV3
19 stereo pairs respectively (Table 3).

20 Turning to the global statistical analysis, the portion of variance explained by the software package
21 turned out to be much lower ($\eta_p^2 = 26.36\%$). In this regards, the DSMs generated by RSP yielded a
22 completeness mean value of 95.62%, whereas the DSMs produced through PCI software achieved a
23 mean value of 80.40%. Overall, the improvement completeness by using RSP software package
24 instead of PCI was about 2%, 18% and 26% for bare soil, greenhouses and urban areas respectively.

25 When per-class statistical analysis of completeness focusing on each land cover was performed, the
26 software package factor proved to be significant ($p < 0.05$), with similar η_p^2 values of around 75.60%

1 for each land cover studied. However, the difference in mean completeness values due to the
2 software was very small for bare soil, while comparatively it was much more important in urban
3 and greenhouse areas. In Table 3, mean values of completeness in the same column followed by
4 different superscript letters are indicating significant differences at $p < 0.05$. Therefore, the four
5 completeness scores attained on bare soil land cover for each combination of sensor and software
6 were not significant since all the values were followed of the same “e” letter. In the case of
7 greenhouse and urban land cover, RSP completeness values turned out to be significant better than
8 PCI for the same land cover and sensor (Table 3). According to [Alobeid, Jacobsen and Heipke](#)
9 [\(2010\)](#), area-based matching algorithms (e.g., PCI software) usually present problems to generate
10 clear building outlines on urban areas, while the SGM algorithm (e.g., RSP) achieves better results
11 on the roof structures and boundaries.

12 Regarding sensor factor, the η_p^2 values were of 2.11%, 3.72% and 18.88% for bare soil, urban and
13 greenhouse respectively. It is important to note that completeness values were only affected by the
14 type of sensor in the case of greenhouse land cover, although statistical analysis revealed that this
15 effect was quite moderate ($p < 0.15$). The completeness was always worse for WV3 (Table 3) in the
16 case of the greenhouse land cover. It was mainly attributed to the stereo pairs viewing geometry and
17 its relationship with the sun position. In certain situations, the plastic cover of the greenhouses may
18 induce specular reflection of sun light, thus causing unusually bright pixel digital values (sun glint
19 effect). This effect contributes to increase the number of missing image matching points. In that
20 sense, the viewing geometry of the WV3 stereo pair produced much more greenhouses affected by
21 glint than WV2. In fact, the two images composing the WV3 stereo pair were collected just in front
22 of the sun position (see satellite and sun azimuth in Table 1), while the WV2 images left the sun on
23 their back (Table 1).

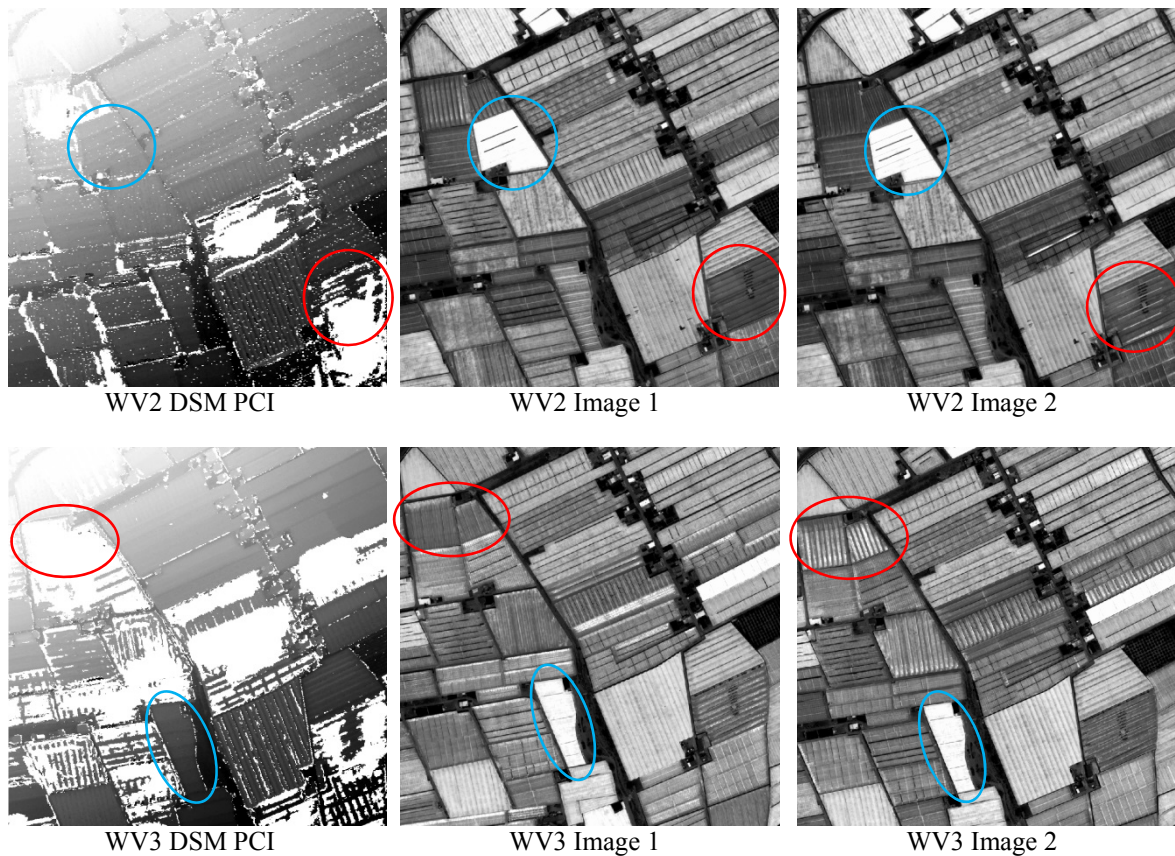
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1 Table 3. Mean and range of values (maximum and minimum) of completeness attained from the three samples per land
 2 cover. Different superscript letters between data along Completeness column indicate significant differences at a
 3 significance level $p < 0.05$.

Land Cover	Sensor	Software	Completeness (%)	Max. (%) - Min. (%)
Greenhouse	WV2	PCI	82.53 ^b	86.00 - 76.42
		RSP	97.92 ^{de}	99.06 - 95.66
	WV3	PCI	70.83 ^a	75.42 - 67.42
		RSP	91.49 ^{cd}	92.18 - 90.40
Urban	WV2	PCI	65.55 ^a	67.49 - 63.97
		RSP	94.83 ^{cde}	95.57 - 93.40
	WV3	PCI	66.39 ^a	69.21 - 63.67
		RSP	89.59 ^c	90.80 - 87.19
Bare Soil	WV2	PCI	97.83 ^{de}	98.85 - 96.75
		RSP	99.94 ^e	100.00 - 99.82
	WV3	PCI	99.27 ^e	99.40 - 99.17
		RSP	99.97 ^e	99.99 - 99.94

4
5

6 The relationship between DSM completeness and the glint effect over greenhouse plastic cover is
 7 shown in Figure 5. In this figure, the WV2 and WV3 DSMs produced by using PCI software
 8 package are depicted alongside the original PAN images from both stereo pairs for the GH2
 9 subarea. The red ellipses highlight greenhouses presenting visible radiometric anomalies due to
 10 glint effect in one of the stereo pair images, thus causing matching errors. However, and when the
 11 greenhouses also present extreme values of digital number because they are painted white (plastic
 12 sheets may be painted white during summer to protect plants from excessive radiation and to reduce
 13 the heat inside the greenhouse), the matching algorithm works well. These painted greenhouses are
 14 marked in blue ellipses in Figure 5 and there are no radiometric changes in the stereo pair images. It
 15 is important to bear in mind the geometric configuration between the sun and sensor positions when
 16 the satellite image is acquired. [Wulder et al. \(2008\)](#) reported important changes in shadow size and
 17 orientation due to the interaction of sun position and VHR satellite geometry, resulting in
 18 inconsistent classification over different scenes.



1 Figure 5. Influence of glint effect over greenhouse plastic cover in relation to DSM completeness at GH2 subarea (600
 2 m x 600 m). WV2 DSM produced by PCI and the original PAN images from WV2 stereo pair are shown in the first
 3 row. WV3 DSM produced by PCI and the original PAN images from WV3 stereo pair are shown in the second row.
 4 Blue ellipses mark greenhouses painted white and red ellipses highlight greenhouses presenting glint changes.

5
6

7 **5.3. DSM vertical accuracy**

8

9 DSM vertical accuracy assessment results (Mean, SD, RMSE and LE95) corresponding to each
 10 land cover, sensor and software packages when all the points from the manually edited LiDAR
 11 DSMs were employed as ICPs and all z-residuals considered (Total z-residuals) are depicted in
 12 Table 4. The land cover was the only statistically significant factor ($p < 0.05$) when random errors
 13 were assessed following a global statistical analysis through the Kruskal-Wallis test including all
 14 the 36 cases. Very similar and high values of η_p^2 were obtained for RMSE (87.34%), SD (88.34%)
 15 and LE95 (88.34%). For instance, significant ($p < 0.05$) mean SD values (12 cases) of 0.89 m, 2.17
 16 m and 0.23 m were achieved for greenhouse, urban and bare soil areas respectively. As for global
 17 statistical analysis related to systematic errors, measured as mean or bias values, the land cover (η_p^2
 18 = 18.86%) and sensor ($\eta_p^2 = 12.83%$) turned out to be significant ($p < 0.05$) factors, although this

1 parameter presented a very high uncertainty. It is worth noting that the software package did not
2 show any influence in the global accuracy assessment for both random and systematic errors despite
3 that RSP presented far better completeness values than PCI.

4 Focusing on the 12 DSMs corresponding to the bare soil land cover in Figure 4, only the sensor
5 factor for SD was pointed out significant ($p < 0.05$) with a η_p^2 value of 39.39%. In the case of bare
6 soil land cover, the DSMs generated by WV3 presented significantly better accuracy in terms of SD
7 (0.20 m) than in the case of WV2 (SD = 0.26 m). However, this improvement could not be
8 confirmed when working with RMSE or LE95. Worse SD values of 0.40 m and 0.53 m were
9 attained by [Aguilar, Saldaña and Aguilar \(2014\)](#) over bare soil areas from GeoEye-1 and WV2
10 stereo pairs respectively. [Shean et al. \(2016\)](#) and [Noh and Howat \(2015\)](#) achieved around
11 approximately 0.21 m vertical RMSE with WorldView-1 and WV2 stereo pairs in glaciated
12 regions, and in both cases removing the offsets through co-registration. A small error in planimetric
13 coordinates between LiDAR data and the photogrammetrically derived DSM (incorrect co-
14 registration) can lead to a systematic shift in height (Z coordinate). This can easily be spotted by
15 visual analysis of the value of the residual over the area to check for spatial patterns which
16 reproduce geomorphology of terrain or features (see for example the Figure 3f published by
17 [Aguilar, Saldaña and Aguilar \(2014\)](#)). It is worth mentioning that a finer co-registration process
18 could have been carried out in our work.

19 Regarding the partial accuracy assessment statistical analysis over the unique greenhouse land cover
20 (12 DSMs in Figure 2), significant differences ($p < 0.05$) were only achieved for the software
21 package factor in the cases of RMSE and LE95. In both measures, PCI yielded better accuracy
22 values (RMSE = 0.85 m and LE95 = 2.07 m) than RSP (RMSE = 1.16 m and LE95 = 2.69 m). It is
23 important to bear in mind that RSP presented higher completeness in DSM generation than PCI,
24 especially for greenhouse and urban areas. Thus, the worse vertical accuracy results attained over
25 greenhouses in the case of RSP seem to point to the fact that RSP is incurring a commission error
26 when working on difficult-to-match image areas (i.e., some greenhouse roofs presenting glint effect

1 or very transparent plastic cover). This hypothesis is supported by the fact that both software
 2 packages did not show any accuracy differences over bare soil land cover with similar completeness
 3 and without glint or transparency problems.

4 Table 4. Vertical accuracy (Mean, SD, RMSE and LE95) computed on the all ICPs. All the depicted values are mean
 5 values corresponding to three samples for each land cover. Minimum and Maximum values for the three samples are
 6 depicted in brackets and italic font for Mean and SD. Different superscript letters between data along the same column
 7 indicate significant differences at a significance level $p < 0.05$.

Land Cover	Sensor	Software	Mean (m)	SD (m)	RMSE (m)	LE95 (m)
Greenhouse	WV2	PCI	-0.08 <i>(-0.31, 0.11)</i>	0.81 ^{ab} <i>(0.70, 0.94)</i>	0.83 ^{ab}	2.03 ^a
		RSP	-0.11 <i>(-0.47, 0.34)</i>	1.10 ^{abc} <i>(0.93, 1.30)</i>	1.16 ^{abc}	2.83 ^{abc}
	WV3	PCI	-0.21 <i>(-0.41, -0.02)</i>	0.82 ^{ab} <i>(0.71, 1.03)</i>	0.86 ^{ab}	2.12 ^a
		RSP	-0.47 <i>(-0.92, 0.34)</i>	0.84 ^{ab} <i>(0.80, 0.87)</i>	1.16 ^{abc}	2.54 ^{ab}
Urban	WV2	PCI	0.10 <i>(-0.04, 0.22)</i>	2.12 ^{cd} <i>(1.74, 2.73)</i>	2.12 ^{cd}	5.21 ^{cd}
		RSP	-0.27 <i>(-0.61, -0.07)</i>	2.92 ^d <i>(2.32, 3.66)</i>	2.95 ^d	7.23 ^d
	WV3	PCI	-0.41 <i>(-0.54, -0.32)</i>	1.89 ^{bcd} <i>(1.43, 2.72)</i>	1.94 ^{bcd}	4.83 ^{bc}
		RSP	-0.54 <i>(-0.77, -0.27)</i>	1.75 ^{bc} <i>(1.31, 2.73)</i>	1.85 ^{bc}	4.62 ^{bc}
Bare Soil	WV2	PCI	0.23 <i>(0.19, 0.32)</i>	0.25 ^a <i>(0.22, 0.29)</i>	0.34 ^a	0.67 ^a
		RSP	-0.03 <i>(-0.08, -0.01)</i>	0.28 ^a <i>(0.23, 0.31)</i>	0.28 ^a	0.56 ^a
	WV3	PCI	0.07 <i>(-0.20, 0.32)</i>	0.21 ^a <i>(0.17, 0.25)</i>	0.30 ^a	0.57 ^a
		RSP	-0.08 <i>(-0.32, 0.10)</i>	0.20 ^a <i>(0.14, 0.23)</i>	0.26 ^a	0.48 ^a

8

9 In the case of urban subareas depicted in Figure 3, none of the vertical accuracy statistics led to
 10 significant ($p < 0.05$) for both sensor and software factors. As in the previous case, PCI presented
 11 better accuracy values than RSP for the WV2 stereo pair. However, in the case of WV3, RSP had a
 12 slightly better performance in terms of SD, RMSE and LE95. RMSE and SD values resulted to be
 13 significantly better at 0.10 signification level for WV3 (RMSE=1.90 m and SD=1.82 m) than in the
 14 case of WV2 (RMSE=2.53 m and SD=2.52 m). In view of these figures, it seems that the better
 15 GSD of the WV3 DSMs yielded better vertical accuracy results in very uneven urban land cover.
 16 Using a similar methodology on GeoEye-1 and WV2 stereo pairs [Aguilar, Saldaña and Aguilar](#)
 17 [\(2014\)](#) achieved SD values over urban areas located in Southern Spain of 2.67 m and 2.74 m. On
 18 the other hand, [Poli et al. \(2015\)](#) reported higher vertical RMSE values on urban areas ranging from

1 6.1 m to 8.5 m by using GeoEye-1, WV2 and Pléiades-1A stereo images, although they tested the
2 accuracy of filled DSMs (i.e., areas without successful matching 3D points were interpolated). Di
3 Rita, Nascetti and Crespi (2017) compared two software packages in urban areas (DATE, based on
4 SGM and PCI) to produce DSMs from Pléiades-HR and GeoEye-1 stereo pairs. Although they
5 worked with the filled DSMs, the obtained accuracy statistics were quite similar, with slight better
6 performances of DATE with Pléiades and of PCI with GeoEye-1.

7 Finally, if a statistical analysis is performed for the values depicted in the columns of Table 4, we
8 can conclude that there was no difference (i.e., no superscript) between systematic errors or Mean
9 values. Regarding random errors, the best accuracy attained for bare soil land cover, WV3 and RSP
10 (e.g., SD=0.20 m) was not significantly different of the rest of accuracy values computed for bare
11 soil and greenhouse land cover because all these figures are followed of the letter “a” (Table 4). The
12 random errors for urban land cover without letter “a” in Table 4 were significantly worse than for
13 bare soil.

14
15 Table 5. Vertical accuracy assessment (Mean, SD, RMSE and LE95) restricted to only common ICPs with z-residuals
16 in each subarea. All the depicted values are mean values corresponding to three samples for each land cover. Minimum
17 and Maximum values for the three samples are depicted in brackets and italic font for Mean and SD. Different
18 superscript letters between data along the same column indicate significant differences at a significance level $p < 0.05$.

Land Cover	Sensor	Software	Mean (m)	SD (m)	RMSE (m)	LE95 (m)
Greenhouse	WV2	PCI	-0.09 (<i>-0.30, 0.09</i>)	0.76 ^{ab} (<i>0.67, 0.87</i>)	0.78 ^{ab}	1.87 ^{ab}
		RSP	-0.22 (<i>-0.48, 0.13</i>)	0.76 ^{ab} (<i>0.66, 0.82</i>)	0.83 ^{abc}	1.85 ^{ab}
	WV3	PCI	-0.20 (<i>-0.40, -0.00</i>)	0.72 ^{ab} (<i>0.64, 0.88</i>)	0.77 ^{ab}	1.87 ^{ab}
		RSP	-0.50 (<i>-0.92, 0.20</i>)	0.58 ^{ab} (<i>0.50, 0.67</i>)	0.91 ^{abc}	1.77 ^{ab}
Urban	WV2	PCI	0.07 (<i>-0.09, 0.16</i>)	1.68 ^c (<i>1.37, 2.27</i>)	1.69 ^c	4.24 ^c
		RSP	-0.02 (<i>-0.09, 0.16</i>)	1.67 ^c (<i>1.32, 2.35</i>)	1.68 ^c	4.30 ^c
	WV3	PCI	-0.16 (<i>-0.38, 0.10</i>)	1.46 ^{bc} (<i>1.06, 2.11</i>)	1.49 ^{bc}	3.84 ^{bc}
		RSP	-0.33 (<i>-0.67, -0.13</i>)	1.31 ^{bc} (<i>0.92, 1.96</i>)	1.39 ^{bc}	3.54 ^{bc}
Bare Soil	WV2	PCI	0.23 (<i>0.18, 0.32</i>)	0.24 ^a (<i>0.22, 0.28</i>)	0.34 ^a	0.66 ^a
		RSP	-0.03 (<i>-0.07, -0.01</i>)	0.26 ^a (<i>0.21, 0.30</i>)	0.26 ^a	0.53 ^a
	WV3	PCI	0.07 (<i>-0.20, 0.31</i>)	0.20 ^a (<i>0.16, 0.24</i>)	0.29 ^a	0.56 ^a
		RSP	-0.08 (<i>-0.32, 0.10</i>)	0.19 ^a (<i>0.13, 0.23</i>)	0.25 ^a	0.47 ^a

1 So far, the statistical analysis on vertical accuracy of VHR satellite DSMs, especially on greenhouse
2 and urban land covers, varied with their differences in completeness. In order to avoid this
3 dependence and ensure a fair comparison, a second strategy was conducted. Table 5 shows the
4 results for the DSM vertical accuracy assessment (Mean, SD, RMSE and LE95) by using only the
5 Common ICPs (see Table 2) producing z-residuals in each subarea. Values in each column followed
6 of different superscript letters presented significant differences ($p < 0.05$). The application of this
7 strategy provided much clearer and more conclusive results. In fact, the systematic errors were not
8 significant ($p < 0.05$) for any factor, and the random errors turned out to be significant at 0.05 level
9 only for the land-cover factor. In that way, the best global SD mean values computed on 12 cases
10 were obtained for bare soil (SD=0.22 m), followed by greenhouse (SD=0.71 m), and finally, urban
11 areas (SD=1.53 m).

12 The results for the bare soil land cover were very similar to those aforementioned in Table 4. It is
13 needed to bear in mind that the completeness values in this land cover were always very close to
14 100%. Again the DSMs generated by WV3 yielded significantly ($p < 0.05$) better accuracy only in
15 terms of SD. Both software packages worked very well and without significant differences in
16 vertical accuracies for this land cover.

17 For greenhouse land cover, neither the sensor nor the software factors were significant at 0.05
18 signification level for Mean, SD, RMSE or LE95. When the residuals were only computed in those
19 LiDAR ICPs successfully matched by the two tested software (Common ICPs), overall, the vertical
20 accuracy measures yielded better values. This fact was particularly important for RSP software
21 package where, for instance, the SD value was improved around of 0.30 m. In the case of Common
22 ICPs strategy, the vertical accuracy results for the two software packages studied were practically
23 identical. Similar results were attained on urban land cover, where the software factor was analysed.
24 Regarding the sensor factor, it is important to note that better accuracy values were achieved by
25 using WV3 stereo pair instead of WV2 one mainly in urban areas. However, these differences were
26 not significant ($p < 0.05$). Agile VHR satellites such as WV2 and WV3, which are capable of

1 operating their on-track and cross-track view angles to reduce the revisit time, can produce imagery
2 with suboptimal geometric configurations. In our case, the WV3 stereo pair was acquired with
3 excessively high off-nadir angles of 22.2 and 32.7 degrees. Satellite imaging stereo geometry,
4 measured as convergence angle (Li et al. 2007), plays a significant role in the final DSM vertical
5 accuracy (Li et al. 2009; Aguilar, Saldaña and Aguilar 2014). Although the stereo pairs used in this
6 work presented similar convergence angles of 35.8 and 32.1 degrees for WV2 and WV3
7 respectively, the two WV3 images were located just in front of the sun, thus causing undesired glint
8 effects over greenhouse plastic covers. This worse WV3 viewing geometry masked the expected
9 improvements due to its better GSD.

10 Poli et al. (2015) reported that in urban areas characterized by small adjacent units and narrow
11 streets, the height of the roofs was estimated quite well in the image-based DSMs, but the height of
12 narrow streets between buildings was overestimated (photogrammetric DSM above LiDAR data),
13 as narrow streets were not visible in the stereo pairs due to occlusion effects or dark shadows. These
14 authors suggested that these problems may be limited by using stereo triplet of VHR satellite
15 imagery including a nadir scene. This strategy could be also recommended for improving the DSM
16 quality (accuracy and completeness) in greenhouse land cover. By having the same greenhouse
17 captured in a large number of images, the probability to find insolvable glint problems would be
18 smaller.

19 In a previous work published by Fratacangeli et al. (2016) working with ZiYuan-3 optical satellite
20 imagery (GSD ranging from 2.1 m to 3.7 m), the DSMs extracted with PCI software package on
21 urban and mountain areas presented better vertical accuracy than the DSMs generated by using a
22 software package based on SGM (DATE). However PCI yielded worse completeness than DATE.
23 These findings seem to point out that SGM algorithm improves DSM quality basically by
24 increasing the success matching ratio, thus improving DSM completeness.

25

26

1 **6. Conclusions**

2

3 To the best of our knowledge, this work provides the first comparison supported by a rigorous
4 statistical study between two widely applied image matching methods to generate DSMs from VHR
5 satellite stereo pairs. In fact, a classical area-based least squares with hierarchical subpixel mean
6 normalized cross correlation matching method (PCI) and a modified hierarchical SGM method
7 (RSP) are tested in order to extract DSMs from WV2 and WV3 VHR satellite stereo pairs. The
8 software packages performance was mainly studied on the unique agricultural plastic greenhouse
9 land cover, although also bare soil and urban land covers were investigated. The DSM quality was
10 statistically analysed in terms of completeness and vertical accuracy.

11 The SGM algorithm included within RSP software improved DSM quality by means of increasing
12 the success matching ratio. Indeed, the DSM completeness resulted to be significantly ($p < 0.05$)
13 better for every land cover when RSP was used, yielding improvements as compared to PCI of
14 approximately 2%, 18% and 26% for bare soil, greenhouses and urban areas respectively.
15 Regarding vertical accuracy, no significant differences were found with regards to the matching
16 algorithm used.

17 The target land cover was the most influential factor for both completeness and vertical accuracy of
18 the extracted DSMs. Bare soil was the terrain type with better completeness value (99.25%) and
19 vertical accuracy ($SD = 0.22$ m). Plastic greenhouses presented better, although non-significant,
20 completeness (85.69%) than urban land cover (79.09%). Regarding vertical accuracy, greenhouse
21 land cover had significant better values than urban areas with SD values of 0.71 m and 1.53 m
22 respectively.

23 The DSMs extracted from the stereo pairs of WV2 and WV3 had a similar quality at 0.05
24 signification level for accuracy and completeness. Overall, the DSM accuracies were slightly better
25 in the case of WV3. In the case of completeness, the values for WV3 were worse than the WV2
26 ones only in the greenhouse land cover. The greenhouse plastic covers may produce specular
27 reflection of sun light causing glint effect. In that way, the viewing geometry of our WV3 stereo

1 pair produced much more greenhouses affected by glint than WV2 one because of the two images
2 from the WV3 stereo pair were collected just in front of the sun position, while the WV2 images
3 left the sun on their back. Bearing in mind the importance of the satellite viewing geometry and its
4 relationship with the sun position in the greenhouse land cover, the use of stereo triplet on this
5 unique landscape could be considered a good strategy in order to improve the DSM quality in terms
6 of both accuracy and completeness.

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