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15 **Improving UAV-SfM photogrammetry for measurement of**
16 **high-relief terrain: image collection strategies and ground**
17 **control quantity**

18 **Abstract:** Image collection strategies and ground control points (GCPs) are of
19 particular importance for UAV-SfM photogrammetry, and the generalization of their
20 effects has proved elusive. This study designed various photogrammetric scenarios to
21 investigate the effects of image collection strategies, ground control quantity, and their
22 interaction on digital elevation model (DEM) errors and their spatial structure in high-
23 relief terrain. The results of 1.77×10^5 UAV-SfM scenarios provide insights for
24 improving UAV-SfM practices. A high image capture angle (20° - 40°) enhances camera
25 calibration quality decreasing the magnitude and spatial correlation of errors. High
26 camera inclination reduces the sensitivity of mean and standard deviation of error to
27 flying height, but not the spatial correlation of error. Including additional data (e.g.,
28 supplemented convergent images; images captured at multiple flying heights) has only
29 a minor effect if imagery is highly inclined. GCPs provide more effective constraints
30 than image collection strategies. The mean error and standard error decline quickly with
31 a small number of GCPs and then become stable in all scenarios, but the spatial

32 correlation of error can be further improved with increasing GCPs. However, the effects
33 of GCP quantity do interact with image collection strategies. High camera inclination
34 reduces requirements for GCPs, while strategies combining different flying heights and
35 image orientations have little effect on necessary GCP quantity. The distribution of
36 GCPs still affects the errors, but the effect of GCP distribution becomes less important
37 with an increase in the number of GCPs. Finally, we show that UAV-SfM
38 photogrammetric quality assessment should routinely assess the spatial dependence of
39 error using a statistic like Moran's I.

40 **Keywords:** UAV-SfM photogrammetry; Terrain modeling; Oblique photography;
41 Ground control points; Combination datasets

42 **1 Introduction**

43 Uncrewed aerial vehicles (UAVs) combined with Structure-from-Motion (SfM)
44 and Multi-View Stereoscopic (MVS) photogrammetric workflows have proven to be
45 capable of producing high-resolution (centimeter-level) orthoimages and digital
46 elevation models (DEMs) at low cost (Eltner et al., 2015; Harwin and Lucieer, 2012;
47 Hugenholtz et al., 2013; Ouedraogo et al., 2014), including over rugged topography and
48 in hardly accessible areas. Recent UAV-SfM applications in geomorphological
49 research notably include terrain modelling (e.g., James et al., 2020; Hugenholtz et al.,
50 2013; Rosnell and Honkavaara, 2012), topographic change detection (Eltner et al., 2015;
51 Lane et al., 2020; Meinen and Robinson, 2020; Roncoroni et al., 2023) and the
52 quantification of mass movements (e.g. Niethammer et al., 2010; Turner et al., 2015).

53 There is a general consensus that UAV-SfM can be effective and accurate for
54 terrain modeling provided basic design guidelines are followed (e.g. James et al., 2020);
55 but that deeper considerations of image collection and ground control are required for
56 improving accuracy (associated with systematic error or bias) and precision (describing
57 random error) in high relief landforms (Aguera-Vega et al., 2018; Carvajal-Ramírez et
58 al., 2016; Nieminski and Graham, 2017), such as gully slopes and sub-vertical cliffs.
59 The accuracy and precision in UAV-SfM terrain modeling depend on a range of factors
60 including: camera properties (camera lens, image resolution), image collection
61 strategies (flying height, flying speed, stability, number and overlapping of images,
62 camera angle), image quality (light, contrast, shadows, blurring), terrain texture, and
63 the number and distribution of ground control points (GCPs) (Escobar Villanueva et al.,
64 2019; Polat and Uysal, 2018; Sanz - Ablanedo et al., 2020). Among these factors,

65 image collection strategies, and ground control quantity and distribution have been
66 identified as of particular importance, and can be controlled by operators (James et al.,
67 2019; James et al., 2017a).

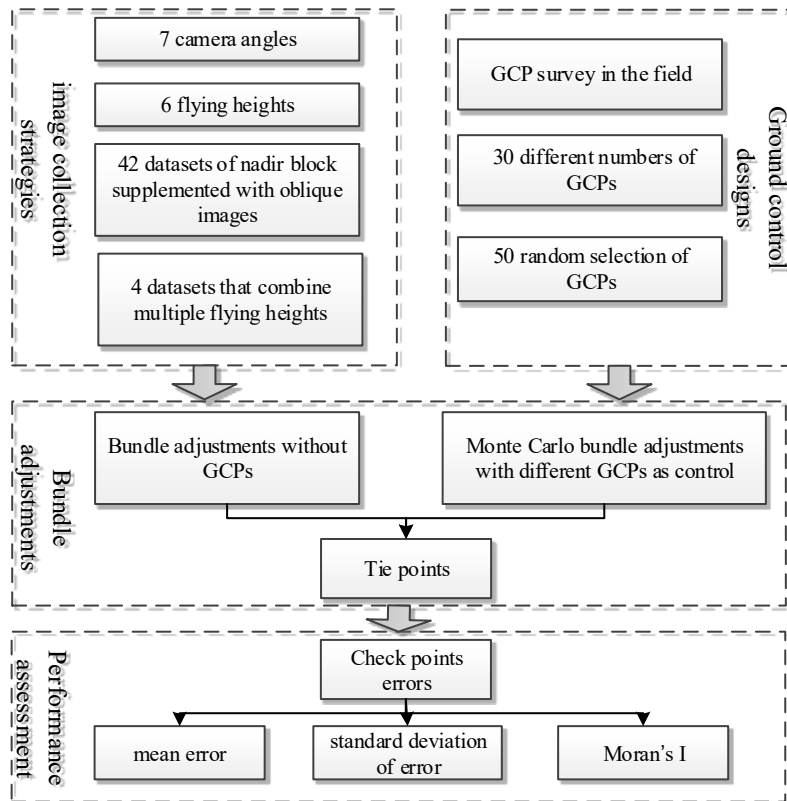
68 Image collection strategies for UAV–SfM are different from conventional airborne
69 photogrammetry. Conventional airborne photogrammetry tended to use metric cameras,
70 which have reliable camera calibrations. As use of this imagery does not require camera
71 calibration image can be acquired at a constant altitude, with sufficient overlap (along-
72 and cross-strip) and nadir image capture (Wolf et al., 2014). Even then, these datasets
73 can produce some systematic error, revealed when digital elevation data from different
74 dates are compared for stable zones, but the error is commonly small in magnitude, a
75 linear function of horizontal coordinates and easily removed (e.g. Westaway et al., 2003;
76 Bakker and Lane, 2017). This is not the case with consumer-grade UAVs. These are
77 mostly equipped with non-metric cameras, with unknown internal camera parameters,
78 significant image distortion and unstable calibration (Harwin et al., 2015; James and
79 Robson, 2014) that have to be determined after data collection. To increase the view of
80 the scene and to improve the quality of the scene reconstruction, oblique photography
81 is generally recommended UAVs (James et al., 2020; Jiang et al., 2017; Rossi et al.,
82 2017) although some studies (e.g. James et al., 2020) suggest we should move beyond
83 ‘off-nadir’ imagery. Theoretically, four oblique and one nadir-facing cameras are ideal
84 for oblique photography (Adams et al., 2014; Toth and Józków, 2016). However, most
85 consumer-grade, low-cost UAVs are equipped with a camera that can only view a single
86 direction during surveys. Hence, flights with a “double grid” pattern (consisting of two
87 orthogonal blocks) with an inclined camera have been widely used in studies using a
88 (James et al., 2020; Nesbit and Hugenholtz, 2019; Roncoroni et al., 2022). Besides
89 camera inclination angle, combination datasets, such as nadir image blocks
90 supplemented with convergent images and the combinations of images captured at
91 different flying heights (Meinen and Robinson, 2020; Sanz-Ablanedo et al., 2020), have
92 been proposed for improving UAV-SfM terrain modeling. However, there is still no
93 consensus on optimal camera angles for these different image collection strategies and
94 it may be that optimal configurations are specific to individual applications.

95 In addition to image collection strategies, ground control points (GCP) appear to
96 be crucial for improving UAV-SfM photogrammetry (James et al., 2020). Ground
97 control has two substantial functions: georeferencing UAV-SfM models on the one hand,
98 and reducing both random and systematic errors during the photogrammetric bundle

99 adjustment on the other hand (James et al., 2017a; James et al., 2017b). The accuracy,
100 number, and distribution of GCPs are key factors (Padró et al., 2019; Rangel et al.,
101 2018). The accuracy of GCPs is mainly controlled by the precision of the measurement
102 instrument (e.g., dGPS, total station), while the number and distribution of GCPs can
103 be flexibly arranged in practice, when surveyed terrains are accessible.

104 In terms of the distribution of GCPs, a general consensus within the community
105 recommends the combination of a stratified distribution of GCPs within the surveyed
106 scene, with beyond-scene GCPs to provide additional support during the bundle
107 adjustment (Cabo et al., 2021; Rangel et al., 2018; Stott et al., 2020). In terms of the
108 number of GCPs, an improvement in accuracy and precision of the reconstructed scene
109 is observable with an increasing number of GCPs, until a certain threshold beyond
110 which adding more GCPs does not improve the model quality any further (James et al.,
111 2017a; Martínez-Carricondo et al., 2018a; Rangel et al., 2018). The requirements in
112 terms of GCP number and distribution also vary according to the type of scene surveyed
113 (e.g. texture, relief; James et al. 2017a; 2020). Although previous studies have
114 individually investigated the effects of image collection strategies (Nesbit and
115 Hugenholtz, 2019) and ground control quantity (Cabo et al., 2021; James et al., 2017a),
116 the interactive effects of image collection strategies and ground control quantity are less
117 considered.

118 In this contribution, we investigate the interactive effects of image collection
119 strategies and ground control quantity on terrain modelling errors and their spatial
120 structure in UAV-SfM surveys, by comparing more than 1.77×10^5 scenarios with
121 various combinations of camera angles, flight heights, nadir and/or oblique imagery,
122 and different number and distribution of GCPs (Fig. 1). We also introduce a new method
123 for determining the extent of spatial structure in error fields by using a spatial
124 autocorrelation statistic, Moran's I. According to the accuracy, precision, and spatial
125 structure of errors of the derived DEMs, this paper aims at synthesizing
126 recommendations for improving UAV SfM-MVS practices in high landscape relief.



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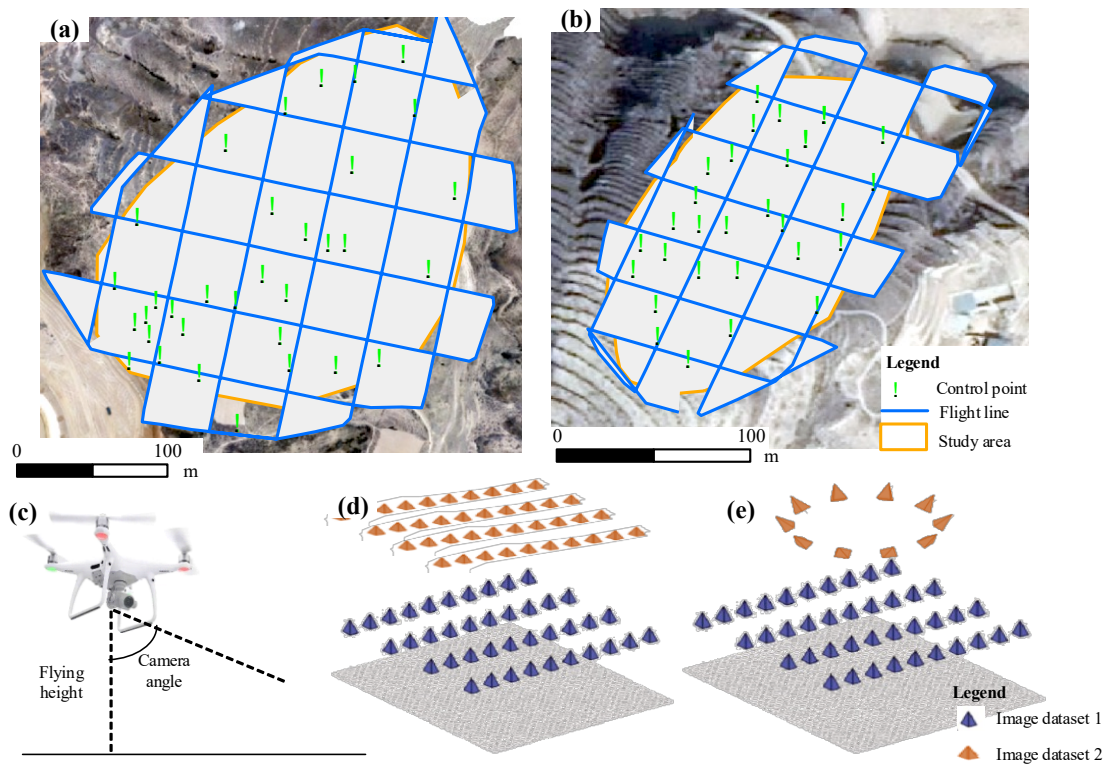
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Figure 1. Flowchart of the processes and analyses.

129 2 Methodology

130 2.1 Study sites

131 The work was conducted in the Loess Plateau of China, a region associated with
 132 severe and active gully erosion (Dai et al., 2022; Dai et al., 2019), resulting in high
 133 relief topography. This research focused on two study areas in Shaanxi province; T1
 134 (110°17'3.2"E, 37°33'48.8"N, 5.1 ha in size) and T2 (110°21'45.7"E, 37°35'12.8"N, 3.6
 135 ha in size), in Suide county. The study sites have high mean slope (~23°) and hence
 136 high relief (~100 m maximum elevation difference) (Fig. 2 a and b). These areas are
 137 covered with grassland and the vegetation is very sparse in winter and spring, which
 138 facilitates UAV-SfM photogrammetry.



140

141 Figure 2. Study areas and flight design: (a) and (b) are orthoimages and ‘double-grid’ designs in
 142 the T1, T2 areas, respectively; (c) is diagram of camera angle and flying height; (d) and (e) are
 143 diagrams of multiple flight height blocks and nadir image blocks supplemented with convergent
 144 images, respectively.

145 2.2 Image acquisition

146 A DJI Phantom 4 Pro quadcopter was used in this study due to its low cost, its
 147 flying stability and the ease with which flights are programmed (e.g., James et al., 2020).
 148 It was mounted with a 1” CMOS camera with a 24-mm focal length (35 mm equivalent).
 149 The on-board GNSS precision of this UAV was ± 1.5 m (horizontal) and ± 0.5 m
 150 (vertical). Due to the low on-board GNSS precision and the need for self-calibration of
 151 the camera, an optimized image collection strategy and ground control are generally
 152 needed (James et al., 2020).

153 We collected the UAV images in March 2021. In this season, vegetation has not
 154 yet grown in the study areas, which means that very few areas were masked during the
 155 flights (Fig. 2). Given the aim of the paper, we explored different strategies for UAV
 156 image acquisition.

157 First, to investigate the effect of camera angle on survey precision and accuracy,
 158 the camera angle was varied from 0 to 40° (0° indicating a nadir inclination) within

159 individual surveys. Given that camera angles higher than 40° would lead to greater
 160 observation distances than the flying height, we did not set a higher camera angle. The
 161 drone rotates through 180° at the end of each strip, which means that with an angle of
 162 10° , the camera angle is actually $+10^\circ$ in one line and -10° in the next strip. During the
 163 flights, to minimize the effects of other flight factors, we set the same flying height
 164 (defined by the elevation of the take-off point, which was held constant in between
 165 surveys), flight path and overlap rate for all UAV surveys. By setting the flying height
 166 as constant from the take-off point, but flying the UAV horizontally over a steep terrain,
 167 different image capture heights result.

168 The image collection comprised two orthogonal blocks ('double-grid') (Fig. 2a
 169 and b), with an 80% overlap both along- and cross-strip. Due to the high relief, the UAV
 170 flights were started halfway up the mountain in each study area. The average flight
 171 height and average ground sample distance (GSD) ranged from 70 to 100 m and 1.9 to
 172 2.7 cm, respectively, for the two study areas (Table 1).

173 Table 1. The experiment of different camera angle

Study areas	Camera angle ($^\circ$)	Number of images for each flight	Flight height (m)	GSD (cm)
T1	0, 5, 10, 20, 30, 35, 40	~200	100	2.7
T2	0, 5, 10, 20, 30, 35, 40	~120	70	1.9

174 Second, we designed a flying height experiment, with the flying heights set from
 175 60 to 160 m (because we expect the required GSD is less than 5 cm for monitoring
 176 gully erosion), with the same 80% image overlap. To investigate whether the camera
 177 angle interacts with flying height, we repeated the flights with both a nadir camera and
 178 a 15° inclined camera in the T1 and T2 areas, respectively (Table 2).

179 Table 2. The experiments with different flight height

Study areas	Flight height (m)	Number of images for each flight	Camera angle ($^\circ$)	GSD(cm)
T1	60, 80, 100, 120, 140, 160	110 ~ 300	0	1.6 - 4.4
T2	60, 80, 100, 120, 140, 160	70 ~ 140	15	1.6 - 4.4

180
 181 These data allowed us to construct and to test the effects of different combination
 182 datasets (Fig. 2c and 2d). First, we added in supplemented convergent imagery (Fig. 2d)
 183 given its potential importance for reducing systematic error in DEMs derived using
 184 SfM-MVS photogrammetry (James et al., 2020). Here, a nadir or off-nadir double-grid

185 block was supplemented with several additional convergent images. We called the
 186 double-grid blocks (nadir or off-nadir) as main blocks. The main blocks used were the
 187 same as those in Table 1. The supplemented convergent images with camera angles
 188 from 0° to 40° were collected at 120 m and 80 m flying heights in the T1 and T2 areas
 189 (Table 3), respectively. Each supplemented convergent dataset includes 16 photos. Then,
 190 we supplied the bundle adjustment with different combinations of the main blocks and
 191 supplementary convergent images (Table 3).

192 Multiple flying heights have been also suggested to improve UAV-SfM
 193 applications in previous studies (James and Robson, 2014). To analyze how the number
 194 of combined flying heights affects precision and accuracy, we designed image
 195 combinations with 2, 4, and 6 flying heights, and kept the mean flight height to be the
 196 same (Table 4). This experiment also allowed demonstration of effects of interactions
 197 between camera angle and flying height, and so we set a nadir camera and 15° inclined
 198 camera in the T1 and T2 areas, respectively.

199 Table 3. The strategies of “main block + supplemented images”

Dataset No.	Main block (°)		supplemented images (°)	
	Camera angle (°)	Flight height(m)	Camera angle (°)	Flight height(m)
1	0		0	
2	0		5	
3	0		10	
4	0		20	
5	0		30	
6	0		35	
7	0		40	
8	5		0	
9	5		5	
10	5	T1 area: 100	10	T1 area: 110
11	5	T2 area: 70	20	T2 area: 80
12	5		30	
13	5		35	
14	5		40	
...	
43	40		0	
44	40		5	
45	40		10	
46	40		20	
47	40		30	

48	40	35
49	40	40

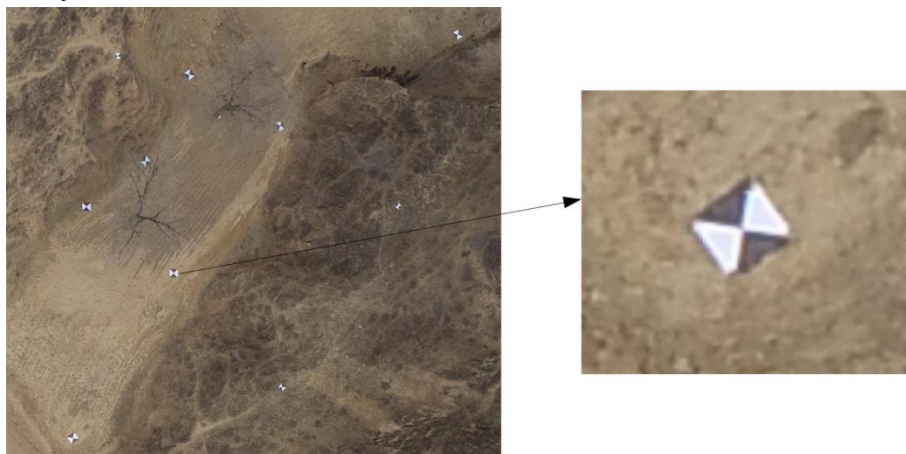
200 Table 4. The experiment of combinations with different flying height

Study area	Camera angle(°)	No.1 Two heights(m)	No.2 Four heights (m)	No.3 Six heights (m)
T1	0	100, 120	80, 100, 120, 140,	60, 80, 100, 120, 140, 160
T2	15	100, 120	80, 100, 120, 140,	60, 80, 100, 120, 140, 160

201

202 2.3 Ground control points

203 We distributed 33 and 31 ground control points (GCPs) in the T1 and T2 (Figure
 204 2), respectively. The GCPs were deployed at peaks, ridges, and gully bottoms in each
 205 study area to ensure that their distribution is even in both low and high points of the
 206 topography (Figure 2). They comprised 1 m × 1 m black and white targets (Figure 3).
 207 The control point (target center) is clearly visible at up to 200 m flight height. All
 208 GCPs were surveyed by a Topcon Hiper SR GNSS-RTK. The horizontal and vertical
 209 accuracy for GCPs surveyed with GNSS-RTK were ±0.010 m and ±0.015 m,
 210 respectively.



211

212 Figure 3. The target used for ground control points

213 2.4 Data processing

214 We applied two data processing procedures to investigate the performance of the
 215 image collection strategies: GCP-free and GCP-constrained. In the GCP-free scenario,
 216 we mainly focus on the effect of image collection strategies. Hence, we use only two

217 GCPs to shift, to rotate, and to scale tie points and hence the acquired topographic data
218 and imagery. The remaining GCPs were used as check points for accuracy assessment.
219 Here, an issue arose: different selection of two GCPs affected the georeferencing. To
220 model the uncertainty of georeferencing, we randomly selected two GCPs 50 times and
221 then used a boxplot to show how tie point accuracy changes.

222 Previous studies (James et al., 2020) showed that poorly designed flight plans may
223 lead to unwanted correlations between parameters of the camera model, which can
224 generate systematic error in derived DEMs. Here, to further understand this effect, we
225 evaluated the correlation of camera calibration parameters to see how it changes with
226 camera angle in the GCP-free scenario.

227 The GCP-constrained scenario used GCPs to improve the bundle adjustment.
228 Previous research (Cabo et al., 2021; Tonkin and Midgley, 2016; Villanueva and Blanco,
229 2019) has shown that continuous increases of GCP quantity had only a limited impact
230 on photogrammetric accuracy when the GCP coverage reaches a certain density. We
231 labelled “optimal number” the number of GCPs beyond which no significant
232 improvement in point cloud accuracy and precision is reached. To investigate whether
233 different image collection strategies affect the photogrammetric accuracy, we employed
234 two Monte Carlo GCP experiments (James et al., 2017a). First, for each Monte Carlo
235 realization, the same number (x) of GCPs was selected to optimize the bundle
236 adjustment, and the rest of the GCPs were used as check points to assess the accuracy.
237 The process was then repeated 50 times with a different random selection of GCPs.
238 Second, for each Monte Carlo realization, the partitioning between optimizing GCPs
239 and check GCPs was varied, with a gradual increase in the percentage (10% in steps of
240 10% to 90%) of GCPs randomly selected. The Monte Carlo GCP tests were carried out
241 in the Agisoft PhotoScan Pro 1.5 and using the Python code (James et al., 2017a).

242 With the image collection, ground control, and data processing strategies used,
243 more than 1.77×10^5 scenarios were processed in this study (2 study areas \times (7 camera
244 angles + 6 flying height + 42 datasets of nadir block supplemented with oblique images
245 + 4 datasets that combine multiple flying heights) \times 30 different numbers of GCPs \times 50
246 random selections of GCPs). This large number of simulations allowed the interactions
247 between image collection strategies and ground control quantity to be accessed.

248 **2.5 Performance assessment**

249 In this study, we focus on the elevation error (Z error) for terrain modeling. We

250 used two standard metrics, the mean error (ME) as a representation of systematic error;
 251 and the standard deviation of error (STD) as a measure of precision (Nesbit and
 252 Hugenholtz, 2019). The main problem with these quantitative measures is that they do
 253 not consider the extent to which error is spatially variable, a commonly reported finding
 254 when DEMs of difference are calculated and “doming” or “dishing” is apparent. For
 255 this reason, we also quantified the extent to which there is a spatial structure to the error.
 256 We used the Moran’s I (Moran, 1950) for this purpose (Eq. (1)). Moran’s I lies between
 257 -1 and 1. The closer its value to 1 or -1, the more positive or negative the spatial
 258 autocorrelation of errors, respectively. A value of 0 indicates a random distribution of
 259 error in space:

$$260 \quad Moran's I = \frac{n}{S_o} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n w_{i,j} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (1)$$

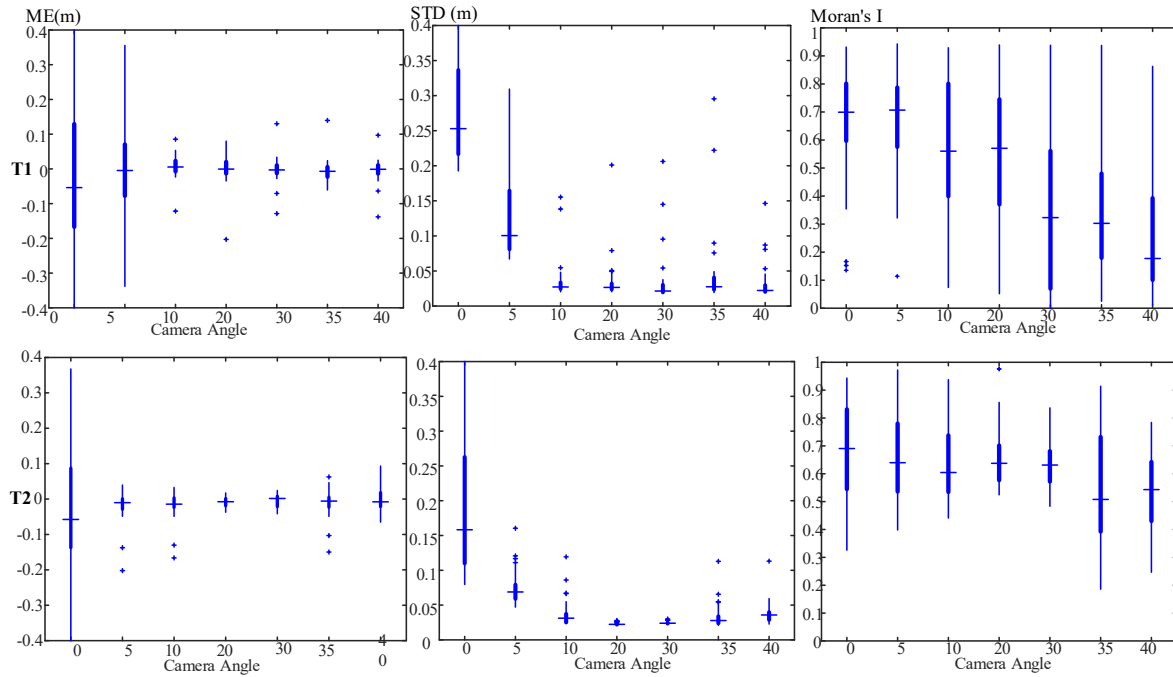
261 where n is the number of spatial units indexed by i and j ; x is the variable of
 262 interest; \bar{x} is the mean of x ; $w_{i,j}$ is a matrix of spatial weights with zeroes on the
 263 diagonal; and S_o is the sum of all $w_{i,j}$. Clearly, a goal for an effective image
 264 calibration is that the Moran’s I statistic is not significantly different from that
 265 associated with a spatially random distribution of error.

266 **3 Results**

267 **3.1 Effects of single camera angle**

268 **3.1.1 Effects of single camera angle without GCPs**

269 The effect of a single camera angle on the ME and the STD is presented in Fig.4.
 270 As the camera angle increases, the ME and STD show the same global trend which
 271 becomes smaller at first and then stable when the camera angle is bigger than 10°. This
 272 indicates that an inclined camera is beneficial to improve both accuracy and precision
 273 in this case, but that very high inclined angles may be unnecessary according to the
 274 stabilization in ME and STD. However, the sensitivity to choice of GCPs is reduced at
 275 greater camera angles (the uncertainty ranges become smaller, Fig.4).



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Figure 4. The ME and STD against camera angle in scenario of control-free

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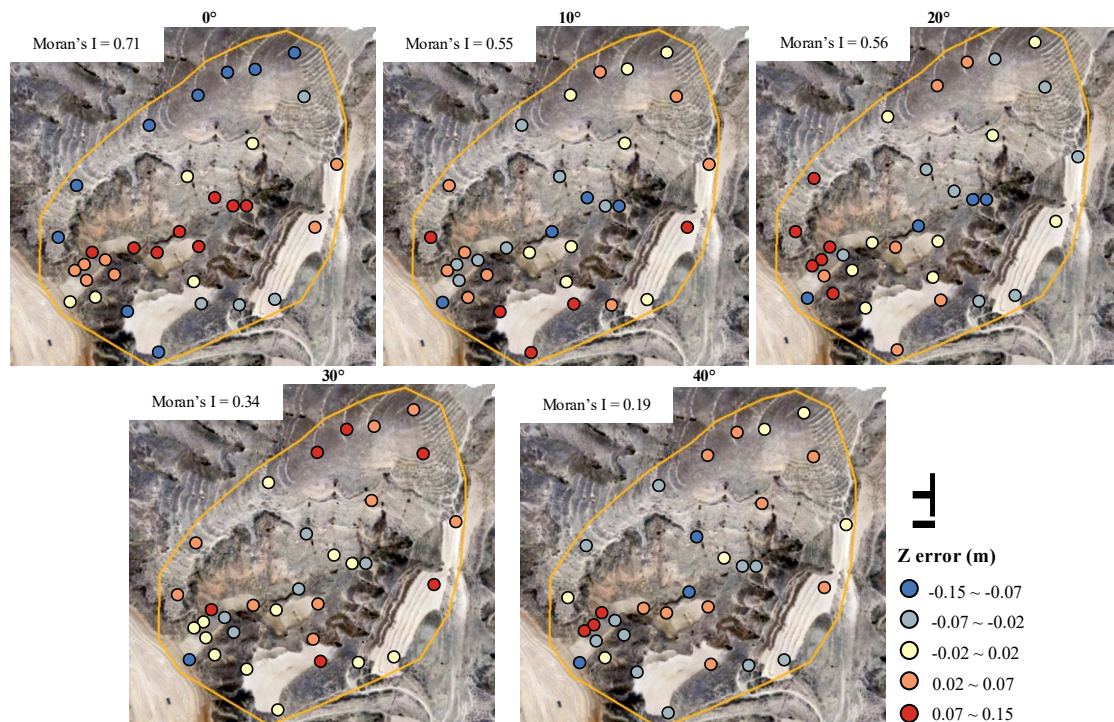
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Besides the ME and STD, it is important to look at the spatial distribution of errors (Eltner et al., 2016; James et al., 2020; Smith and Vericat, 2015). Fig. 5 shows an example of the spatial distribution of GCP errors. When the images are captured with a nadir camera inclination, the distribution of error appears spatially-structured at both sites, which suggests the presence of some systematic distortions (e.g., ‘doming’). For example, in T1 area, many negative errors were located on the ridges in the northeast and southwest, whilst positive errors located on the gully bottom (Fig.5). The Moran’s I values trend towards zero as camera angle increases (Fig.4). This result indicates that the spatial correlation of errors is reduced with higher camera angles (especially greater than 20°). Thus, the use of an inclined camera is likely to have improved calibration and so reduced the degree of spatially-dependent systematic error.



289

290 Figure 5. The spatial distribution of GCP errors under different camera angle in the T1 area

291 To understand further these results, we investigated the correlations between
 292 camera parameters for different camera angles (Fig.6). Correlation between radial
 293 distortion parameters ($K1$, $K2$, $K3$) is expected. Similarly, correlations between focal
 294 length (f) and principal point offset (Cx , Cy), and (Cx , Cy) and tangential distortion
 295 parameters ($P1$, $P2$) are also common. Work has shown (James et al., 2020) that
 296 correlation between radial distortion parameters and principal point offset and
 297 tangential distortion parameters (marked by the red dashed ellipse in the Fig. 6) is
 298 indicative of calibrations with a higher probability of causing systematic error in
 299 derived data. For the camera angles of 0 and 5 °, the correlations are strong (Fig. 6).
 300 With increasing camera angle, the correlations decrease to low levels by 20°. This result
 301 suggests that higher camera angle enhanced the camera calibration.

302

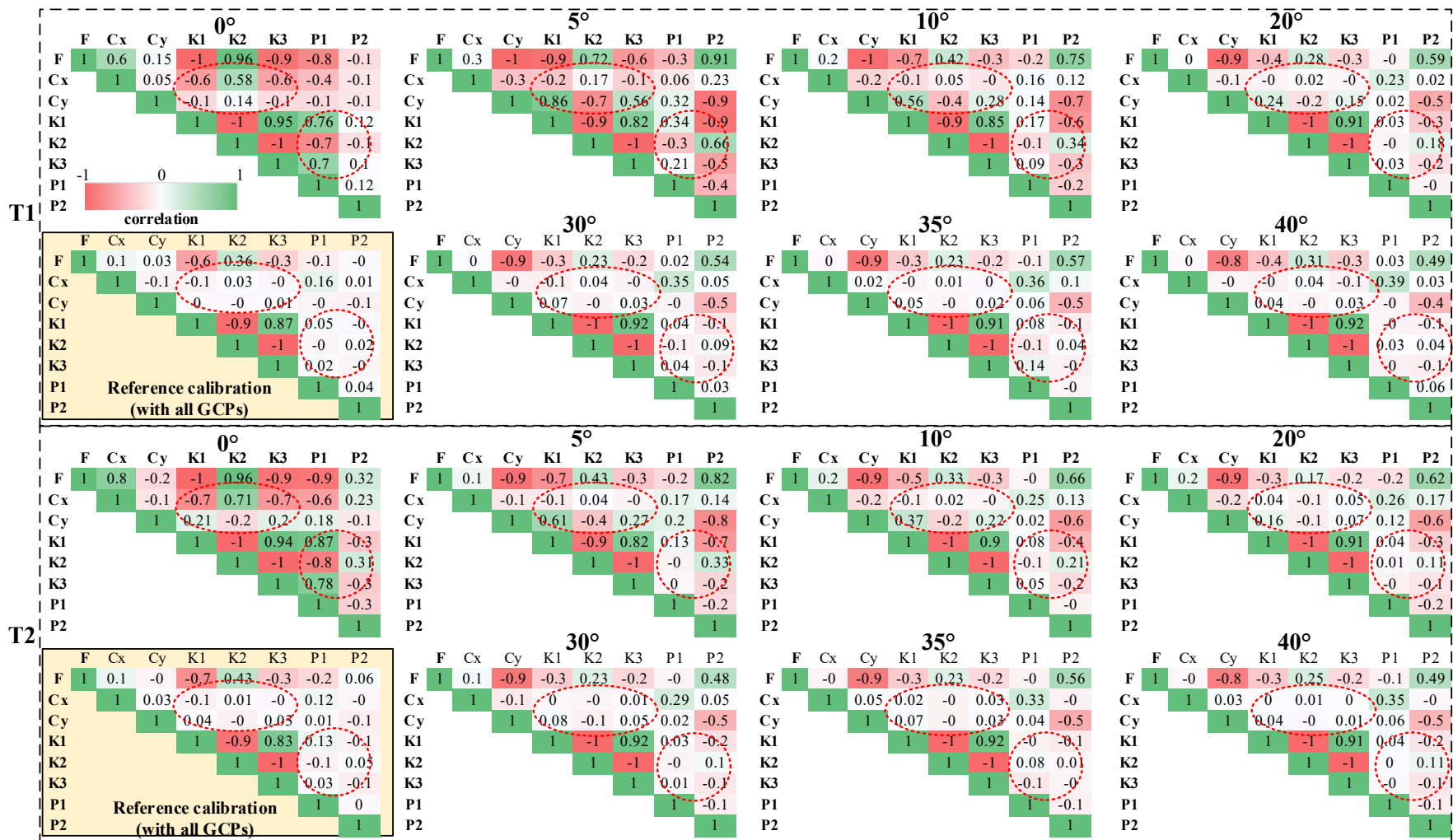


Figure 6. Correlations of camera parameters with different camera angle (The box with yellow back ground is the correlations of reference calibration.)

3.1.2 Interactions between camera angle and GCPs

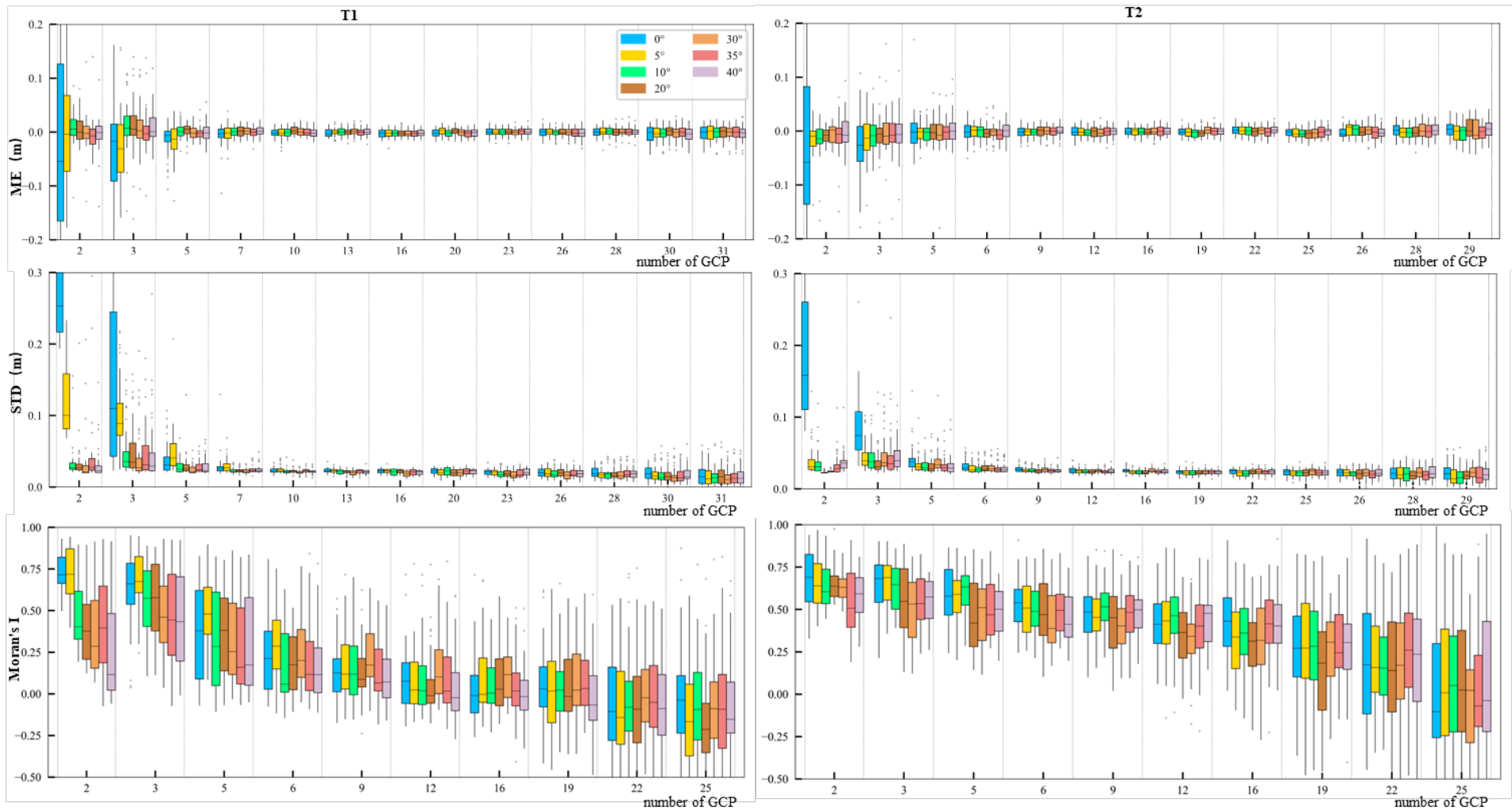
The results of the Monte Carlo experiments considering GCP quantity and distribution are presented in Fig. 7. The median of ME and STD of check points declines with the number of GCPs at first and then becomes stable close to ~ 0 m and ~ 0.02 m, respectively. Adding a relatively small number of GCPs quickly improves the accuracy (from ~ 0.5 m to ~ 0 m) and precision (from $\sim \pm 0.25$ m to $\sim \pm 0.02$ m). Further increases in the number of GCPs have only a minor effect on error. However, when the number of GCPs is very large (i.e. 30 – 31 in the T1 area and 28 – 29 in the T2 area), the ME and STD slightly increase to $\sim \pm 0.01$ m and 0.03 m, respectively (Fig. 7), because the small number of check points increases the uncertainty in the validation data, that is estimates of ME and STD.

Fig. 7 also shows the effect of camera inclination angle on the optimal number of GCPs. On the one hand, higher camera inclination clearly reduces ME and STD when there are no or only a few (< 5) of GCPs (Fig. 7); but, once GCPs are more than ~ 5 , the camera inclination angle seems to have little effect on ME and STD. On the other hand, high camera inclination appears to reduce the number of GCPs needed to obtain the same accuracy (Fig. 7). For example, the ME and STD with 3 GCPs is ~ 0 and ~ 0.05 m, respectively, with the $20 - 40^\circ$ camera inclination scenarios; but it needs 6 – 7 GCPs for the $0 - 5^\circ$ camera inclination scenarios.

The changes in the ranges of boxes in Fig. 7 implies an effect of GCP distribution (or selection of GCPs). The box ranges decrease with the number of GCPs, which suggests the distribution of GCPs is crucial when the number of GCPs is small (≤ 5), but becomes less important with increasing number of GCPs (> 5). This may be because the probability of better distributed GCPs increases with number of GCPs. On the other hand, although the box ranges are relatively high with a small number of GCPs, high camera inclination is beneficial to reduce the variability (box range in Fig. 7).

To better reveal the structure of errors, Figure 7 shows the Moran's I of different scenarios. Note that we did not calculate the Moran's I when the number of GCPs was more than 25, because the number of remaining check points became too small for Moran's I calculation. The Moran's I tended towards 0 with an increasing number of GCPs (from 2 to 25). Addition of GCPs is thus beneficial for improving the structure of errors. With fewer GCPs (≤ 5), the Moran's I declined with camera angle, but this effect became less clear with an increasing number of GCPs (> 5). Although the ME

34 and STD are stable when GCP number is more than 5, Moran's I can be further
35 improved with more GCPs. Thus, increasing the number of GCPs beyond that
36 suggested by the ME and STD is necessary to eliminate the spatial dependence of errors.



37

38

Figure 7. The results of Monte Carlo GCP test with different camera angle

39 **3.2 Impacts of flying height**

40 **3.2.1 Impacts of flying height without GCPs**

41 The sensitivity of precision and accuracy to flying height is relative to the camera
42 angle in the control-free scenario (Fig. 8). We used a nadir (0°) camera in the T1 area
43 and find increasing ME and STD values with increasing flight height (Fig.8).
44 Meanwhile, the ME and STD are relatively stable in the T2 area where a 15° camera
45 angle was used. Thus, oblique photography reduces the sensitivity of ME and STD to
46 flying height. However, the Moran's I values have an increasing trend with flying height,
47 and this effect is not affected by camera angle (same trend in T1 and T2 area).

48 Generally, the ME and STD would increase with flying height due to an increase
49 of observation distance and coarser image resolution. The T2 area shows an unexpected
50 result. This could be due to two reasons. First, in this study, the vertical measurement
51 precision of the RTK survey of the GCPs was about ± 2 cm. The measurement precision
52 would be not enough to capture the changes of ME and STD in T2 area because the
53 oblique photography reduced the ME and STD. Second, this result could mean that the
54 photogrammetric solutions were still dominated by camera calibration effects, not
55 flying height.

56 Fig. 8 also supports previous observations (Fig. 4, 6, 7) that the accuracy of results
57 using oblique photography is higher than that of vertical photography. The ME and STD
58 are always around decimeters in T1 area (nadir photography); whereas, with the oblique
59 photography, they all are around centimeters in T2.

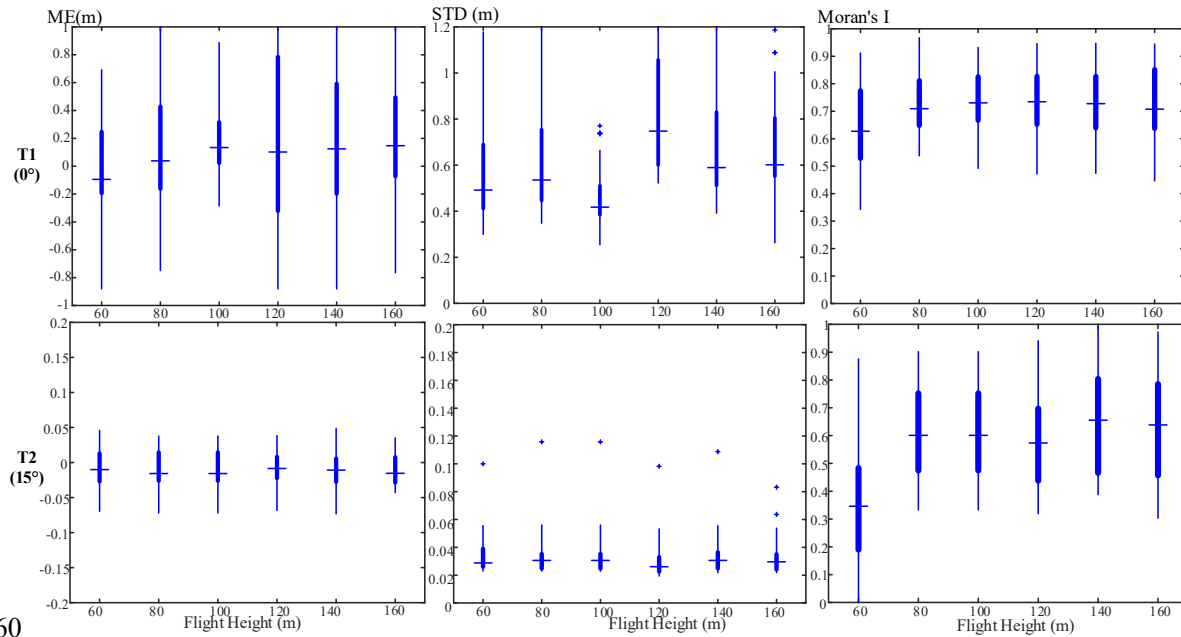
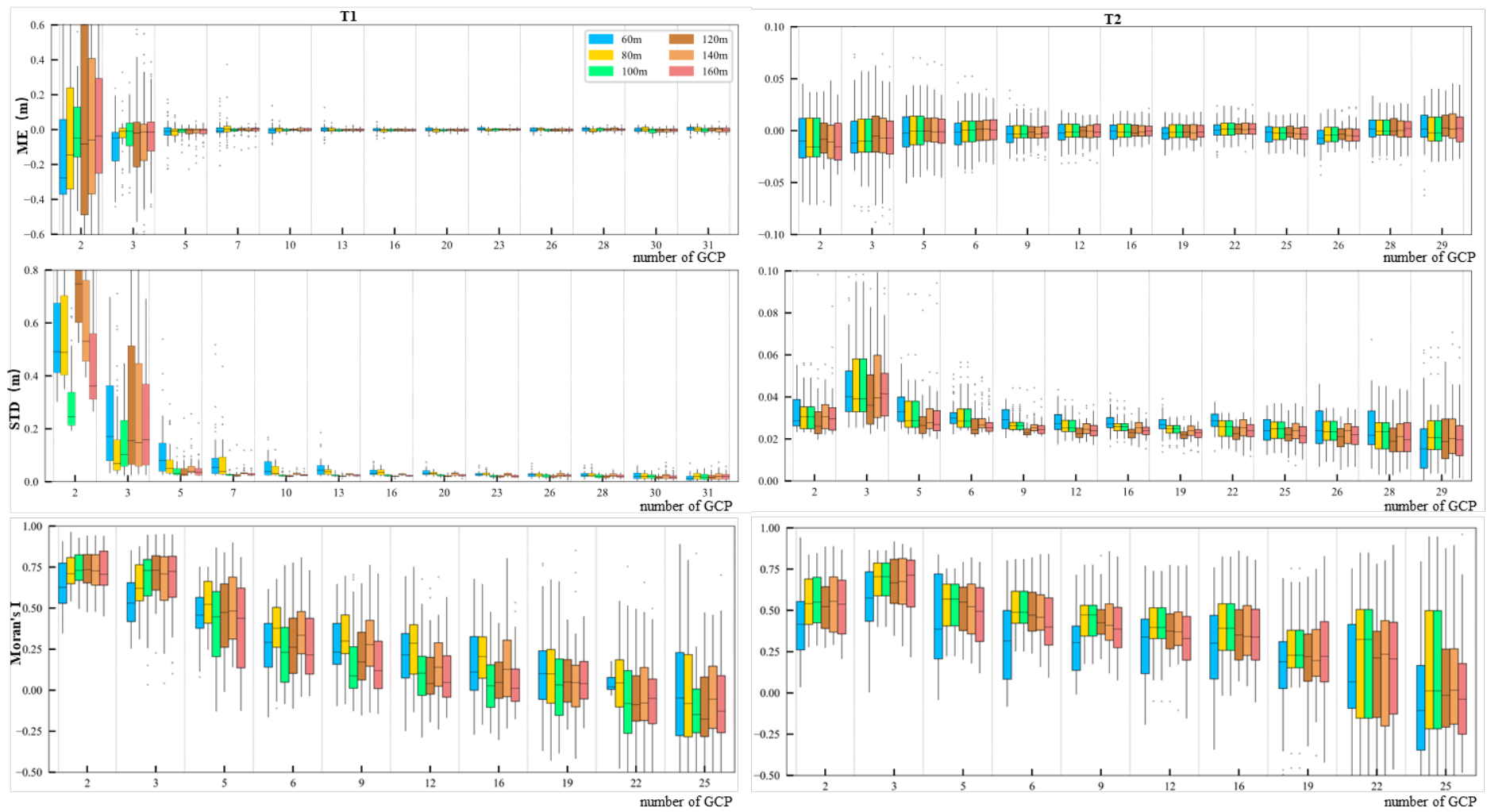


Figure 8. The ME and STD against flight height

3.2.2 Interactions between flying height and GCPs

The Monte Carlo GCP experiment was carried out with images captured at different flying heights. As observed earlier, the addition of a small number of GCPs quickly improves the accuracy and precision, but further increases in the number of GCPs has only minor effect, which is also supported by Fig. 9. With a small number of GCPs (2 – 3 GCPs), the ME increases with flying height for T1; while, the changes for T2 were not obvious due to the use of oblique photography. With more GCPs, the flying height had a minor effect on ME. However, with 5 – 19 GCPs, the variability (box range) in STD decreased with flying height in the two areas. This means that with low flying height (high ground resolution), the selection of GCPs becomes important. Fig. 9 also shows that the optimal GCP number is not sensitive to the flying height. Although the flight height changes from 60m to 160m, the GCP optimal number in the T1 area (0° camera) is always about 7 and that of the T2 area (15° camera) is always about 9.

With a small number of GCPs, the Moran's I increases with flying height. However, the flying height had only a minor effect on the Moran's I when more GCPs were used. Fig. 9 also confirmed that the Moran's I can be further improved with more GCPs after the ME and STD have stabilised. Note that the variability (box range in Figure 9) of Moran's I increases with the number of GCPs. This is because the decreasing number of check points would lead to uncertainty in calculating Moran's I.



81

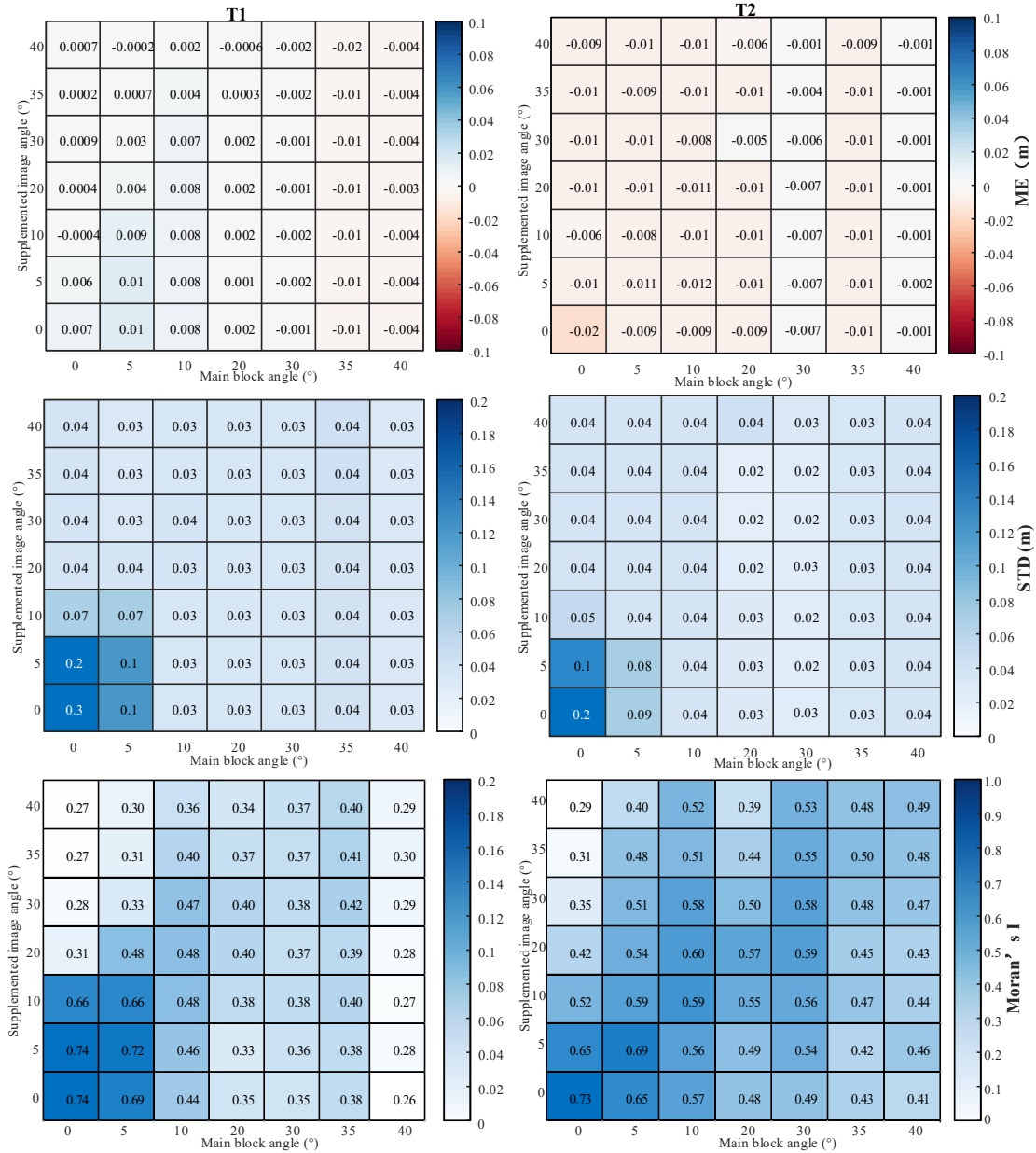
82

Figure 9. The results of Monte Carlo GCP test with different flying heigh

83 3.3 Effects of combination datasets

84 3.3.1 Effects of combination datasets without GCPs

85 Fig. 10 shows the ME, STD, and Moran's I for different combinations of camera
86 angle for the GCP-unconstrained scenario. The ME is low and stable for each main
87 block and only marginally changes with the angle of added images. The STD and
88 Moran's I changes more obviously than ME. With main block angles of 0 to 5°, the
89 STD and Moran's I decrease with progressively higher angles of added images
90 (especially if the angle of supplemented images is greater than 20°). However, if the
91 main block angle is greater than 10°, adding imagery with greater angles has negligible
92 effect on the STD and Moran's I. Thus, higher angle of supplemented imagery is
93 necessary for situations where most imagery is nadir or close to nadir but not otherwise.

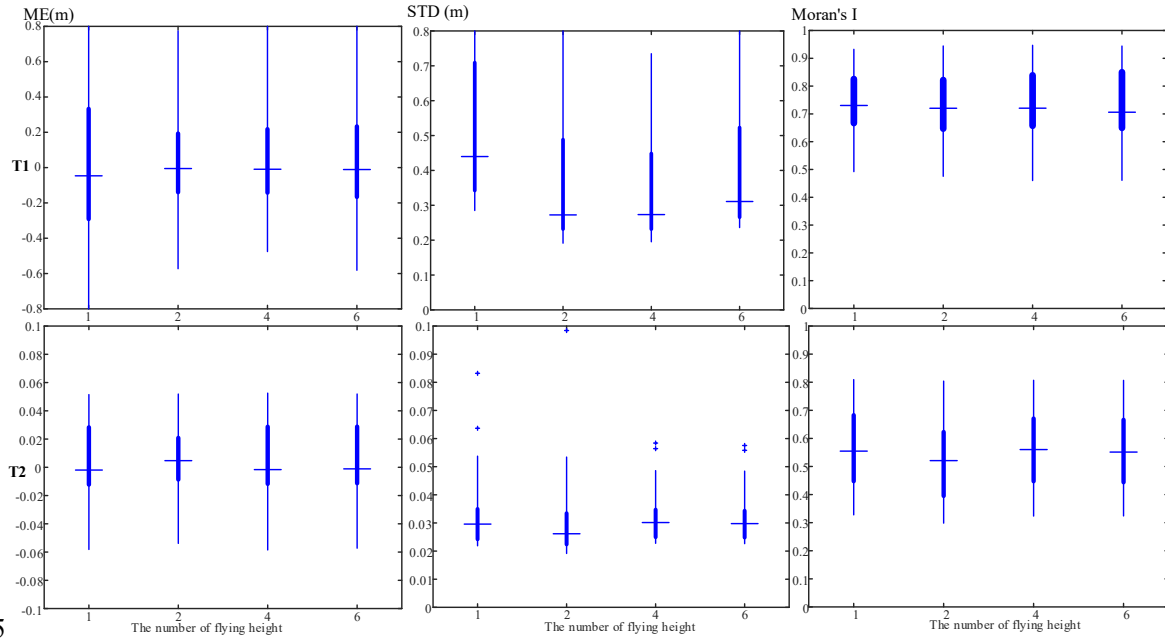


94

95 Figure 10. The ME and STD of different combinations of main blocks and supplemented images.

96

97 Fig. 11 shows the ME, STD, and Moran's I with different combination of flying
 98 heights. The combined multiple flying height has no effect on ME and Moran's I, but
 99 does affect the STD. In the T1 area, the STD shows a decreasing trend when the number
 100 of flying heights increases from one to two. Flying height seems to have no effect on
 101 STD in area T2. The difference between T1 and T2 may be because in T2, with all
 102 flights conducted with a 15° inclined camera, the within-image observation distances
 103 are variable, such that adding different flying heights has no clearly distinguishable
 104 effect with off-nadir imagery.



105

106

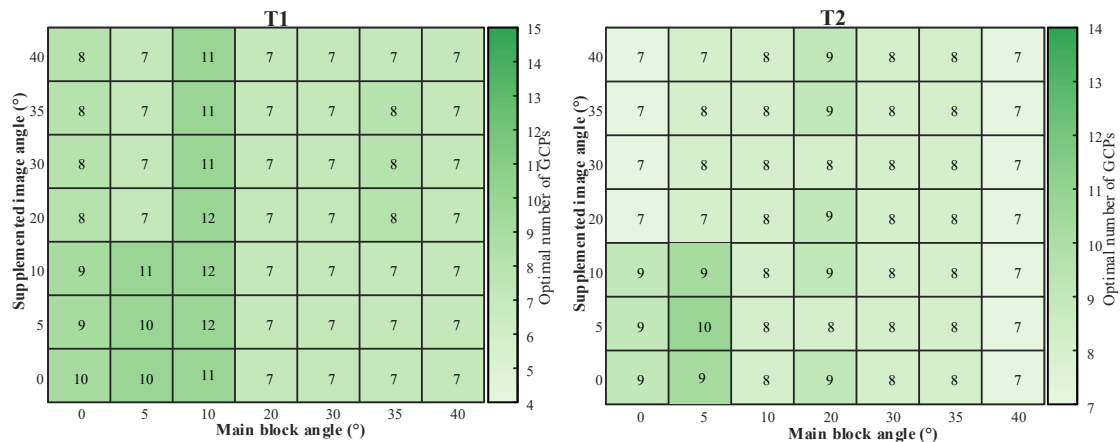
Figure 11. The effect of multiple flying height combination on ME and STD.

107

3.2.2 Interactions between combination datasets and GCPs

108

The Monte Carlo GCP experiment was implemented for different combinations of
 109 main blocks and added images. The effect of GCP quantity on ME and STD for each
 110 combination is similar to Fig. 7: the errors decline with the number of GCPs at first and
 111 then become stable. Here, we mainly focus on whether the combinations of main blocks
 112 and added images affect the optimal GCP number. Starting with initial angles of 0 – 5°,
 113 the optimal number declines marginally with addition of higher angle imagery (Fig. 12).
 114 Moreover, there are no obvious changes in the optimal GCP number when the initial
 115 angles are greater than 10. Thus, whilst combining higher angle imagery with low angle
 116 imagery may improve precision and accuracy (Fig. 10), the number of required GCPs
 117 is insensitive to whether high angle imagery is added or not.

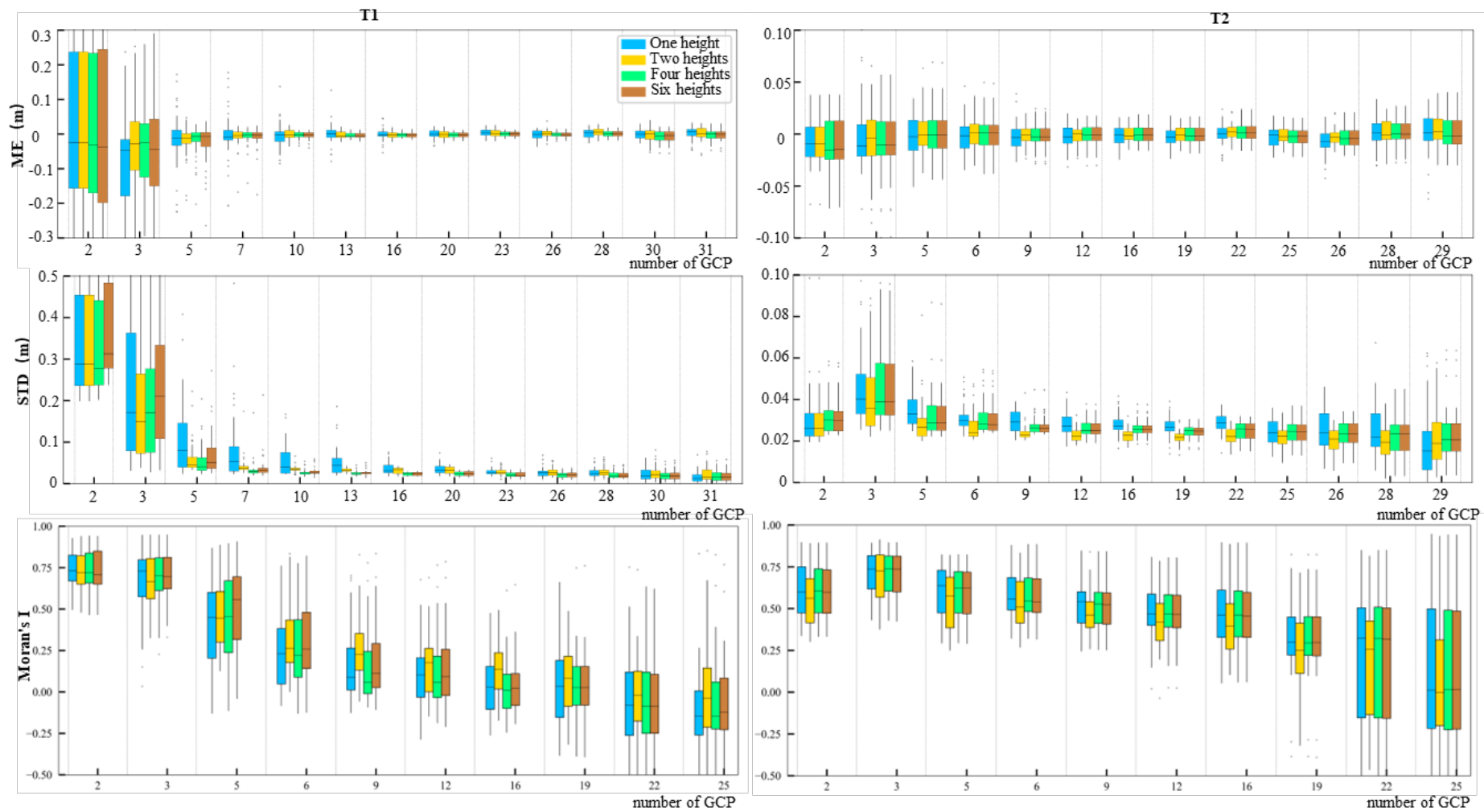


118

119 Figure 12. The GCP optimal number in different combinations of main blocks and supplemented
120 images.
121

122 Fig. 13 shows the Monte Carlo GCP experiment with different combinations of
123 flying heights. The ME, STD, and Moran's I have similar patterns to Fig 7 and 9: ME
124 and STD decrease with addition of a small number of GCPs and then become stable,
125 whilst Moran's I can further decrease with number of GCPs.

126 For the same number of GCPs, the number of combined flying heights seems to
127 have no effect on ME and Moran's I; whilst, for T1 only, the greater the combined
128 number of flying heights, the lower the STD at 5 to 20 GCPs. This is consistent with
129 Fig. 11, which means that combinations of multiple flight heights (observation
130 distances) are beneficial for reducing errors with imagery at nadir, but this seems
131 unnecessary in the scenario with a highly inclination camera. Even a small number of
132 GCPs, 5 or more, substantially reduces STD and has much more effect than addition of
133 flying heights. Indeed, with a larger number of GCPs, the optimal precision and
134 accuracy are not higher than blocks with only one flight height (Fig. 9 and 13).



135
136

Figure 13. The results of Monte Carlo GCP test with different combinations of flying heights

137 **4 Discussion**

138 **4.1 Image collection strategies**

139 Systematic errors such as ‘doming’ and ‘dishing’ in nadir image blocks and small
140 off-nadir blocks have now been frequently described in applications of SfM-MVS
141 photogrammetry using UAVs (Carbonneau and Dietrich, 2017; James et al., 2020;
142 Nesbit and Hugenholtz, 2019). Oblique photography and combined dataset strategies
143 have been proposed for addressing this challenge by seeking more robust camera
144 calibrations (James and Robson, 2014; Nesbit and Hugenholtz, 2019; Rossi et al., 2017;
145 Wackrow and Chandler, 2011). Our results confirm the improvement of derived DEM
146 accuracy and precision of SfM-MVS derived point clouds when oblique imagery is
147 used. However, this study also provides further insights into optimal image collection
148 strategies.

149 A high camera inclination not only decreases the magnitude of errors (Fig. 4), but
150 also mitigates its spatial correlation (Moran’s I) (Fig. 5) and hence the degree of
151 doming/dishing. It enhances camera calibration by reducing unwanted correlation
152 between radial and decentering distortion parameters of the camera model (Fig. 6). This
153 improvement may be related to the fact that the increasing intersection angles of rays
154 of tie points enhances the bundle adjustment, and then improves camera calibration and
155 mitigates errors. Additionally, steep slopes, which are not easily visible in nadir images,
156 may be better captured by oblique images (Petrie, 2009), resulting in more potential
157 matching points during the bundle adjustment. This result is consistent with findings of
158 Vacca et al. (2017), who reported that oblique images enhanced tie point matching.
159 Notably, James et al. (2020) reported that a small inclination angle could increase
160 systematic errors and suggested that we should move beyond ‘off-nadir’ imagery. We
161 also found that the use of small inclination angle needs more GCPs in the T1 area (Fig.
162 12); but this effect does not appear in the T2 area, which means that this effect could be
163 relative to other factors (such as topographic characteristics, image quality, and camera
164 properties). Nevertheless, a small inclination angle is not recommended in UAV-SfM
165 practice.

166 Generally, the precision and accuracy decrease with flying height. Scholars
167 (Smith and Vericat, 2015) used the precision ratio between precision and average
168 observation distance to quantifying the effect of flying height. In this study, the results

169 show that the effect of flying height is relative to the camera angle (Fig. 8). The
170 precision ratio increased from 1:800 to 1:2000 with high camera inclination. This
171 finding is important because it means that with the same requirement of precision, the
172 flying height in field work can be relatively higher by using oblique photography thus
173 improving workflow efficiency. However, notably, the spatial correlation of error
174 (Moran's I) increases with flying height if GCP-free (Fig. 8). Thus, need for GCPs
175 increases as the flying height increases.

176 A nadir image block supplemented with convergent images and combinations of
177 multiple flying height were suggested for improving UAV-SfM calibrations in previous
178 studies (James and Robson, 2014; Nesbit and Hugenholtz, 2019). A high camera
179 inclination block supplemented with convergent images and combined multiple flying
180 height blocks were first investigated in this study (Fig. 10). Our results show that such
181 additional data may not be necessary if there is imagery with a high inclination. With
182 inclined imagery, the need for multiple flying heights was reduced which we attributed
183 to the effects of off-nadir imagery on the range of image to object distances present in
184 anyone scene.

185 **4.2 Ground control quantity**

186 Image collection strategies are crucial when surveys are GCP-free or only a small
187 number of GCPs is used, but become less important with more GCPs (Fig. 7, 9, and
188 13). GCPs provide constraints for the bundle adjustment and define absolute position
189 and orientation to SfM-derived point clouds (James and Robson, 2014; James et al.,
190 2017a; Rupnik et al., 2015), which substantially improve model accuracy and precision.
191 Our results show that the ME and STD of check points decline quickly with a small
192 number of GCPs in all scenarios (Fig. 7 and 9), but a large number of GCPs are
193 unnecessary. This finding is similar to Stöcker et al (2020). However, we also found
194 that the effects of GCP quantity interact with image collection strategies.

195 High camera inclination seems to reduce requirements for GCPs (Fig 7). This may
196 be related to the terrain characteristics at each site. We selected the study areas (T1 and
197 T2) in high-relief terrain. Oblique images with higher inclination angle are expected to
198 capture steep slopes and match more tie points (Vacca et al., 2017). Due to more tie
199 points and more uniform spatial resolution (or point density) in oblique photography
200 (Petrie, 2009), the aerial triangulation should be enhanced, so reducing dependency on
201 GCPs.

202 The flying height and combination dataset strategies had little effect on the number
203 of GCPs needed. In most of the scenarios we studied, 5 to 9 GCPs (1.39 to 1.76 GCP/ha)
204 were enough to improve the bundle adjustment. The suitable GCP number could be
205 related to the area of study sites. In this study, the study area is small (3.6 – 5.1 ha)
206 which requires fewer GCPs. However, Cabo et al. (2021) reported that 50 GCPs were
207 necessary for a 1220 ha study area (0.041 GCP/ha). Thus, the average GCP density is
208 more useful than optimal GCP number in practice. The average required GCP density
209 appears to vary between studies (Cucchiaro et al., 2018; Dai et al., 2022; James et al.,
210 2020; Stöcker et al., 2020), which means that it is still relative to other factors, such as
211 terrain relief, surface texture, and image quality. Hence, with the exception of the effect
212 of image collection strategies, there is no uniform recommendation for average GCP
213 density or optimal number of GCPs in different areas.

214 Although the magnitude of errors (ME and STD) stabilizes rapidly with increasing
215 GCPs, the structure of errors (Moran's I) can be further improved with more GCPs (Fig.
216 7, 9, and 13). The addition of GCPs is necessary for improving the structure of errors.
217 In this study, the median of Moran's I is close to 0 with more than 22 GCPs (Fig. 7, 9,
218 and 13); it only needs 5-9 GCPs for ME and STD stable. Moreover, the camera angle,
219 flying height, and combination dataset strategies have only minor effects on the
220 necessary GCP numbers for Moran's I to stabilize.

221 Besides the number of GCPs, the spatial distribution of GCPs should be addressed
222 (Cabo et al., 2021; James et al., 2017a). Our study showed that, with the fixed number
223 of GCPs, the different selections of GCPs have different ME, STD, and Moran's I (Fig.7,
224 9, and 13). Studies proposed that a combination of edge distribution and stratified
225 distribution is the best practice for GCPs (Martínez-Carricondo et al., 2018b). Our study
226 argues that the effect of GCP distribution is less important than the number of GCPs in
227 small study areas, which is supported by the reduction of error variability in Fig.7 and
228 Fig. 9. This may be because the probability of better distributed CGPs increases with
229 number of GCPs. However, the small size of the study areas may prevent the effects of
230 spatial distribution of GCPs being thoroughly assessed and that the spatial distribution
231 is likely to be more important over larger areas.

232 Finally, the image collection and ground control strategies are not only applicable
233 for high-relief areas, but also low-relief regions. The oblique photography is also
234 beneficial for improving terrain modeling accuracy in low-relief regions (e.g.,
235 Carbonneau and Dietrich, 2017; James et al., 2020). However, the terrain relief seems

236 to be another variable that influence UAV-SfM photogrammetry accuracy. The UAV-
237 SfM terrain modeling errors in low-relief regions is less complex than that of high-relief
238 regions (James et al., 2020), which could reduce the requirement of GCPs.

239 **5 Conclusion**

240 This study designed various photogrammetric scenarios and investigated the
241 effects of image collection strategies, ground control quantity, and their interaction on
242 terrain modelling errors (ME and STD) and their spatial structure (Moran's I) in high-
243 relief terrain. The latter is an important addition to the error metrics that should be used
244 in assessing SfM-MVS results. The work showed clearly that standard error statistics
245 like ME and STD may be found to be acceptable even when spatial structure in the
246 error field remains, something that is revealed with Moran's I. The latter should be
247 routinely applied in evaluations of the quality of UAV SfM-MVS results.

248 The results provide insights for improving UAV SfM-MVS practices. First, a high
249 camera inclination (20° - 40°) enhances camera calibration by reducing unwanted
250 correlation between radial and decentering distortion parameters of the camera model.
251 This not only decreases the magnitude of errors, but also mitigates its spatial correlation
252 (Moran's I). Second, a high flying height increases ME, STD, and Moran's I. However,
253 the effect of flying height interacts with camera angle. Oblique photography reduces
254 the sensitivity of ME and STD to flying height, but not for Moran's I. Third, the
255 supplemented datasets (a main block supplemented with convergent images and
256 combined multiple flying height blocks) is not necessary if there is imagery with a high
257 inclination.

258 GCPs provide more substantial constraints for bundle adjustment than image
259 collection strategies. On the one hand, the magnitude of errors (ME and STD) declines
260 quickly with a small number of GCPs and then become stable in all scenarios, but the
261 structure of errors (Moran's I) can be further improved with increasing GCPs. This
262 means that the structure of errors (such as "doming") needs more attention in UAV-SfM
263 practice. On the other hand, the effects of GCP quantity interact with image collection
264 strategies. High camera inclination seems to reduce requirements for GCPs, while the
265 flying height and combination dataset strategies have little effect on necessary GCP
266 quantity. Moreover, the distribution of GCPs still affects the errors, but the effect of
267 GCP distribution becomes less important with the increase in the number of GCPs.

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