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1 Quantifying fault interpretation uncertainties and their impact on fault seal and  
2 seismic hazard analysis

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14 Key words: Bias, Seismic reflection, Displacement analysis, Faults

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19 **Abstract**

20 Fault-horizon cut-off data extracted from seismic reflection datasets are used to study the  
21 geometry, displacement distribution, and growth history of normal faults. Our study  
22 assesses the influence of three fault interpretation factors (repeatability, measurement  
23 obliquity, and cut-off type) on derived fault properties. We investigate uncertainties in  
24 throw, heave, displacement, and dip, extracted from continuous and discontinuous cut-offs  
25 along multiple horizons across four sub-linear faults in the Chandon-3D seismic cube,  
26 located offshore NW Australia. Mean differences between repeated interpretations are  
27  $\sim\pm 10\%$  for throw and 13-23% for heave, with greater uncertainties observed locally (e.g., in  
28 areas of structural complexity). Measurement obliquity, where cut-offs are interpreted  
29 along non-perpendicular transects to fault strike, introduces uncertainty depending on the  
30 degree of obliquity (particularly when  $>20^\circ$ ), horizon, fault, and the fault property being  
31 measured. Obliquity related uncertainties were found to not decrease the repeatability of  
32 the derived fault parameters, with the seismic image data found to have a greater influence.  
33 For both the aforementioned interpretation factors, continuous cut-offs generally exhibit  
34 greater uncertainties compared to discontinuous cut-offs. Our findings indicate that  
35 obliquity and repeatability have a limited impact on fault transmissivity calculations but may  
36 significantly affect fault-based seismic hazard assessment.

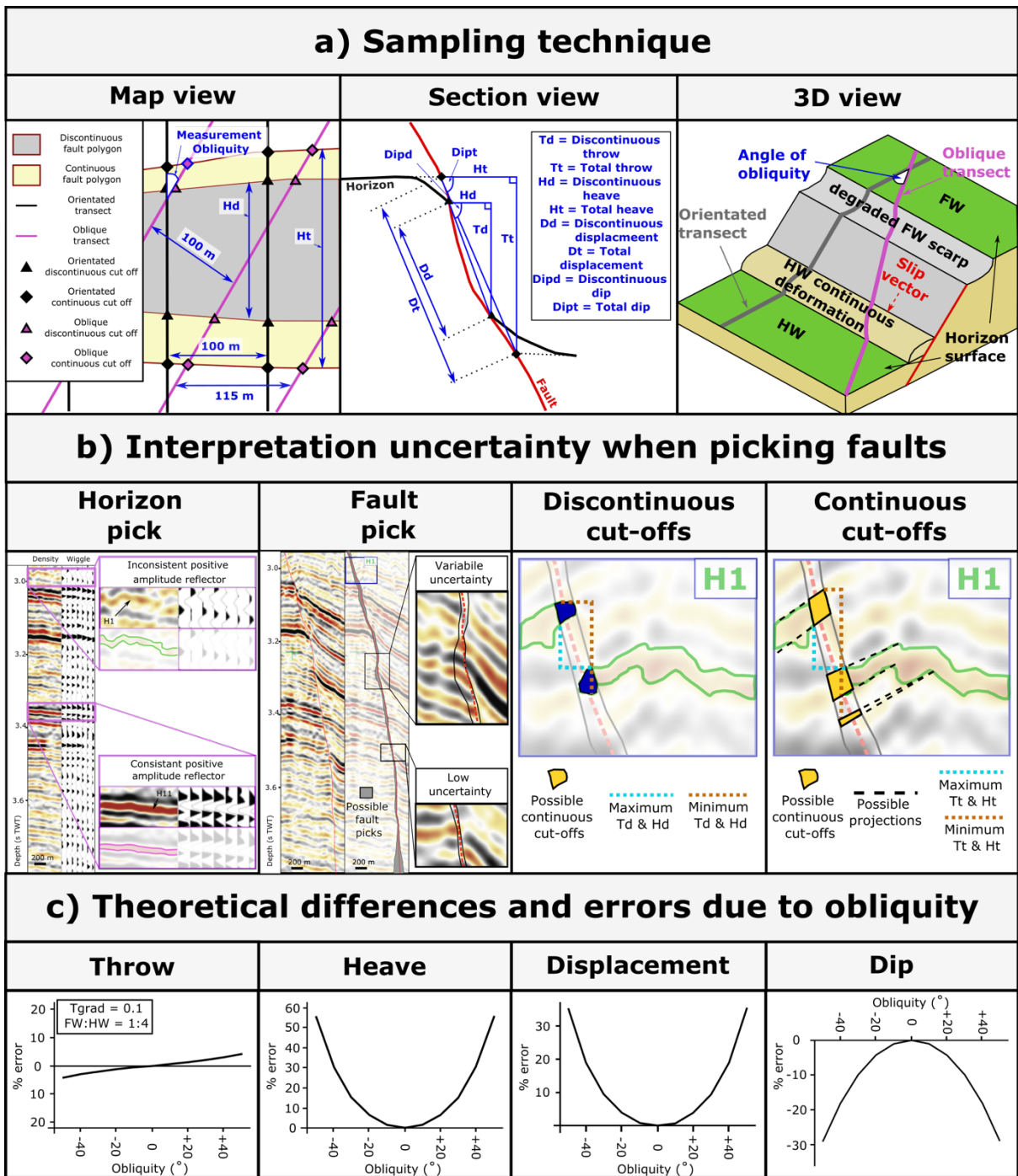
## 37 **1 Introduction**

38 The measurement of horizon-fault cut-offs from seismic reflection datasets enables  
39 extraction of key fault properties such as heave, throw and fault dip. Analysis of these  
40 properties have to advanced our understanding of fault geometry and evolution (e.g., Nicol  
41 et al., 2005; Jackson and Rotevatn, 2013; Pan et al., 2021; Roche et al., 2021; Rodríguez-  
42 Salgado et al., 2023), strain rate and its evolution in active and inactive rift systems (e.g.,  
43 Meyer et al., 2002; Cowie et al., 2005; Marsh et al., 2010); and fluid-flow properties of faults  
44 within hydrocarbon and/or CO<sub>2</sub> reservoirs (e.g., Yielding, 2002; Gibson and Bentham, 2003;  
45 Yielding et al., 2011; Miocic et al., 2014). The use of horizon-fault cut-off data, combined  
46 with well data, is routinely used to infer the sealing potential of faults cutting these  
47 reservoirs. This is of particular importance for CO<sub>2</sub> storage projects (Klusman, 2003;  
48 Amonette et al., 2010), where schemes are required to ensure at least 99% of injected CO<sub>2</sub>  
49 must remain within the target reservoir for >1000 years (IPCC, 2005). Fault cut-off data can  
50 also be used to infer key properties to feed into fault based seismic hazard assessment (e.g.,  
51 fault dip, geological slip rate) (Nicol et al., 2005). Nuclear waste disposal sites require  
52 geologically stable subsurface locations, and hence must be subject to detailed seismic  
53 hazard assessment (Fenton et al., 2006; Connor et al., 2009; Mörner, 2013). Where 3D  
54 seismic data is involved in this assessment, any uncertainty in cut-off data could lead to  
55 uncertainties in the expected hazard at the site and therefore its suitability for storing  
56 nuclear waste. It is therefore imperative to have confidence in conclusions drawn from the  
57 analysis of fault properties extracted from seismic reflection datasets and therefore, the  
58 uncertainties and biases associated with extraction of underpinning data.

59 Uncertainties can be broadly classified as objective and subjective (Frodeman, 1995;  
60 Tannert et al., 2007; Bond, 2015). Objective uncertainty, also known as “stochastic  
61 uncertainty”, relates to the methods used for data acquisition, analysis, or interpretation of  
62 the raw data (Tannert et al., 2007; Pérez-Díaz et al., 2020). In the case of seismic reflection  
63 data, these include the velocity model used for the conversion between two-way-time to  
64 depth (Schaaf and Bond, 2019; Faleide et al., 2021), the effect of compaction of fault  
65 properties (Taylor et al., 2008), the spacing of picks during data extraction (Michie et al.,  
66 2021), and whether the throw across a given fault exceeds or falls below the limit of  
67 separability (Brown, 2011; Osagiede et al., 2014). Subjective uncertainties pertain to biases  
68 and variability in results caused by the individual analysing the data (Tannert et al., 2007),  
69 these include the geological interpretation and its repeatability. Repeatability, which is the  
70 ability to replicate the data and interpretations of a study, is recognised as a crucial aspect  
71 of any experiment (e.g., Goodman, 2016). Geology, in particular, is susceptible to subjective  
72 uncertainty due to incomplete datasets and the lack of consensus within the research  
73 community regarding key concepts and research methods (Frodeman, 1995; Bond, 2015;  
74 Pérez-Díaz et al., 2020; Steventon et al., 2022; Magee et al., 2023; Robledo Carvajal et al.,  
75 2023). For seismic reflection datasets, subjective uncertainties can lead to multiple  
76 interpretations being drawn from the same seismic image (e.g., Bond et al., 2007; Alcalde et  
77 al., 2017). Previous work has suggested that fault properties extracted from seismic  
78 reflection data should have an error associated with them of between  $\pm 5\%$  (Magee and  
79 Jackson, 2020a) and  $\pm 10\%$  (Magee et al., 2023), however, no parametric studies have been  
80 undertaken to date to test these essentially qualitative values.

81 Motivated by the discussion above, this paper addresses three previously understudied  
82 uncertainties in fault interpretation using seismic reflecton images: repeatability;  
83 measurement obliquity; and interpreted cut-off type. We examine the impact of the related  
84 uncertainties on the following fault properties: throw, heave, dip, and displacement. Finally,  
85 we discuss the implications of our findings for understanding fault transmissibility and  
86 seismic hazard assessment.

### 87 ***1.1 Expected sources of uncertainty in fault interpretation***



88

89 Figure 1: Sample strategy and theoretical impact of obliquity on extracted fault parameters: a) sample strategy  
 90 and extracted parameters showing in map and section and 3D views. Discontinuous and continuous fault  
 91 polygons represent the horizon gap created by a fault, extending between the hanging wall and footwall for  
 92 discontinuous and continuous cut-offs, respectively; b) examples of expected interpretation uncertainty when  
 93 picking fault cut-offs; c) Theoretical % error across a range of oblique transects for throw, heave and  
 94 displacement assuming a fault dip of 40°. For throw, a throw gradient of 0.1 and a FW:HW displacement ratio  
 95 of 1:4 was assumed. The shape of the theoretical % error graphs implies that heave, and therefore  
 96 displacement and dip, will have a high theoretical error at high obliquity, whereas throw will have a lower  
 97 theoretical error.

98 In this section we summarise the literature and theoretically expected contribution of each  
99 uncertainty element on the repeatability of fault data extraction.

100 *Interpretation repeatability:* The repeatability of measurements from seismic reflection data  
101 is influenced by human bias, leading to uncertainties in locating cut-offs (Schaaf and Bond,  
102 2019). The position of cut-offs will be influenced by the interpreted horizon and fault, the  
103 interpreted intersection point and the projection of regional dip onto the fault plane. These  
104 factors are expanded upon below:

105 *Interpreted horizons (Figure 1bi):* Horizons picks are made along prominent  
106 reflections, ideally with consistent waveforms (Brown, 2011). Inconsistent  
107 waveforms can result in high rugosity structure maps, attributed to post-acquisition  
108 processing or geological features (Chellingsworth et al., 2015). Auto trackers and  
109 smoothing algorithms are commonly used to create geologically reasonable  
110 horizons, with the choice of methods used introducing subjective uncertainty  
111 (Brown, 2011; Chellingsworth et al., 2015). Previous studies have shown that horizon  
112 picking uncertainties decrease near wells, potentially due to an increase in  
113 interpreter confidence (Schaaf and Bond, 2019). Conversely, horizon picking  
114 uncertainties increase away from wells, especially in areas of low seismic image  
115 quality and near faults (Alcalde et al., 2017b; Schaaf and Bond, 2019). The image  
116 quality around faults can be affected by the presence of a damage zone, which can  
117 vary in width based on fault displacement and the structural position on the fault  
118 (Shipton and Cowie, 2003; Childs et al., 2009; Choi et al., 2016). Furthermore,  
119 correlating horizons across faults may be challenging due to variations in reflection  
120 properties, the presence of footwall degradation (Bilal et al., 2020), and/or changes



121 in seismic stratigraphy in the footwall/hangingwall, and especially when reflectors  
122 cannot be traced around fault tips (Bond et al., 2007; Bond, 2015; Chellingsworth et  
123 al., 2015). We anticipate increased horizon picking uncertainty for faults with large  
124 displacement, at segment boundaries/fault tips, or in locations where footwall  
125 degradation has occurred.

126 *Interpreted faults:* Uncertainties in fault placement are influenced by the strength of  
127 seismic reflect and image quality (Alcalde et al., 2017b; Schaaf and Bond, 2019)  
128 (Figure 1bii). Interpretation uncertainty increases in areas with decreased reflector  
129 strength (Schaaf and Bond, 2019). Strong seismic reflectors overlying or underlying  
130 weak reflectors reduce uncertainty in our interpretation of the latter, and faults that  
131 conformed to expected geometries (e.g., matching the regional trend) are more  
132 reliably picked (Bond, 2015; Alcalde et al., 2017a; Schaaf and Bond, 2019).

133 *Interpreted horizon-fault intersection (i.e., cut-offs):* The way that reflections  
134 (mapped as horizons) intersect with faults, ie cut-offs, is open to interpretation and  
135 is therefore potentially uncertain. This arises at least partly from there being two  
136 components of fault-related deformation; *discontinuous*, which relates to the fault-  
137 related, brittle strain, and *continuous*, which relates to folding (i.e., ductile strain)  
138 and/or brittle deformation below the resolution of the seismic reflection dataset. As  
139 such, two types of fault cut-off are measured: discontinuous cut-offs, and continuous  
140 cut-offs (Figure 1b), which account for both the discontinuous and continuous  
141 components of deformation (Childs et al., 2017; Delogkos et al., 2017, 2020). These  
142 cut-offs can then be used to calculate fault throw, heave, dip, and displacement. The  
143 inclusion or not of continuous deformation depends on the scientific objective and

144 the nature of the faulting. For example, to derive long-term fault slip-rates only the  
145 continuous portion of deformation is considered (Lathrop et al., 2021; Pan et al.,  
146 2021). In contrast, only the discontinuous portion is required to calculate lithological  
147 juxtapositions, shale gouge ratio and ultimately fault transmissivity.

148 Uncertainties affect cut-off types differently. Discontinuous cut-offs (Figure 1biii), are  
149 influenced by uncertainties in the position of the fault plane and horizon. Analysis of  
150 fault cut-offs suggests that areas of low image quality are associated with large  
151 uncertainty, leading to increased uncertainty with depth (Alcalde et al., 2017b;  
152 Schaaf and Bond, 2019). Moreover, cut-offs on faults with low displacement near the  
153 limit of separability (Magee et al., 2023) and the hanging wall cut-off of large  
154 displacement faults, which are deeper and due to additional accommodation space  
155 often show changes in seismic stratigraphy compared to the footwall (Alcalde et al.,  
156 2017b), are prone to higher uncertainties. Continuous cut-offs require the regional  
157 dip of the horizon to be projected onto the fault plane (Figure 1biv). In cases of  
158 small-displacement faults where continuous deformation comprises a significant  
159 portion of the displacement, the interpreter must choose where the fault intersects  
160 the deflected horizon (Faleide et al., 2021; Magee et al., 2023). This introduces  
161 uncertainty as there are multiple feasible locations for projecting the horizon onto  
162 the fault plane, and the position of the fault plane itself becomes more uncertain (Fig  
163 1b). Where both types of deformation are present (e.g., fault growth through fault-  
164 propagation folding), the position of the fault plane will have lower uncertainty, but  
165 the interpreter still needs to subjectively determine where the regional dip  
166 transitions into near-fault continuous deformation.

167 Seismic image quality and the chosen vertical exaggeration are common factors that  
168 influence subjective uncertainties. To minimise their impact in our datasets, horizons at  
169 similar depths, with similar resolutions, are selected and a consistent vertical exaggeration is  
170 used during fault picking.

171 Previous studies have focused on the impact of subjective bias on data extracted from  
172 multiple interpreters (Bond et al., 2007, 2012; Bond, 2015; Schaaf and Bond, 2019).  
173 However, limited attention has been given to the consistency of an individual's  
174 interpretation. Magee et al. (2023) conducted a study where an individual made repeat  
175 picks on the same horizon of a low-displacement fault, revealing variations in fault cut-off  
176 positions that affected the extraction of throw and heave. Nevertheless, the datasets were  
177 found to be statistically equivalent and exhibited lower uncertainty compared to another  
178 interpreter's interpretation of the same horizon. Similar 'internal consistency' within  
179 individuals interpretations has also been observed in the field classification of faults and  
180 fractures (Andrews et al., 2019; Shipton et al., 2020) and seismic reflection-based models  
181 (Alcalde and Bond, 2022). This study aims to build on these findings by investigating the  
182 magnitude of individual internal consistency in fault properties, examining variations across  
183 different horizons, faults, cut-off types and measurement obliquity.

184 *Measurement obliquity:* Measurement obliquity is the angle relative to the fault strike that  
185 fault and fracture properties are sampled (Figure 1a), and it can affect the extraction of key  
186 properties such as spacing and dip (Terzaghi, 1965; Watkins et al., 2015). Optimal fault  
187 interpretation strategies for normal faults involves sampling using transects that are  
188 perpendicular to fault strike, i.e., parallel to the inferred slip vector, and avoiding measuring

189 apparent dip. This approach reduces pick spacing along the fault, which is important for  
190 accurate interpretations of throw minima and fault segmentation (Michie et al., 2021).

191 Theoretical error estimates for the studied fault properties due to measurement obliquity  
192 can be obtained by considering the change in cut-off position caused by an oblique sample  
193 line (Fig 1c). For a fault with  $40^\circ$  dip, throw errors remain low even at high measurement  
194 obliquities (Fig 1ci). However, heave errors exceed 50% at measurement obliquities of  $\pm 50^\circ$   
195 and exceed 10% at a measurement obliquity of  $\sim 25^\circ$ . These errors would lead to moderate  
196 over- and under-estimates of displacement and dip, respectively, at high measurement  
197 obliquities. Therefore, we expect measurement obliquity to have a small effect on the  
198 extraction of throw, but greatly impact measurements of heave, and therefore  
199 displacement and dip (Fig 1c).

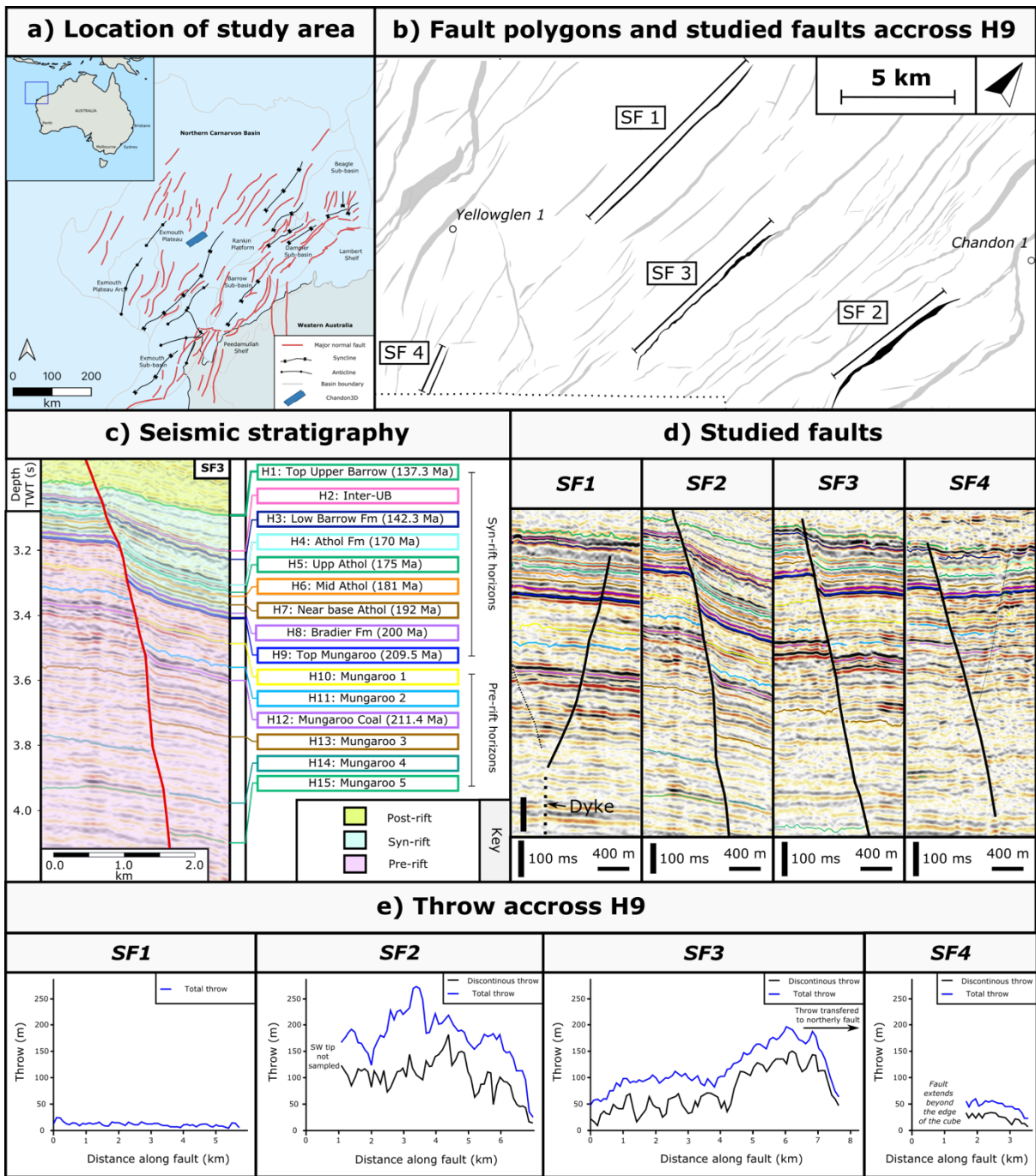
200 Given the non-linear morphology of faults and the scale-dependant nature of strike,  
201 ensuring all data are extracted using orthogonal transects can be difficult and time  
202 intensive. Furthermore, if 2D seismic lines are the only available datasets, the lines may not  
203 be optimally orientated (i.e., perpendicular) to local fault strike. This study aims to  
204 investigate the threshold at which measurement obliquity significantly affects the extraction  
205 and interpretation of fault properties, and therefore to provide quantified errors that can be  
206 applied to other studies.

## 207 **2. Dataset/methodology**

### 208 **2.1 Seismic data**

209 We use a high-resolution 3D seismic survey (Chandon3D) located on the Exmouth Plateau,  
210 offshore NW Australia (Fig 2). Chandon3D is a time-migrated, zero-phase survey that has a  
211 record length of 6 seconds two-way time (TWT) and bin-spacing of 25 m. The data are  
212 displayed with a SEG reverse polarity, i.e., a downward increase in acoustic impedance  
213 corresponds to a trough (black) reflection, and a downward decrease in acoustic impedance  
214 corresponds to a peak (red) reflection (Figure 1b). We used four wells to constrain the age  
215 and lithology of mapped reflections (Chandon-1, Chandon-2, Chandon-3, Yellowstone).  
216 Check shot data from these boreholes were used to establish the time-depth relationships  
217 for the seismic survey, which we use to convert measurements in TWT to meters  
218 (Supplementary 2). Using this time-depth relationship and given the dominant frequencies  
219 in the interval of interest are  $\sim 30\text{-}40$  Hz, the limits of separability and visibility are estimated  
220 at  $\sim 20 \pm 4$  m and  $3 \pm 1$  m respectively (Magee and Jackson, 2020a). Where reflectors are  
221 separated by a distance below the limit of separability, individual reflectors cannot be  
222 resolved and they will appear as a tuned reflection package (Brown, 2011) (i.e., no  
223 discontinuous deformation will be visible). This resolution is sufficient to enable the  
224 investigation of small errors in our datasets caused by the three elements of interpretation  
225 uncertainty we are interested in.

## 226 **2.2 Geological setting**



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Figure 2: Regional geology and studied faults: a) Overview of the North Carnarvon Basin showing the major faults and sub-basins (adapted from Bilal and MacClay, 2021). The study area, as marked as a blue box, is not located on one of the major faults and as such displays little footwall degradation compared to other faults in the area; b) fault polygons for Horizon H9, highlighting the location of the four quasi-straight faults studied; c) Seismic stratigraphy highlighting the key horizons used in this study; d) strike-perpendicular transects for each fault showing the structural style of each fault; e) along-strike profiles depicting the throw extracted using discontinuous (black) and continuous (i.e., total throw) (blue) cut-offs across the H9 horizons for data extracted using an strike-perpendicular transect. Note that the difference between the two lines represents the magnitude of deformation accommodated by folding and/or sub-seismic scale faulting.

237 The study area is situated in the Exmouth Plateau region of the Northern Carnarvon Basin,  
238 offshore NW Australia (Figure 2a). The region experienced several phases of rifting from the  
239 Late Carboniferous to the Early Cretaceous (Tindale et al., 1998; Stagg et al., 2004; Direen et  
240 al., 2008). The Triassic to recent tectono-stratigraphy of the Exmouth Plateau can be divided  
241 into four main megasequences (Bilal and McClay, 2022). The main phase of WNW-directed  
242 extension, which is associated with deposition of Megasequence-II, resulted in the  
243 formation of north-south striking normal faults, including three of the four faults we focus  
244 on (SF1, 3, 4) (Figure 2b) (Stagg et al., 2004; Bilal et al., 2020; Bilal and McClay, 2022). During  
245 rifting, the basin was sediment-starved, meaning it now contains a relatively condensed  
246 ( $\leq 100$  m thick), largely marine syn-rift succession (Karner and Driscoll, 1999). This  
247 succession is separated from the overlying Late Jurassic marine Dingo Claystone by the end-  
248 Callovian regional unconformity (Tindale et al., 1998; Yang and Elders, 2016; Bilal et al.,  
249 2020; Bilal and McClay, 2022). Tectonic faulting slowed, or stopped, during the Late Jurassic,  
250 but resumed after the formation of the regional unconformity ( $\sim 148$  Ma), being  
251 synchronous with the deposition of the Barrow Group ( $\sim 148$  to 138 Ma) (Gartrell et al.,  
252 2016; Reeve et al., 2016; Paumard et al., 2018). During the second phase of faulting, new N-  
253 S to NW-SW striking, low-throw ( $< 0.1$  km) normal faults developed (Black et al., 2017), with  
254 some of the earlier faults being reactivated (Bilal and McClay, 2022). Continental breakup  
255 occurred during the Early Cretaceous ( $\sim 135$  to 130 Ma) was followed by thermal subsidence  
256 and passive margin development (Robb et al., 2005; Direen et al., 2008; Reeve et al., 2021).

257 In addition to tectonic faults, a series of dyke-induced faults are identified across the study  
258 area (Magee and Jackson, 2020b, 2020a; Magee et al., 2023), of which SF2 is an example.  
259 These dykes are expressed as sub-vertical, low-amplitude zones that disrupt the seismic

260 reflectors within the pre-rift sedimentary succession (Magee and Jackson, 2020b). Several  
261 associated grabens occur directly above and along the dykes, bound by oppositely dipping  
262 faults that intersect with the upper dyke-tip (Magee and Jackson, 2020b, 2020a). These  
263 dyke-induced faults are often long (10s km), show variable dip and displacement  
264 distributions along strike, typically have low maximum throw values (often <50 m), and  
265 terminate upwards at the Base Cretaceous unconformity (Magee and Jackson, 2020b,  
266 2020a; Magee et al., 2023).

267 Four sub-linear faults (SF1-4) were analysed in this study, varying in length from 2.4 to 7.9  
268 km and exhibiting maximum total throw (i.e., throw extracted using continuous cut-offs)  
269 ranging from 32 to 273 m (Fig 2b, d, e). Discontinuous and continuous cut-offs can be  
270 measured for faults SF2-4; however, the average throw across SF1 ( $13 \pm 6$  m) is between the  
271 limit of separability and visibility for the seismic cube. Therefore, only a small number of  
272 picks along this fault display discontinuous throw, meaning we report only data extracted  
273 from continuous cut-offs for this fault. Figure 2e shows the throw distributions of the base  
274 syn-rift horizon (H9), showing variations between faults. Along Horizon 9, faults exhibit  
275 moderate dips ( $52^\circ \pm 8^\circ$ ) with lower dips observed at shallower depth, within the syn-rift  
276 succession ( $H1 = 32^\circ \pm 6^\circ$ ).

277 The studied faults have been buried beneath a thick layer of post-Cretaceous sediments,  
278 which can lead to compaction and rotation of pre-existing structures to shallower dips  
279 (Allen and Allen, 2013). Burial-related compaction will also act to reduce the throw across  
280 syn-sedimentary faults by <15% in sand-shale mixed lithologies (Taylor et al., 2008) similar  
281 to those observed in the study area (Bilal and McClay, 2022). However, decompaction was  
282 not performed in this study due to uncertainties in decompaction parameters, particularly



283 for more deeply buried hanging wall sediments not sampled by well data. As a result, the  
284 extracted values of fault throw, dip and displacement represent minimum estimates. Since  
285 all faults have been buried to a similar depth, the impact of compaction on the extracted  
286 fault properties should be consistent across the datasets, and thus should not affect our  
287 statistical analysis or related conclusions.

### 288 **2.3 Sample strategy**

289 Oblique transects relative to fault strike were created close to the location of maximum  
290 throw at an interval of  $10^\circ$  from perpendicular to the quasi-straight fault. This resulted in a  
291 total of 11 transects for each fault (i.e., from  $0^\circ$  to  $\pm 50^\circ$ ; Fig 1a). Each transect was then  
292 transposed to parallel positions 100 m apart using the arbitrary line tool in DUGInsight to  
293 enable sampling (following the strategy shown in Fig 1a). This means that for oblique  
294 datasets, the along-strike distance between adjacent cut-offs will be  $> 100$  m ( $\sim 156$  m for  
295  $50^\circ$  obliquity) and the exact location on the fault the data is collected from will differ  
296 between transects of different obliquity.

297 At each sample location, we collected discontinuous and continuous cut-off data for 8-13  
298 horizons, depending on the regional continuity of mapped reflectors. For the discontinuous  
299 cut-offs, we identified the location where the horizon intersects the fault in the footwall and  
300 hanging wall (Fig. 1a). In cases where continuous deformation was present, we projected  
301 the regional horizon dip onto the fault plane and measured the intersections in the hanging  
302 wall and footwall (Fig. 1a). Depth values were converted from two-way travel time (TWT) to  
303 metres, and the following fault properties were calculated: throw, heave, dip, and  
304 displacement (Fig. 1a). For dip and displacement, we assumed that the slip vector is dip-

305 parallel (cf. Magee and Jackson, 2020a). Where both discontinuous and continuous cut-offs  
306 are extracted (along SF2-4), we also calculated the ratio between the different types of  
307 throw.

308 To facilitate the plotting and comparison of data between oblique and strike-perpendicular  
309 transects, we determine the equivalent sample location of the cut-offs relative to the strike-  
310 perpendicular transect. This allows us to calculate the distance along the fault that the data  
311 is collected from. For oblique cut-offs, the equivalent strike-perpendicular sample location  
312 will differ for the footwall and hanging wall (Fig 1a). To account for this, we take an average  
313 of the two cut-offs to obtain the equivalent strike-perpendicular sample location.

#### 314 **2.4 Data presentation and statistical analysis**

315 We analyse and present our data on three aspects of fault interpretation uncertainty:  
316 interpreted measurement type, interpretation repeatability, and measurement obliquity.  
317 We examine these aspects using dataset statistics and individual picks. Dataset statistics  
318 involve statistically comparing population means or medians to determine their equivalence,  
319 with our approach outlined in Supplementary 8. To compare datasets based on specific  
320 uncertainty element (e.g., obliquity, cut-off type), we report the average difference  
321 between population means, the average percentage (%) difference, and the proportion of  
322 datasets that can be considered equivalent. Aggregated dataset statistics allow for a direct  
323 comparison of properties with varying dataset numbers (e.g., different faults). Initially, we  
324 combine and discuss the obliquity and repeatability statistics for each fault property (i.e.,  
325 take the average values for absolute difference, % difference, and % of equal datasets of the  
326 discontinuous and continuous datasets). Subsequently, we compare discontinuous and

327 continuous obliquity and repeatability datasets in the same manner as described above and  
328 in Supplementary 8.

### 329 **3. Results and the impact of uncertainties on fault properties**

330 In this section we initially discuss the effect of our three investigated uncertainty elements  
331 (i.e., interpretation repeatability, measurement obliquity, and measurement choice) for  
332 combined extracted fault properties (Section 3.1), before considering their impact on  
333 individual properties (i.e., throw, heave, displacement, dip) (Sections 3.2 to 3.4).

#### 334 ***3.1 All fault properties***

335 *Repeatability:* Among all repeatability datasets, only 46% (283 out of 616) were statistically  
336 equivalent, with an average difference in population mean/median of 16% (Table S1). The  
337 percentage of equivalent datasets varied between faults, ranging from 31% (SF1) to 56%  
338 (SF2), and the difference in population means ranged from 9% (SF2) to 28% (SF1). Repeat  
339 picks showed more uncertainty for H9 (32% equivalent datasets, 20% difference) compared  
340 to H12 (59% equivalent datasets, 13% difference). This trend was consistent across all faults,  
341 although the magnitude of difference caused by horizons varied between faults. Overall,  
342 less than half repeat datasets could be considered equivalent, and the percentage  
343 difference depended on the fault and horizon from which the data was extracted.

Obliquity	a) % of oblique datasets that are statistically equal to the fault perpendicular dataset					Colour scale	b) % error between oblique and fault perpendicular datasets					Colour scale
	SF1	SF2	SF3	SF4	All faults		SF1	SF2	SF3	SF4	All faults	
-50	20%	28%	29%	54%	34%		65%	28%	38%	35%	38%	
-40	45%	19%	38%	64%	40%		26%	26%	26%	22%	25%	
-30	61%	38%	45%	83%	54%		17%	15%	17%	15%	16%	
-20	73%	72%	74%	88%	77%		13%	10%	8%	12%	10%	
-10	80%	84%	91%	95%	89%		16%	6%	4%	9%	7%	
10	73%	58%	66%	86%	70%		13%	10%	10%	11%	11%	
20	61%	88%	56%	85%	73%		19%	6%	12%	14%	12%	
30	39%	38%	42%	88%	52%		5%	15%	16%	18%	19%	
40	57%	30%	31%	58%	41%		21%	22%	25%	29%	25%	
50	30%	23%	22%	64%	34%		43%	41%	42%	25%	38%	
<b>Total</b>	<b>54%</b>	<b>48%</b>	<b>49%</b>	<b>76%</b>	<b>56%</b>	<b>27%</b>	<b>18%</b>	<b>20%</b>	<b>19%</b>	<b>20%</b>		

344

345 Figure 3: The effect of obliquity on extracted fault properties: a) the percentage error of all fault properties  
346 split by fault and obliquity; b) the % of datasets for that fault and obliquity that are statistically equal to the  
347 dataset extracted for that horizon using an strike-perpendicular transect. Colour scales differ between  
348 individual faults and all fault datasets so that red represents datasets that are highly affected by obliquity, and  
349 blue represents datasets where obliquity has a limited effect on extracted fault properties. Note how most  
350 values are blue (smaller errors) where obliquity is  $\leq \pm 20^\circ$ , suggesting that oblique sampling above this value  
351 should be avoided to minimise obliquity related errors.

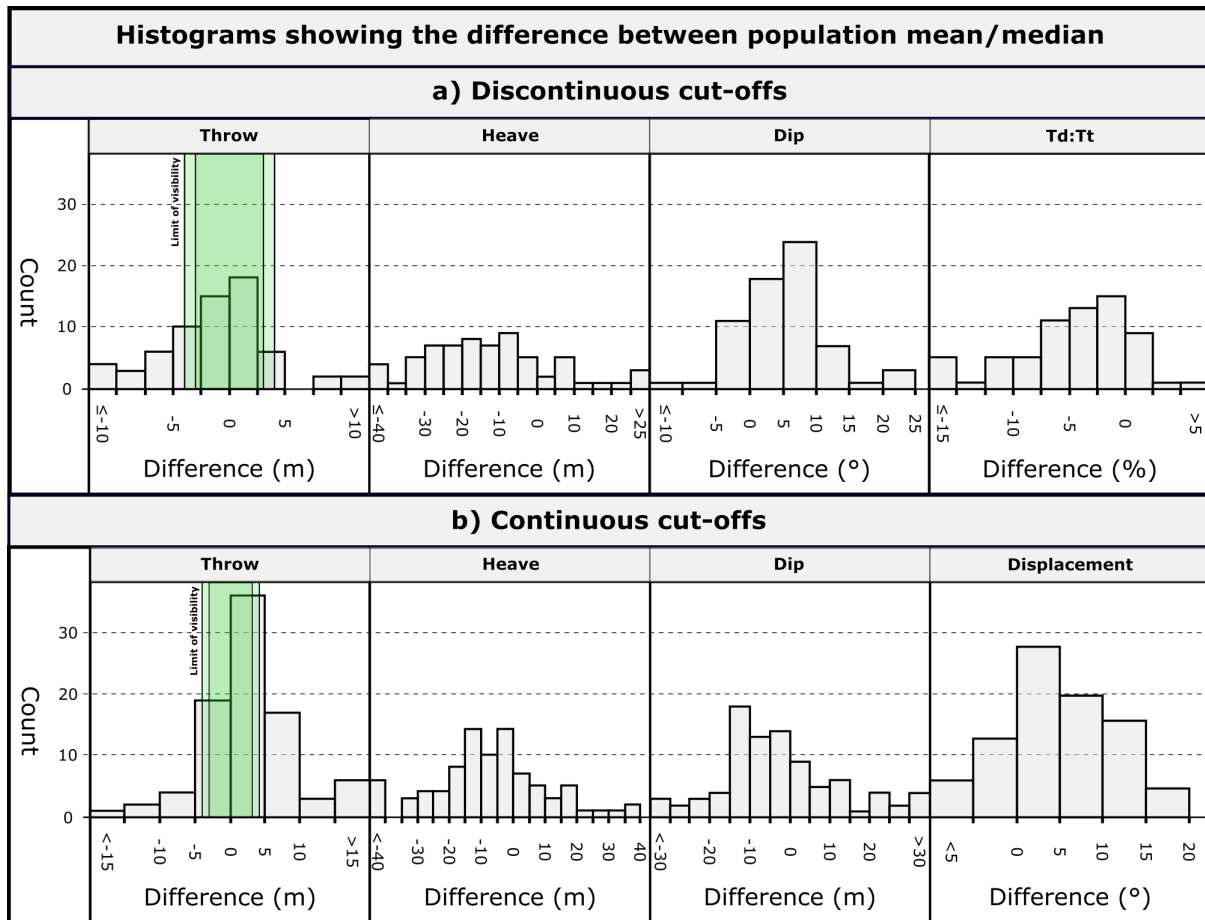
352 *Obliquity:* Greater errors were observed where the degrees of obliquity exceeded 20° (Fig.  
353 3). The same overall pattern was observed for individual faults, although there was more  
354 scatter in the data (Fig. 3). The percentage difference for any given obliquity also varied for  
355 each fault. Some horizons are more prone to obliquity related errors (Table S2), suggesting  
356 that horizon properties (e.g., reflection amplitude) contribute to interpretation errors.  
357 Nevertheless, all horizons exhibited the same general trend of increased uncertainty with  
358 increasing obliquity.

359 *Interpreted cut-off type:* The effect of cut-off type differed between obliquity and  
360 repeatability datasets. For repeat interpretations, little difference was observed in the  
361 uncertainty between continuous and discontinuous cut-offs, with 48% and 44% of datasets  
362 considered equal. Conversely, the obliquity datasets displayed greater uncertainty for  
363 continuous cut-offs (51% equal datasets) when compared to discontinuous cut-offs (63%  
364 equal datasets) (Table 2). The horizon where the cut-offs were measured influenced the  
365 error and uncertainty of the extracted data. Some horizons exhibited low or high percentage  
366 differences and proportion of equal datasets for both measurement types (e.g., Horizons 9  
367 and 10). However, certain horizons showed greater uncertainty in data extracted from  
368 continuous cut-offs (e.g., H13 and H14) (Table S2). This suggests the interpreted cut-off type  
369 has a moderate effect on obliquity datasets and a minor to negligible effect on repeat picks,  
370 with the horizon from which the data is extracted being a key controlling factor on the  
371 magnitude of uncertainty.

372 Overall, when considering all fault properties, the interpreted cut-off type, the magnitude of  
373 obliquity, and the fault and horizon from which the data is extracted, are identified as key  
374 factors controlling interpretational uncertainty. To assess the effect of obliquity on

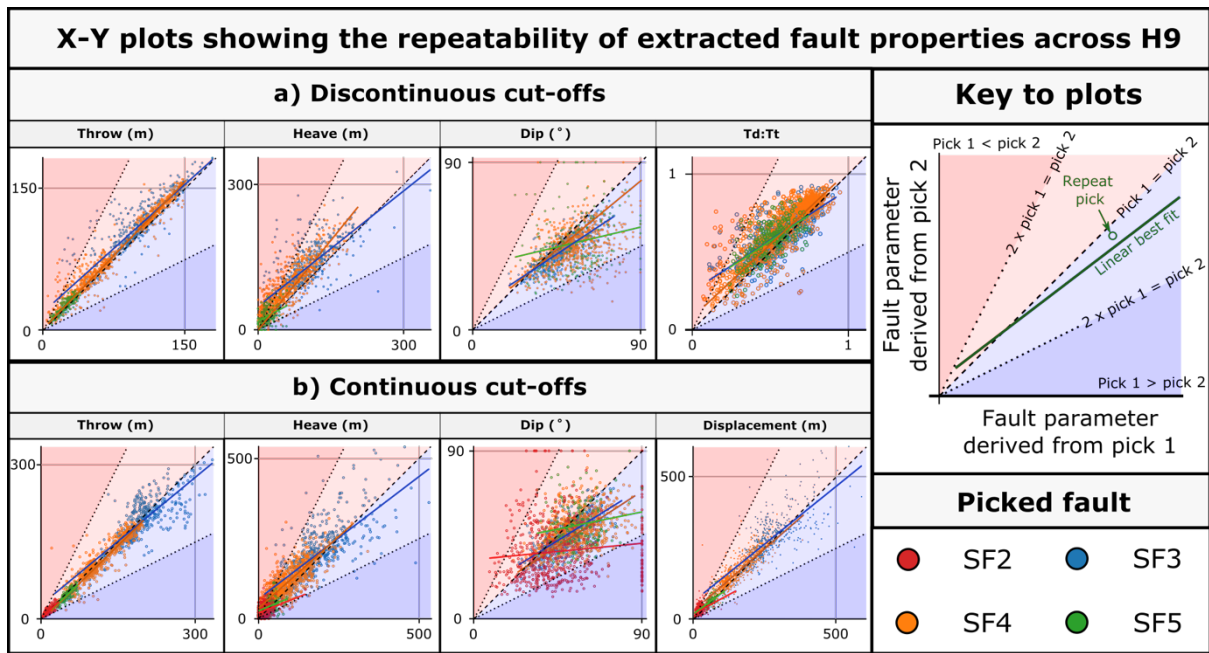
375 repeatability, it is important to separately considered the influence of uncertainty factors on  
 376 each fault property separately. This approach allows for the isolation of factors and the  
 377 comparison of obliquity errors to the theoretical errors introduced in Figure 1c.

378 **3.2 Throw**



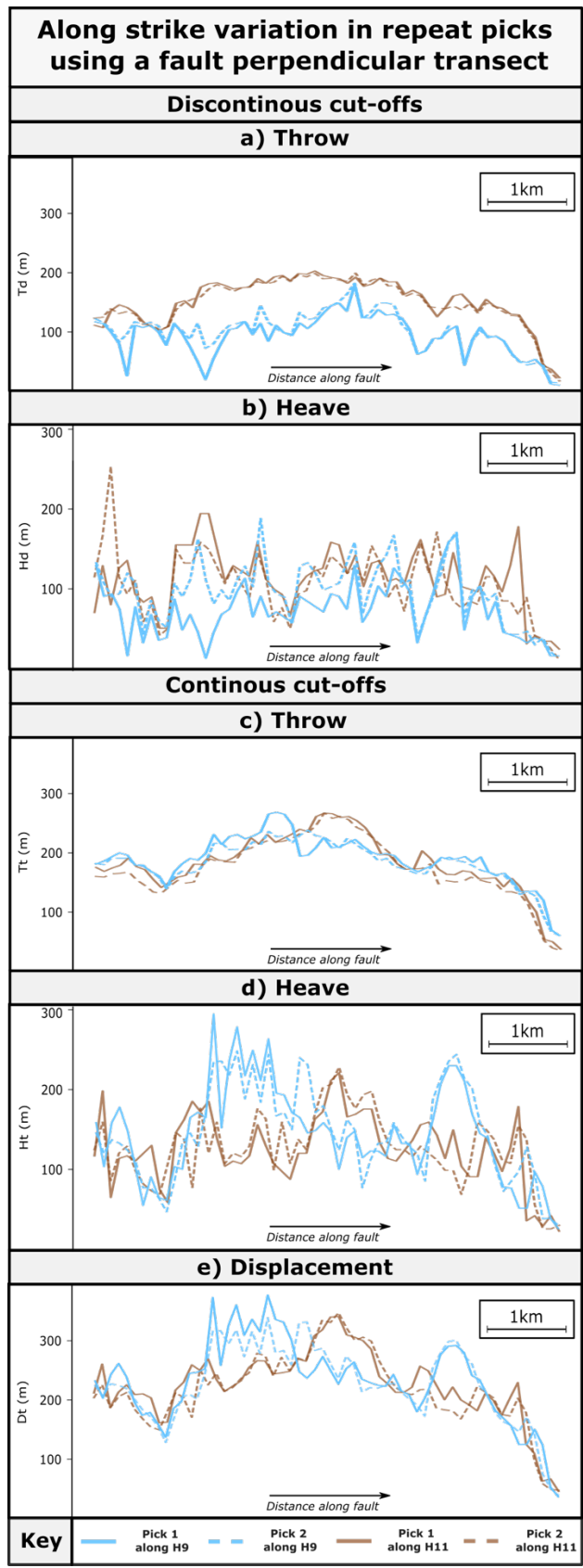
379

380 Figure 4: Histograms to summarise the mean/median difference in fault properties extracted from  
 381 discontinuous (a) and continuous (b) cut-offs between repeat picks at identical points, across a series of  
 382 horizons and faults. Each 'count' represents a population mean or median for all data points collected for a  
 383 single horizon across a single fault. The green box on the throw histograms highlights the minimum and  
 384 maximum limit of visibility for the seismic cube. Differences within this box can be considered as below the  
 385 resolution limit, and therefore not caused by repeatability errors. Note that for all extracted properties,  
 386 continuous measurements show lower repeatability than discontinuous measurements.



387

388 Figure 5: x-y plots showing the variations in repeatability in discontinuous (a) and continuous (b) fault  
 389 properties extracted from horizon H9 across all faults. If the interpretation is repeatable, then all points should  
 390 plot along the black dashed x-y line; however, where picks differ the points will plot within the red or blue  
 391 zone depending on the ratio of pick values. Data plotting in the darker red or blue zones represent data where  
 392 one pick is over double the other. Note how the difference between picks varies between faults, extracted  
 393 property, and the magnitude of the extracted property. Additionally, throw shows less repeatability error than  
 394 heave.



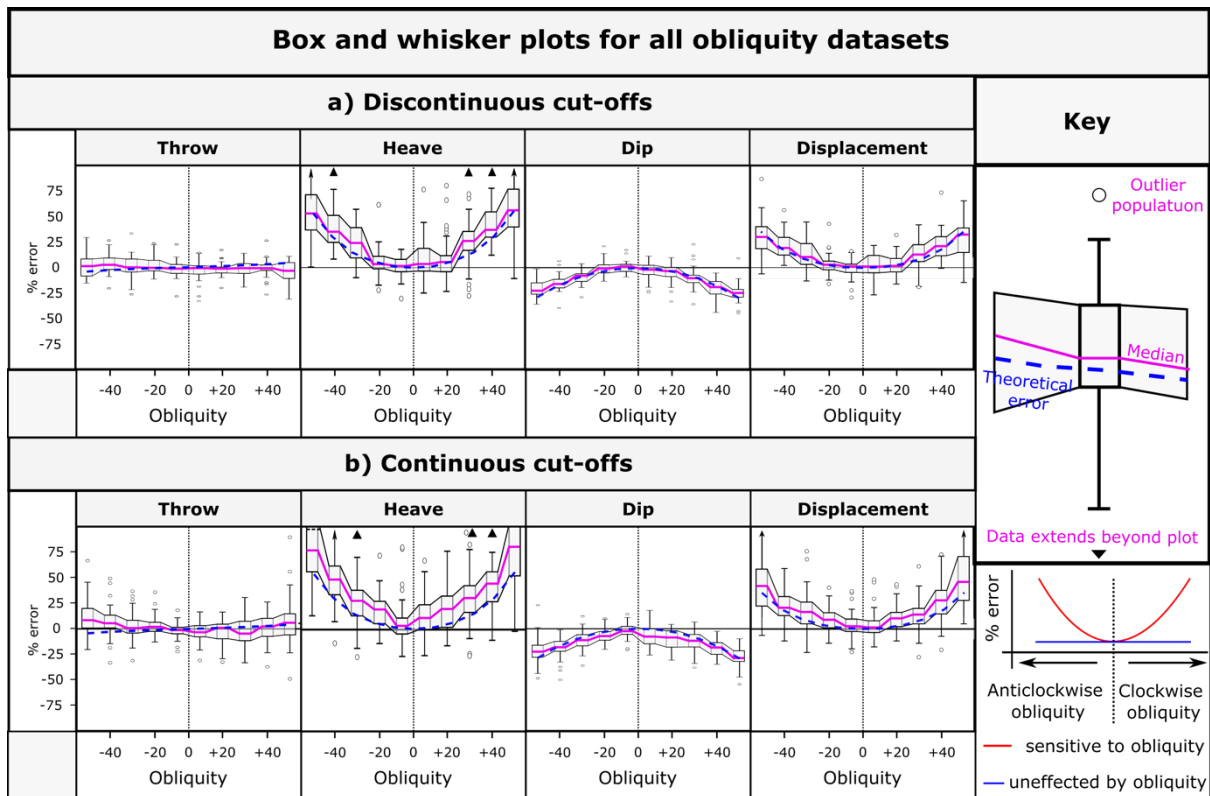
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Figure 6: Along-strike profiles showing the repeatability of fault property extracted from H9 and H12 using a strike-perpendicular transect along SF2. Pick one is shown as a solid line, whilst pick two is dashed and each horizon is a different colour. Note how the general shape of the profiles are similar between picks; however, the difference can be locally quite large.

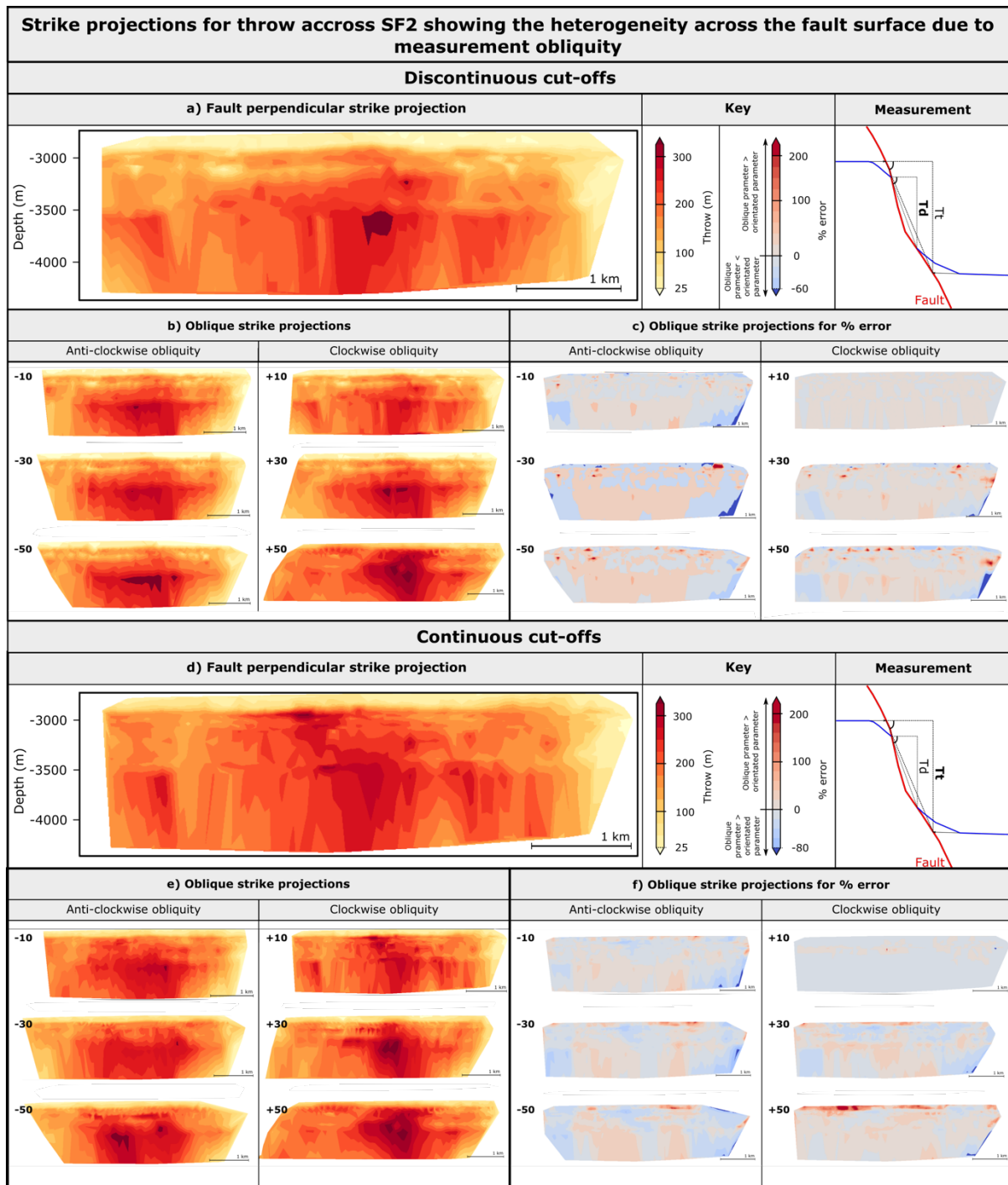


400 *Repeatability:* Throw exhibits low uncertainty across all repeatability datasets (Table S1, Fig  
401 4, 5), with 60% of datasets considered equivalent, and there being only small differences in  
402 means (5m, 7.4%). The mean absolute difference differs between faults, with differences  
403 across all faults typically below the estimated seperability limit of the seismic data (Table  
404 S1). Whereas differences in population means are minimal, this was not the case for all  
405 picks along the fault. For example, Figure 6a and 6c shows multiple locations where the  
406 difference between picks on throw profiles extracted from discontinuous and continuous  
407 cut-offs exceeds 22 m. The profiles also highlight sections of the fault with high and low  
408 differences between picks, and that the location of these sections are not consistent  
409 between horizons (i.e., H9 may show high variability at a particular along-strike location  
410 where H12 shows low variability, and vice versa). This suggests that whereas horizons have  
411 a limited effect on population statistics, they do influence individual picks. Overall,  
412 repeatability errors primarily affect throw at a local scale (e.g., <500 m) and have a  
413 negligible effect on population statistics.



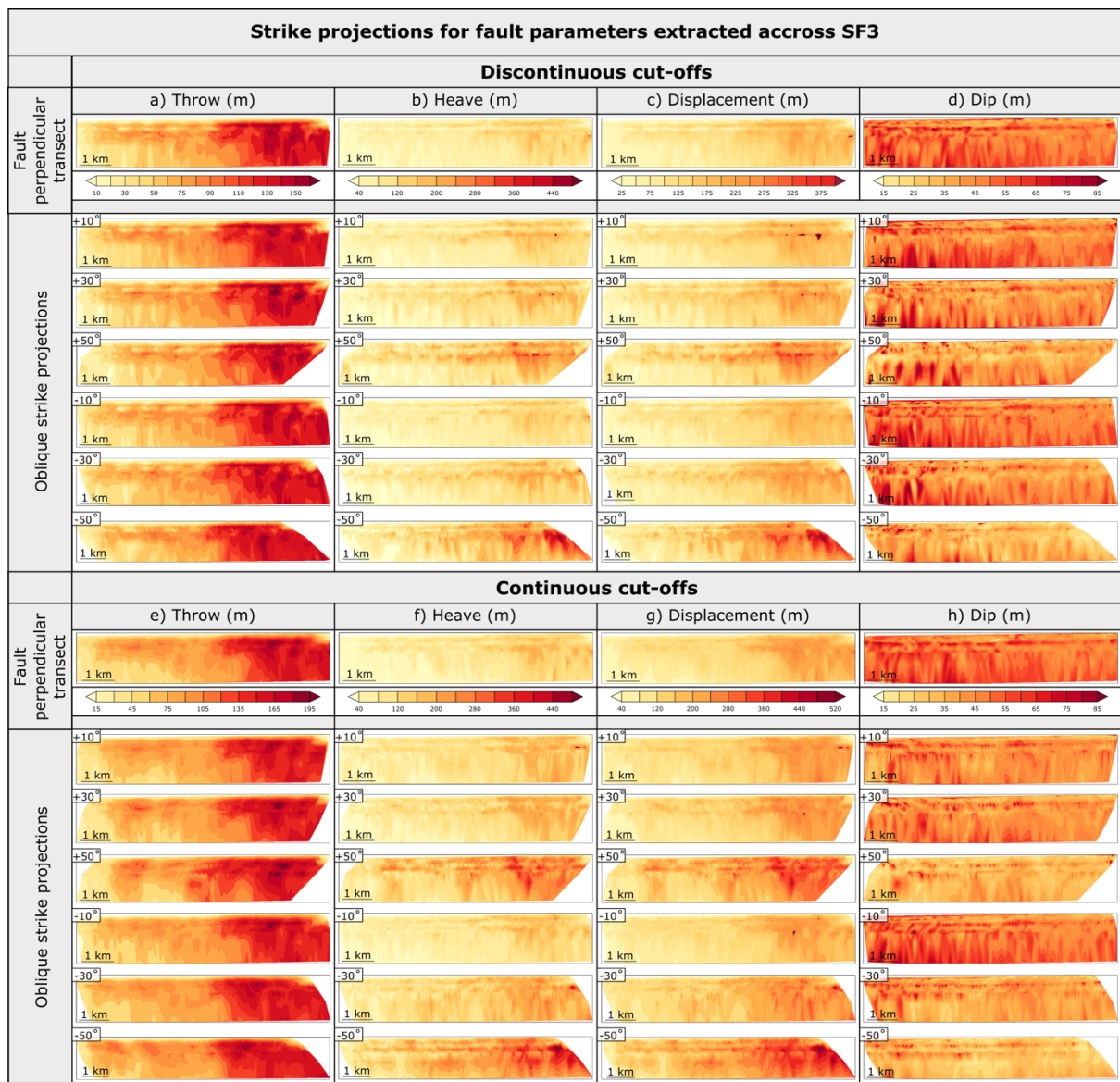
414

415 Figure 7: The effect of obliquity on individual fault properties extracted from discontinuous (a) and continuous  
 416 (b) cut-offs. Box and whisker plots are constructed from the population mean/medians of individual horizons  
 417 picked across individual faults. Note how obliquity has the greatest effect on heave, and therefore dip and  
 418 displacement, suggesting that additional care needs to be taken when sampling fault cut-offs for these  
 419 properties. Furthermore, the median % error for all datasets typically exceeds the theoretical value for  
 420 continuous cut-offs, suggesting some of the error is caused by non-geometrical effects.



421

422 Figure 8: Strike projections showing the along-strike and down-dip variability caused by oblique sampling for  
 423 throw extracted using discontinuous (a-c) and continuous (d-f) cut-offs along SF2. Data extracted from strike-  
 424 perpendicular (a & d) and oblique (b & e) transects are shown, along with the % error associated with the  
 425 oblique measurement (c & f). Note how the distribution and % error of throw depends on both the direction  
 426 and magnitude of measurement obliquity. Strike projections are created using a python script that undertakes  
 427 a linear interpretation between known datapoints, resampled to a regular sample spacing to enable the %  
 428 difference between datasets to be calculated.



429

430 Figure 9: Strike projections showing the along strike and down dip variability of all studied fault properties  
 431 calculated from discontinuous (a-d) and continuous (e-h) cut-off data extracted from SF3. Note how throw is  
 432 less sensitive to measurement obliquity than heave and displacement and that dip shows high spatial  
 433 variability across all datasets.

434 *Obliquity:* Overall, throw typically displays increasing uncertainty as the obliquity increases

435 (Table S2, Fig. 7); however, the error across the range of obliquity is low. Where individual

436 faults are considered, not all faults show greatest error at high degrees of obliquity (e.g.,

437 SF1, SF4; Table S3). The picked horizon also has a large impact on the % difference for

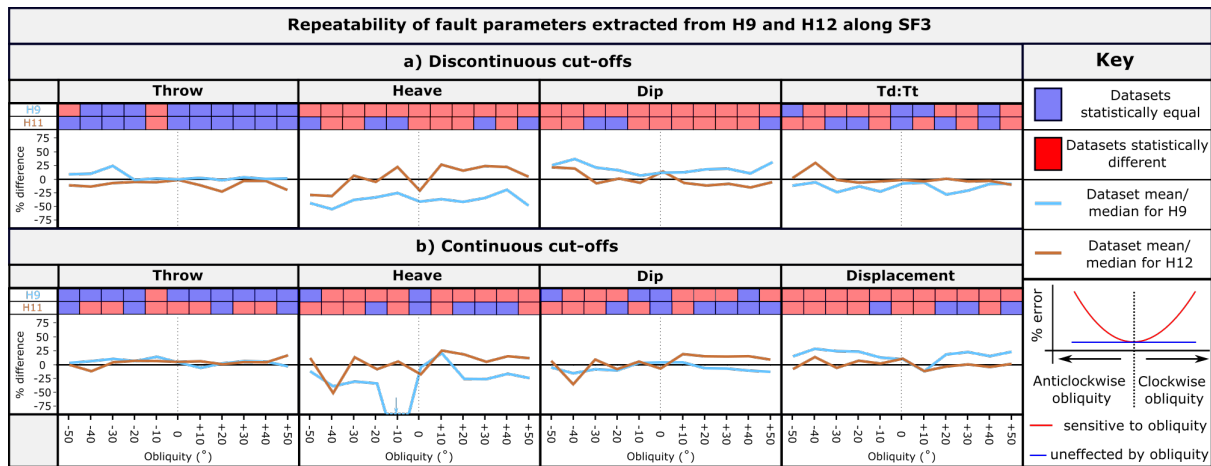
438 throw, although the overall trends of increasing uncertainty with increasing angles of

439 obliquity are still observed. The distribution of throw across the fault plane varies at

440 different degrees of obliquity (Figure 8, 9a, 9e) and can be over- or under- estimated at  
441 different locations, with % errors locally exceeding 100%. Overall, our data suggests that  
442 horizon properties (e.g., acoustic impedance, amplitude of the reflection) strongly affect the  
443 measurement of throw and the effect of measurement obliquity depends on the fault the  
444 data is extracted from. Obliquity errors exceed the theoretical geometrical errors (Figure 1c)  
445 for throw for faults by  $<\pm 5\%$ , with some horizons exceeding the expected error by a factor of  
446 5 (Figure 7). The repeatability of throw does not appear to be sensitive to the degrees of  
447 obliquity as highlighted by: i) the distribution of statistically equal datasets and ii) given  
448 angle of obliquity can show both high and low % differences for the same cut-off type and  
449 horizon (Figure 10).

450 *Interpreted cut-off type:* The interpreted cut-off type affects the magnitude of repeatability  
451 and obliquity errors. Average repeatability errors for throw are marginally higher for  
452 continuous cut-offs (6.0 m, 9%) compared to discontinuous cut-offs (4.0 m, 5%) (Table S1).  
453 In most cases, H9 showed greater errors compared to H12 for both cut-off types, with the  
454 only exception being continuous cut-offs extracted from SF2 (Table S1). The magnitude and  
455 location of along-strike variations between individual picks differed between horizons and  
456 cut-off type (Fig 6). Indeed, there are examples where throw calculated from the first  
457 discontinuous cut-off pick exceeds the second, with the opposite being true for continuous  
458 cut-offs. For oblique transects, a far greater proportion of datasets are equal (91%), with a  
459 lower % error (7%) for discontinuous cut-offs when compared to continuous cut-offs (75%,  
460 11%; Table S7, S8). The magnitude of error increases for low-throw faults where the same  
461 horizons show large and small error, albeit with continuous cut-offs showing a greater  
462 errors. The distribution of throw along- and down- dip is highly variable at different degrees

463 of obliquity (Fig 8, 9a, 9e), with the distribution and magnitude of throw depending on the  
 464 direction and degrees of obliquity. Additionally, the patterns are not constant between  
 465 discontinuous and continuous cut-offs, as shown by the location of throw maxima in Figure  
 466 8b and e.



467

468 Figure 10: Repeatability of fault picks for fault parameters extracted using discontinuous (a) and continuous (b)  
 469 cut-offs along horizons H9 and H12 for SF3. The plots show whether pick one and pick two can be considered  
 470 equal, and the mean % difference between each pick. Note how there is no correlation between obliquity and  
 471 repeatability error, suggesting that obliquity and repeatability are independent sources of error for this  
 472 dataset.

### 473 **3.2 Heave**

474 *Repeatability:* Heave shows high uncertainty across all repeat picks (Fig. 4, 5), with only 37%  
475 of datasets considered equivalent and a reasonable difference between population  
476 mean/median values (17.8 m, 27%). SF2 is less prone to repeatability errors when compared  
477 to other faults (Fig. 5; Table S1). Repeatability errors are greater at lower values of heave, as  
478 indicated by the higher % difference for SF1 and the x-y plots in Figure 5. Along-fault heave  
479 profiles (Fig. 6b, d) show a large variability in the magnitude and difference between picks  
480 for adjacent measurement positions (i.e., a large amount of noise in the data). Errors are not  
481 consistent between horizons or measurement types and the difference between picks can  
482 locally exceed 50 m (Fig 6b, d). This suggests that repeatability errors in fault and horizon  
483 picks and how these vary along-strike effect the extraction of heave, creating uncertainty in  
484 heave measurements.

485 *Obliquity:* The degree of obliquity has a large effect on heave, with uncertainty increasing  
486 with increasing degrees of obliquity (Table S4). The mean absolute difference in heave  
487 exceeds the average difference for repeat picks at obliquities of  $\pm 30^\circ$  and shows a maximum  
488 difference of 54.3 m (72%). This trend is observed across all faults; however, each fault  
489 shows a different magnitude of error and proportion of equal datasets, with SF2 and SF3  
490 appearing to be most prone to obliquity errors. When compared to theoretical geometric  
491 errors (Figure 1c, 7) most datasets show % errors that exceed the expected values by  
492 between 5% and 10%, with the heave measurement for some horizons being particularly  
493 prone to high errors. The effect of obliquity on the distribution of heave across the fault  
494 plane depends on the fault and the direction and degree of obliquity (Figure 9b, f). For all  
495 faults, the overall trend is that as obliquity increases, the proportion of positive % difference

496 also increases (irrespective of the absolute magnitude of heave). On top of these general  
497 trends however there is a large amount of scatter which for some faults (e.g., SF1) lead to a  
498 high spatial variability in heave (Figure 9b, f). For all datasets, the angle and direction of  
499 obliquity does not appear to affect the % difference between picks (Fig 10). Overall, the  
500 degree of obliquity greatly affects the measurement of heave, with the error compounded  
501 by large differences between along-strike sample locations.

502 *Interpreted cut-off type:* The interpreted cut-off type has a large effect on obliquity  
503 statistics, although the effect on repeatability depends on the fault which the data are  
504 extracted from (Table S1, Figure 10). For repeat picks, heave extracted from continuous cut-  
505 offs shows a smaller difference in population mean (16.5m, 26%) and a higher proportion of  
506 equivalent datasets (41%) compared to discontinuous cut-offs (19.0 m, 33% and 28%  
507 respectively). However, this is not the case for SF2 where the opposite is true. Both cut-off  
508 types show large along-strike variability; however, continuous cut-offs show less differences  
509 between adjacent sample locations than discontinuous cut-offs (Figure 6). The  
510 measurement of continuous cut-offs greatly increase the % error in obliquity statistics, with  
511 the error nearly always greater than discontinuous cut-off data and the theoretical  
512 geometrical error (Figure 1c, 7). Smoother profiles observed in the repeatability datasets are  
513 mirrored where heave is calculated from continuous cut-offs, with these strike projections  
514 appearing less noisy than the discontinuous cut-offs (Figure 9b, f).

### 515 **3.3 Displacement**

516 *Repeatability:* Displacement shows moderate uncertainty across all repeat picks (Table S1,  
517 Figures 4, 5) with 47% of datasets considered equivalent and an absolute difference of 15.3



518 m (16%). The level of uncertainty differed between faults, with SF1 displaying the lowest  
519 number of equivalent datasets (27%) and greatest % error (31%). The along-strike  
520 displacement profiles (Figure 6e) show the same along-strike variability observed in the  
521 heave profile, but with a lower magnitude of variability caused by the low variation in  
522 throw. Sections of faults that show high, or low, differences between picks are more  
523 laterally extensive (up to 1.5 km) than heave and match more closely the differences  
524 observed in throw (Figure 6e).

525 *Obliquity:* Displacement exhibits increasing uncertainty at higher degrees of obliquity,  
526 surpassing repeatability errors at  $\pm 30^\circ$  (Table S5). The pattern observed in heave strongly  
527 impacts the population statistics, with SF2 and SF3 showing the lowest proportion of  
528 consistent datasets. Displacement varies across fault planes, with increasing magnitude at  
529 higher obliquities (Figures 7, 9c, g). Like the heave datasets, the base syn-rift displays a  
530 pronounced displacement maxima and significant variability between along-strike data  
531 points (Figure 9c, g). Measurement obliquity does not systematically effect the repeatability  
532 of fault displacement (Figure 10). Overall, displacement is more susceptible to the degree of  
533 obliquity than throw, with uncertainty in heave influencing the magnitude of displacement  
534 and how this varies along the length of the fault.

535 *Interpreted cut-off type:* Interpreted cut-off type impacts repeatability and obliquity errors  
536 differently (Table S1, Figure 7, 10). Displacement calculated from discontinuous cut-offs  
537 exhibits greater differences between picks, and a lower proportion of equivalent datasets  
538 compared to continuous cut-offs (Table S1). Both cut-off types show increasing uncertainty  
539 with increasing degrees of obliquity; however, the magnitude of difference is greatest for  
540 continuous cut-offs (Figure 7). However, for some faults, highly oblique continuous cut-off

541 datasets may exhibit low uncertainty (e.g., SF4, Table S12) and the displacement strike  
542 projections constructed for continuous cut-offs are smoother than discontinuous cut-offs  
543 (Figure 9c, g). Despite this, repeatability errors are usually exceeded where measurement  
544 obliquity is at or above  $\pm 30^\circ$ . Overall, interpreting continuous cut-offs reduces the  
545 repeatability of displacement on some horizons and measurement obliquity greatly affects  
546 continuous datasets .

### 547 **3.4 Dip**

548 *Repeatability:* Of all the fault properties, dip exhibits the highest uncertainty in repeat picks  
549 (Figure 4, 5, Table S1), with only 32% of datasets considered equivalent and an absolute  
550 difference of  $6.6^\circ$  (16%). The fault from which the data is extracted from influences the  
551 magnitude of uncertainty in dip, with SF1 showing a mean absolute difference of  $9.2^\circ$ ,  
552 whereas SF2 only has a difference of  $3.2^\circ$ . Unlike heave and displacement, the magnitude of  
553 dip appears to only have a weak effect on repeatability (Figure 5). Individual picks on SF1  
554 show very large differences, with several picks having a dip of  $90^\circ$  (indicating zero heave),  
555 whereas the paired pick ranges from  $\sim 15^\circ$  to  $\sim 65^\circ$  (Fig 5). These picks are taken from where  
556 there are very small offsets along SF1, thus heave is likely below the resolution the data is  
557 extracted (minimum heave values of  $\sim 6$  m). Due to the compound errors caused by the  
558 uncertainty in heave, dip shows low repeatability and along-strike variations can be masked  
559 by measurement errors (Figure 9d, h).

560 *Obliquity:* Fault dip is strongly affected by measurement obliquity, with repeatability errors  
561 exceeded for most oblique datasets (Figure 7, Tables S1, S5). In a similar manner to  
562 displacement, the effect of uncertainties on heave strongly affects the calculation of dip

563 (i.e., SF2 and SF3 showing the lowest % of equal datasets), although greater uncertainty is  
564 observed for the latter (Table S5). Repeatability errors are exceeded where the angle of  
565 obliquity exceeds  $\pm 20^\circ$  for all faults, apart from SF1 where repeatability errors were  
566 particularly high (Table S5). The distribution of dip across the fault plane displays a high  
567 degree of variability between points leading to noisy strike-projections (Figure 9d, h).  
568 Despite this, general trends are observed across all obliquities (e.g., shallower dips at the  
569 syn-rift horizon (H9)); however, the magnitude of dip is lower at higher degrees of obliquity.  
570 In most cases, there is no correlation between the degree of obliquity and repeatability  
571 (Figure 10).

572 *Interpreted cut-off type:* The choice of cut-off type affects repeatability and obliquity  
573 datasets differently. Across all faults, the choice of cut-off type does not affect the  
574 repeatability of dip, with similar differences and percentage of equal datasets observed.  
575 Whether discontinuous or continuous cut-offs show greater uncertainty depends on the  
576 fault and horizon the data is collected from, with H9 broadly showing greater uncertainty  
577 than H12. Where individual picks are considered, there is more scatter where continuous  
578 cut-offs are measured (Figure 5), with many picks exceeding 100% difference. Despite this,  
579 profiles constructed from continuous cut-offs show less along-strike variability (Figure 5).  
580 Measurement obliquity affects both cut-off types; however, the effect is greater where  
581 continuous cut-offs are measured (Table S13, S14). This trend is observed across all faults,  
582 however, the magnitude of error and difference between cut-off types depends on the fault  
583 and the horizon that the data are extracted from. It is difficult to assess the effect of cut-off  
584 type on the distribution of dip across the fault plane as both exhibit a highly variable  
585 distribution of dip across the fault plane for all datasets (Figure 9d, h). Overall, no systematic

586 difference between cut-off type is observed for the the repeatability of dip and whereas the  
587 measurement of continuous cut-offs increases errors associated with obliquity, datasets are  
588 very noisy and it is not possible to deduce along-fault trends.

### 589 ***3.5 Summary of results***

590 Our data show that fault properties extracted from fault-horizon cut-offs are variably  
591 influenced by interpretation repeatability, measurement obliquity, and the measured cut-  
592 off type (Table 1). When all properties were considered together, less than half of the  
593 datasets could be considered statistically equal. Errors due to measurement obliquity were  
594 found to greatly increase when obliquity exceeded  $\pm 20^\circ$ . Measurements of continuous cut-  
595 offs showed greater errors than discontinuous cut-offs in both the obliquity and  
596 repeatability datasets. The magnitude of error was also influenced by which fault and  
597 horizon the data were collected from.

598 When individual fault properties are considered, throw is found to be the least sensitive  
599 fault property to the studied interpretation factors, and heave the most sensitive (Table 1).  
600 The uncertainties in throw increased when measurement obliquity exceeded  $\pm 20^\circ$ ; however,  
601 the magnitude of uncertainty was often below or close to the limit of separability of the  
602 seismic cube (i.e., not a significant source of error) apart from at a local (<500 m) scale.  
603 Heave was found to show statistically significant differences for both repeat and oblique  
604 datasets. Differences were particularly evident at a local scale and caused strike projections  
605 and along-strike profiles to be noisy. The fault and horizon cut-off data were extracted from  
606 had a subsidiary effect on extracted fault properties (e.g., heave and throw) and the  
607 magnitude of obliquity did not appear to compound repeatability errors for any fault

608 property. Across most fault properties, continuous cut-off picks were more susceptible to  
609 repeatability and obliquity errors. Despite showing greater uncertainty for continuous picks,  
610 continuous datasets show less along-strike variability between adjacent picks, leading to  
611 smoother along-fault profiles and strike projections. The ratio of throw extracted from  
612 discontinuous to continuous cut-offs indicates that the errors from the continuous and  
613 discontinuous datasets were compounded where the properties were compared, and the  
614 noisiness of the discontinuous profiles lead to large variations in the ratio between  
615 discontinuous and continuous throw between adjacent picks across a fault. Uncertainty in  
616 heave also increases uncertainty in displacement and dip (as these properties are  
617 geometrically derived using heave), with the effect particularly noticeable in a long-fault  
618 profiles and strike projections. For dip, it was found that this local scale uncertainty often  
619 masked overall trends in dip and caused profiles and strike projections to be very noisy  
620 (Figure 9d, h). In the following section, we investigate how the aforementioned uncertainties  
621 in cut-off derived fault properties affect the assessment of fault transmissivity and the  
622 evolution of throw- and slip-rate through time.

Fault property	Repeatability	Measurement obliquity	Interpreted cut-off type
<b>All fault properties</b>	Repeat datasets are often not equivalent, with the % difference depending on the fault and horizon that the data is extracted from.	Error is found to increase where obliquity exceeds $\pm 20^\circ$ . The fault and horizon that the data is collected from also has a subsidiary effect.	Greater uncertainty in continuous cut-offs compared to discontinuous; however, the difference is low to moderate for obliquity datasets and negligible for repeat picks.
<b>Throw</b>	High repeatability  Errors only significant at a local scale (i.e., <500 m).	Moderate sensitivity  Errors increase as obliquity increases and are larger than predicted.  Overall differences in population means are generally small.	High sensitivity  Uncertainty increases in faults with low throw. Throw distribution is variable and influenced by the horizon and measurement obliquity.
<b>Heave</b>	Low repeatability  Depends on the fault, horizon, and along-strike position that the data is collected from.	High sensitivity  Errors are compounded due to differences between along-strike sample locations.	High sensitivity  Continuous cut-off data exhibits smoother along-strike profiles but with increased errors at high obliquities.
<b>Displacement</b>	Moderate repeatability  Along-strike patches of low repeatability more closely	High sensitivity	Moderate sensitivity

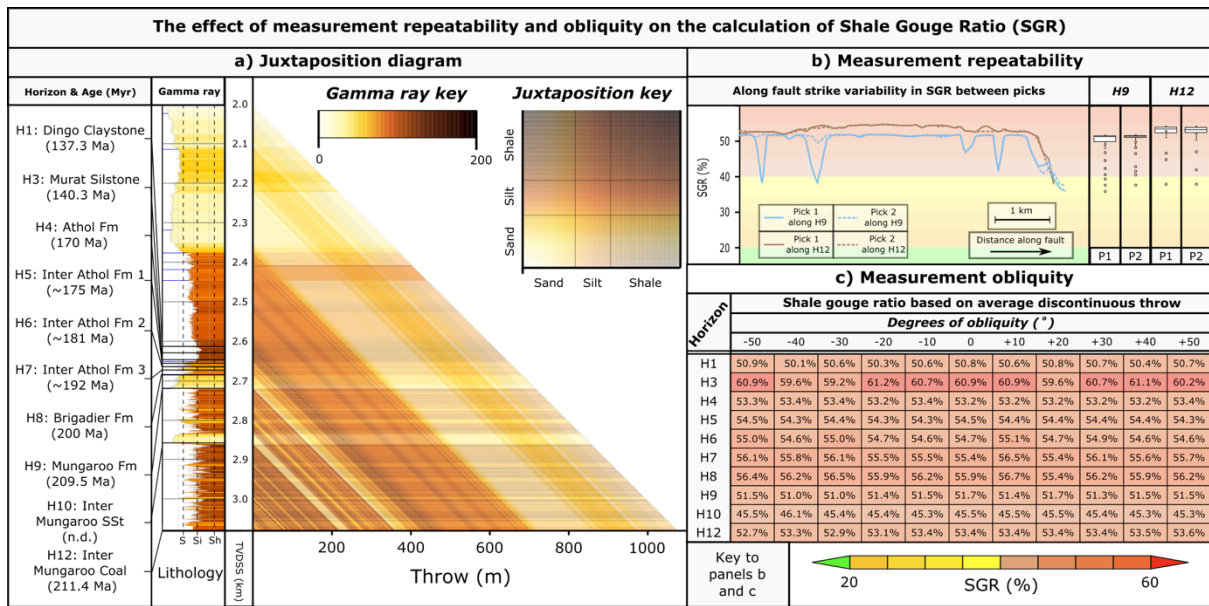
	match the shape of the throw profile.	Due to high uncertainty in heave influencing the distribution and magnitude of displacement.	Measurement obliquity greatly effects continuous cut-off datasets, whilst also causing strike projections to be smooth.
<b>Dip</b>	Low repeatability Along-strike variations are often obscured by measurement errors	High sensitivity Overall dip increases with obliquity, and there are large spatial variations across the fault plane.	Low sensitivity Datasets are very noisy and it is not possible to deduce along-fault trends.

623 Table 1: Summary of the effects of interpretation uncertainty on the extracted fault properties. Note how  
624 heave is more prone to interpretational uncertainty than throw, which also affects the extracted dip and  
625 displacement.

#### 626 **4 Effect of obliquity and repeatability uncertainty on inferred fault properties**

627 Data extracted from 3D seismic reflection surveys are used across a range of scientific  
628 studies, and therefore the sources of uncertainty presented in this paper have implications  
629 for the geological interpretations that arise. Drawing on data from SF2, we discuss the  
630 implications for two such interpretations, fault transmissivity which is important for  
631 quantifying fluid flow, and slip/throw rates used to inform seismic hazard assessment.  
632 Throw extracted from discontinuous cut-offs is used for fault transmissivity and throw-rate  
633 calculations, whereas continuous cut-offs are used when assessing the evolution of slip-rate  
634 to account for non-discrete deformation (e.g., monocline development). These examples  
635 demonstrate the practical effect of the investigated uncertainty elements on fault property  
636 predictions.

##### 637 ***4.1 Fault transmissivity interpretation using discontinuous deformation***



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Figure 11: The effect of repeatability and obliquity on the estimation of shale gouge ratio for fault transmissivity studied. Note how for this fault all values are above the sealing threshold, and the effect of repeatability and obliquity related errors are only locally important.

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Fault transmissivity is a measure of the permeability of a fault zone, and it is important to

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quantify for hydrocarbon exploration, CO<sub>2</sub> sequestration and the geological disposal of

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nuclear waste. A common way to assess the fault transmissivity is to calculate the shale

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gouge ratio (SGR, e.g., Yielding et al., 2002), which is calculated by considering the

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proportion of shale that has moved past a given point on a fault using the following

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equation:

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$$SGR = \frac{\sum(V_{shale} \times \Delta z)}{throw}$$

649

( $V_{shale}$  = proportion of shale in a given rock volume,  $\Delta z$  = bed thickness)

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A higher SGR ratio suggests that there is a high proportion of phyllosilicates within the fault

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core (e.g., Foxford et al., 1998; Yielding, 2002) and a SGR of 15-20% has been suggested as a

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sealing limit (Yielding, 2002). We use the Chandon-1 well to calculate  $V_{shale}$  of the succession

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and construct a juxtaposition diagrams (Figure 11a). We calculate SGR for each point along

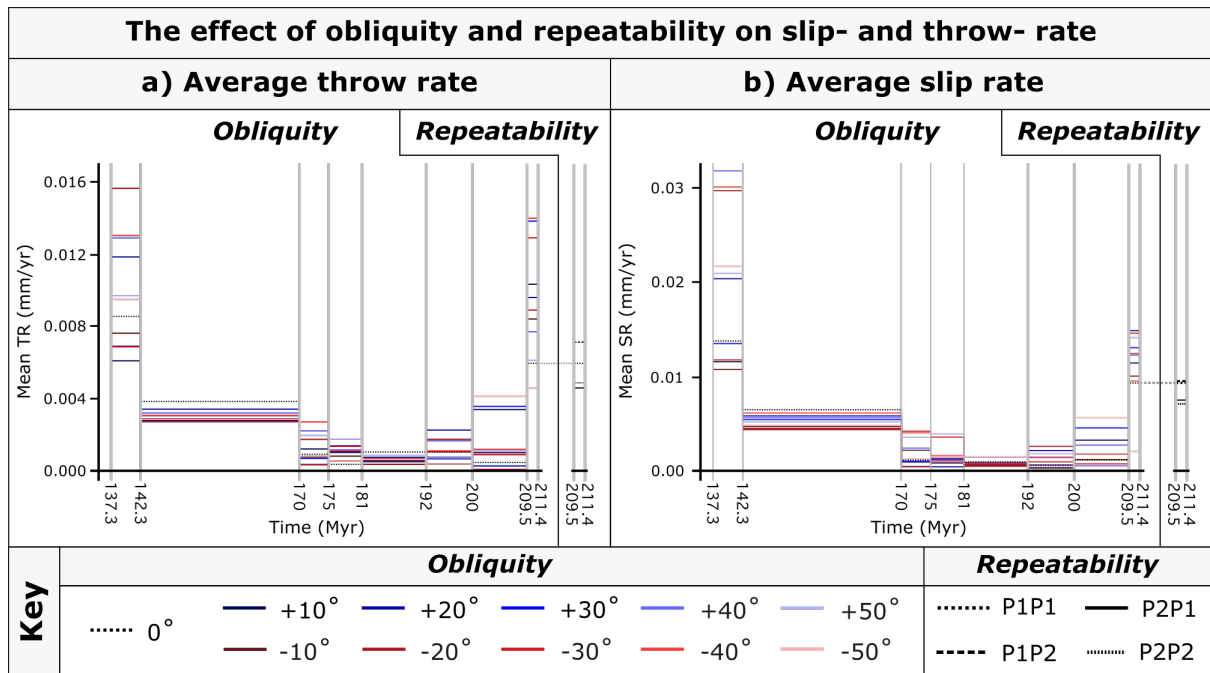
654 the strike-perpendicular repeat picks of Horizons H9 and H12, and use the mean throw for  
655 obliquity datasets to compare how repeatability and obliquity errors influence the  
656 calculations.

657 Our assessment shows that repeatability and obliquity errors have only a minor impact on  
658 the SGR calculation for fault transmissivity (Figure 11b, c), with the  $V_{\text{shale}}$  of the intervening  
659 succession playing a more significant role in the calculation. The interval of interest between  
660 H1 and H12 is characterised by high  $V_{\text{shale}}$  values (average = 50%). As a result, most offsets  
661 exhibit siltstone-shale or shale-shale juxtapositions (Figure 11a). Despite some differences  
662 between repeat datasets, the mean values of SGR for H9 and H12 show negligible  
663 variations, with larger differences observed only locally over short distances (<500 m).

664 Obliquity datasets also demonstrate variations in SGR between horizons, but the differences  
665 between datasets for the same horizon are low (Figure 11c). One case where the SGR may  
666 be more sensitive to uncertainties in throw is where the sandstone content of the  
667 succession is close to the SGR sealing threshold, and as such a small change in throw could  
668 push the SGR above the threshold. However, in general, repeatability and obliquity related  
669 errors can be considered insignificant when investigating fault transmissivity.

670 ***4.2 Throw and slip on faults over time using discontinuous and continuous deformation***

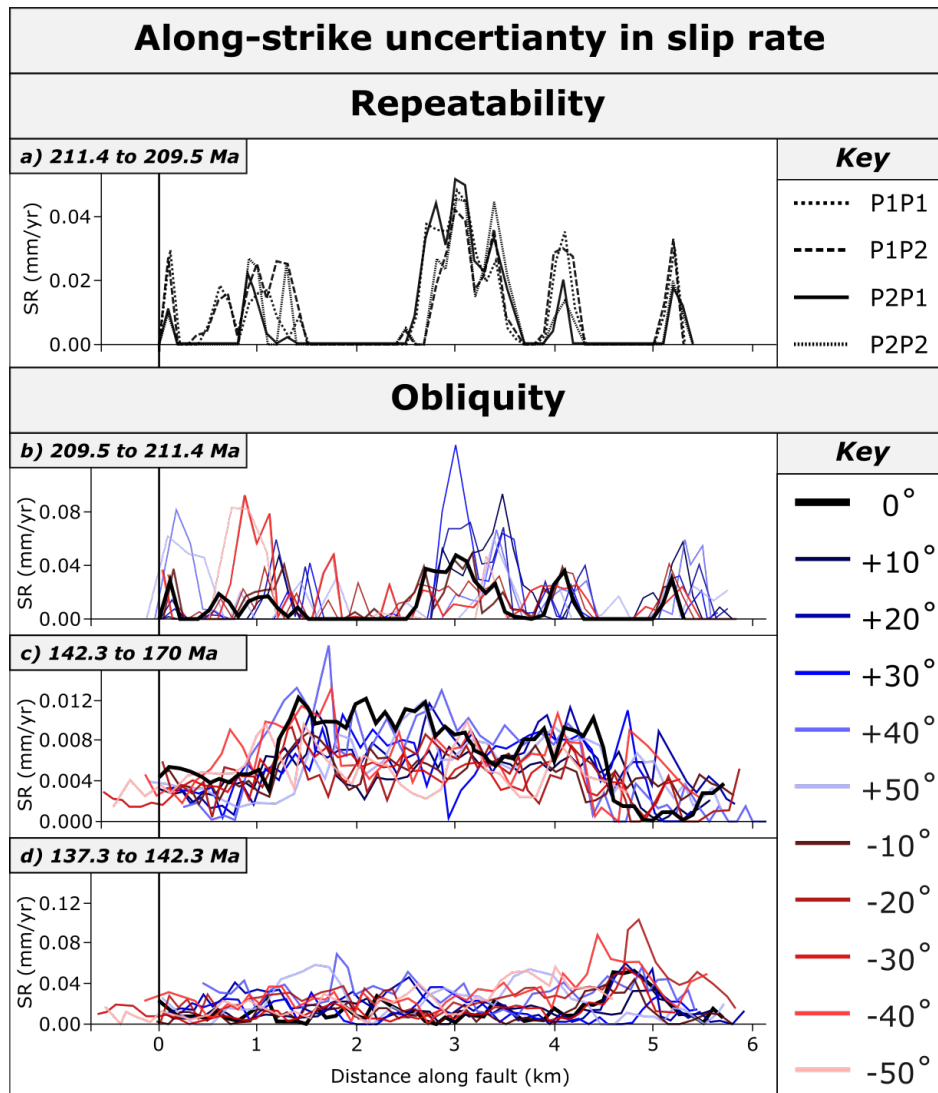




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Figure 12: The effect of repeatability and obliquity on the throw- and slip- rate of SF3 over time. Obliquity errors exceed repeatability errors for both mean throw- and slip-rate, and the effect of obliquity varies between time periods. P1 and P2 relates to the first and second pick across a given horizon, with the first value relating to H12 and the latter to H9. I.e., P1P2 relates to slip rate calculated using the 1<sup>st</sup> pick across H12 and the second pick across H9.



677  
 678 Figure 13: The effect of repeatability and obliquity on the throw- and slip- rate evolution of SF3. Note how the  
 679 shape of the profile differs between time periods, and between different measurement obliquities within that  
 680 time period.

681 When sediment accumulation rate exceeds fault throw rate, comparing the difference in  
 682 throw or slip across two age-constrained horizons allows for the investigation of long-term  
 683 throw or slip rate, which has applications for understanding fault growth (Marsh et al.,  
 684 2010; Osagiede et al., 2014; Pan et al., 2022), strain partitioning between genetically related  
 685 fault systems (Meyer et al., 2002; Cowie et al., 2005; Marsh et al., 2010) and using slip rates  
 686 to understand and quantify seismic hazard (Nicol et al., 2005; Gambino et al., 2022). In our  
 687 study, we focus on comparing the measurement obliquity uncertainty in throw and slip rate  
 688 across SF2 using multiple age-constrained horizons. Repeat picks were limited to Horizons  
 689 H9 and H12, restricting our examination of repeatability's effect on temporal slip-rate

690 evolution, enabling the comparison of repeatability and obliquity errors for the 211.4 to  
691 209.5 Ma period (Figure 12). Whereas uncertainties exist in the age of horizons, we do not  
692 consider these uncertainties here as they affect each dataset equally. Additionally, using the  
693 same horizon for each obliquity pick eliminates uncertainty introduced by mapping different  
694 reflections of potentially different ages.

695 *Repeatability (211.4 to 209.5 Ma):* Uncertainty in throw and slip rate, obtained from repeat  
696 picks, is influenced by the picks used and along-strike variations in fault properties (Figure  
697 12, 13). Four pick combinations were analysed, resulting in mean throw rates ranging from  
698 0.0045 to 0.0071 mm/yr. The percentage difference of these values (-14% to 26%) exceed  
699 the repeatability of throw extracted from continuous cut. Mean slip rates ranged from  
700 0.0071 to 0.0095 mm/yr. Unlike throw rates, no correlation was observed between picks  
701 and mean slip rates, with the greatest difference occurring where horizon picks from the  
702 same interpretation session were used. The difference in behaviour between throw and slip  
703 rates indicates that whereas throw was consistently lower for pick 1 when compared to pick  
704 2, the same trend does not hold for heave. Along the fault, the slip rate profile showed  
705 similar shapes for all pick combinations, but subtle differences were observed, making  
706 certain locations more susceptible to repeatability errors. Therefore, in cases with low to  
707 modest difference in slip (average 11 m) between horizons, the shape and magnitude of the  
708 slip profile may be more susceptible to repeatability errors.

709 *Obliquity:* The errors for throw and slip rates due to measurement obliquity exceed the  
710 repeatability errors for datasets (Figures 12, 13). Measurement obliquity can affect the  
711 estimates of mean throw and slip rates compared to data collected from a strike-  
712 perpendicular transect (Figure 12). From 211.4 to 209.5 Ma, throw rates extracted from

713 oblique transects ranged from 0.0045 to 0.0140 mm/yr (absolute errors ranging from 3 to  
714 135%), with only the -50° dataset having a lower throw rate than the strike-perpendicular  
715 transect. For the same time period, mean slip rates range from 0.0095 and 0.0149 mm/yr  
716 (absolute errors ranging from 1 to 60%), with all datasets (except -50°) exceeding the strike-  
717 perpendicular transect. The effect of measurement obliquity varies through time and  
718 differed between throw- and slip-rate (Figure 12). Oblique sampling resulted in over- or  
719 under-estimations of throw and slip rates, with no consistent pattern observed. Along-fault  
720 profiles were sensitive to both repeatability and obliquity errors, altering the location and  
721 magnitude of throw- and slip-rate minima and maxima (Figure 13). The influence of  
722 measurement obliquity on slip-rate profiles depended more on the time period measured  
723 (i.e., which pair of horizons were sampled) than the magnitude of measurement obliquity.  
724 Overall, even modest measurement obliquities (i.e.,  $\pm 20^\circ$ ), and to a lesser extent  
725 repeatability errors, led to large differences in fault length inferred from along-fault profiles  
726 and throw- or slip-rate used to calculate fault-based seismic hazard.

## 727 **5. Discussion**

### 728 ***5.1 Impact and mitigation of fault interpretation uncertainty***

#### 729 ***Interpretation repeatability***

730 From our study, we conclude that where the quality of the seismic imagery is good and the  
731 data are extracted by an interpreter with a similar level of experience, the repeatability of  
732 extracted data will depend on the fault property being extracted, and the fault and horizon  
733 that the data is extracted from (Table 1). Throw was found to be least sensitive to

734 repeatability errors (7%), with heave (27%), displacement (16%) and dip (16%) showing  
735 greater sensitivity. Previous work has suggested that the interpretation of fault properties  
736 from low-displacement dyke-induced faults could be affected by measurement  
737 uncertainties of between  $\pm 5\%$  (Magee and Jackson, 2020a) and  $\pm 10\%$  (Magee et al., 2023).  
738 Our study highlights that this range is not sufficient to capture the uncertainty in heave (and  
739 therefore displacement and dip), particularly if multiple interpreters with greater subjective  
740 bias are involved.

741 *Suggestions:* Repeatability errors are difficult to quantify and will depend on the quality of  
742 the seismic image, the experience of the interpreter, and other human factors. As such the  
743 appropriate size of the error bars will differ from the values presented in this study.

744 However, our study provides a first-pass parametric study of the influence of repeatability  
745 errors on the extraction of fault properties, suggesting errors  $>10\%$  are to be expected,  
746 particularly in low-quality datasets or where low-displacement faults are present. Study  
747 specific values could be obtained by undertaking repeat picks on a subset of the data.

#### 748 ***Measurement Obliquity***

749 From our study, we conclude that the derived measurement obliquity broadly follows the  
750 theoretical trends (Figure 1c), but that the magnitude of the resulting error exceeds the  
751 theoretical values. The higher than expected errors may be due to 'non-geometrical'  
752 obliquity errors of the type discussed in Section 5.2. Our findings suggest that measurement  
753 obliquity should be limited, where possible, to  $\pm 20^\circ$  around the orthogonal to the local fault  
754 strike.

755 However, it may not be practical to always interpret orthogonal to the local fault strike, for  
756 example when only 2D seismic datasets are available, or when the fault strike is highly  
757 variable. For a fault that is highly sinuous, it would be time-consuming to construct  
758 numerous arbitrary lines orthogonal to differently orientated fault sections. In that case,  
759 additional steps would be required to ensure that the picks from differentially orientated  
760 arbitrary lines are combined in a mathematically and geometrically appropriate way.

761 *Suggestions:* Measurement obliquity should not exceed  $\pm 20^\circ$ , and where possible  $\pm 15^\circ$ . This  
762 ensures that obliquity errors are minimised, whilst still ensuring that data is collected in a  
763 time-efficient manner. This rule is particularly important where the continuous cut-offs are  
764 measured. Where it is not possible to reduce the measurement obliquity, results could be  
765 improved by 'correcting' heave, dip, and displacement values based on local strike  
766 calculated from measured cut-offs and the theoretical relationships outlined in Figure 1c.  
767 However, whilst this would decrease the overall errors, it cannot account for any non-  
768 geometrical errors in the dataset.

#### 769 ***Interpreted cut-off type***

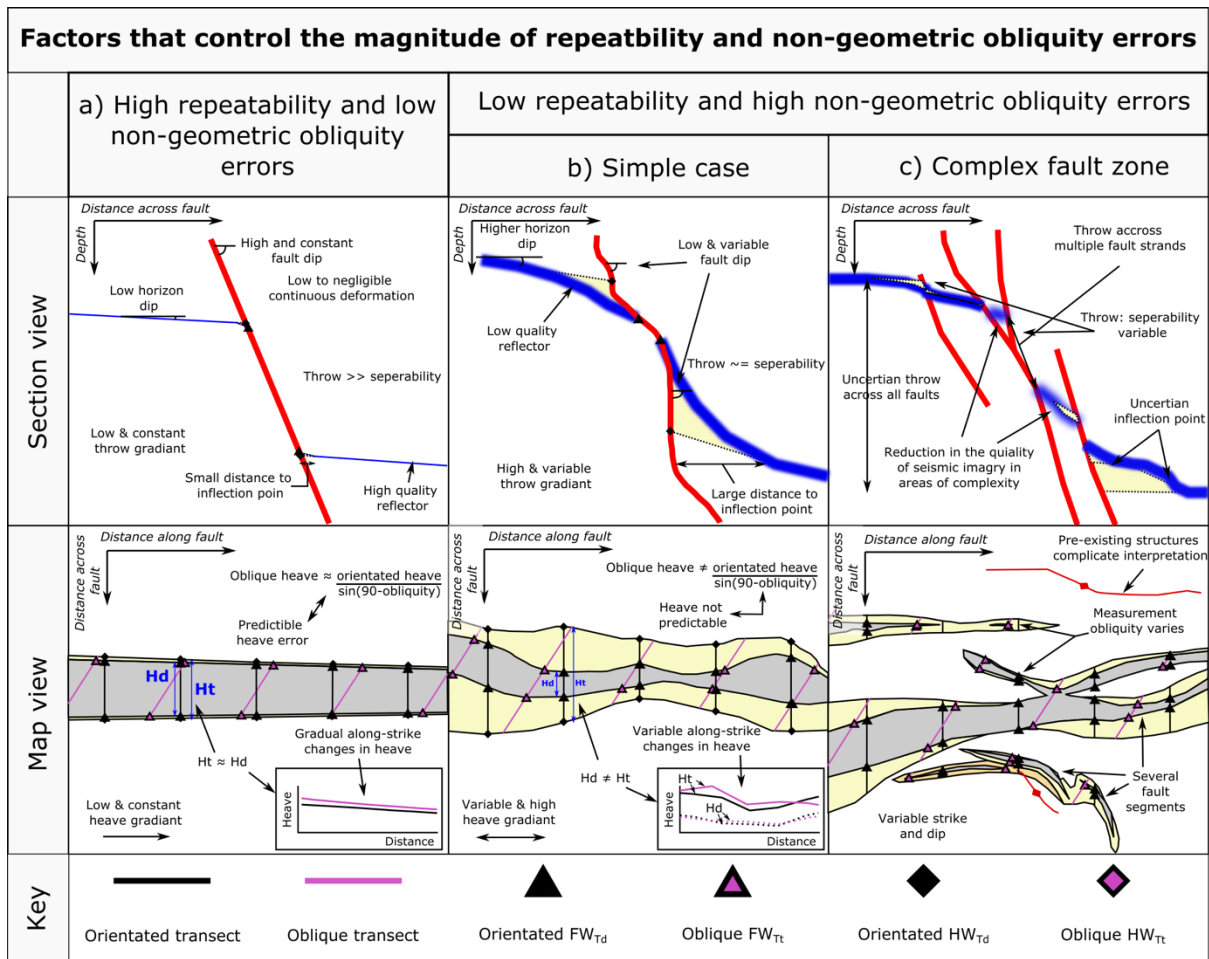
770 Our work highlights that the interpreted cut-off type influences the magnitude of both  
771 repeatability and obliquity related errors (Tables 1, S7-14, Figures 4-10). Greater uncertainty  
772 was observed where continuous cut-offs are included in the analysis, with the effect  
773 particularly clear when extracting heave (Table 1, Figure 7).

774 *Suggestions:* The choice of interpreted cut-off type is often driven by study design (e.g.,  
775 whether slip-rate or fault transmissivity is important), and therefore it is limited how much

776 this can be mitigated against. However, we found that the extraction of heave from fault  
777 cut-offs is particularly sensitive to both repeatability and obliquity errors and that the  
778 magnitude of error for the latter can greatly exceed theoretical values. Therefore, it may be  
779 better to use an average dip between two or more mapped horizons to calculate heave  
780 from the measured throw value. This will also reduce the effect of sample-specific  
781 measurement errors on the extraction of slip-rate.

782 ***5.2 Factors that control the magnitude of repeatability and non-geometrical obliquity***  
783 ***errors.***

784 Our study suggests that the extraction of fault properties from cut-off data is strongly  
785 affected by the three elements of fault interpretation focused on in this study, and that  
786 these elements contribute to uncertainty in deriving interpretations from these data.  
787 Additionally, the effect of each element can vary both between faults and spatially along a  
788 single fault. During the work, we identified several additional factors that combine to  
789 increase, or decrease, the uncertainty at a given point along the fault, which are  
790 summarised below and in Figure 14.



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Figure 14: Cartoons showing the factors that control the repeatability and magnitude of non-geometric obliquity errors. Examples are shown for a fault with high repeatability and low geometric errors (a), low repeatability and high geometric errors (b), and a more complex fault zone that is representative of relay zones observed in the seismic cube. See text for discussion of these factors.

796

Our data suggests that the quality of the mapped reflection plays a large role in non-

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geometrical errors and low repeatability, as evidenced by certain horizons (e.g., H1) showing

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high errors (Table S2). Our findings thus agreed with previous studies, in that XXX (e.g.,

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Alcalde et al., 2017; Schaaf and Bond, 2019; Chellingsworth et al., 2015). The effect of the

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reflection quality does not influence each fault property equally, with heave (and thus

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displacement and dip) affected more than throw, due to the low regional dip ( $<3^\circ$ ) across

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the study area.



803 Our data shows that the uncertainty is affected by the size of the fault in terms of  
804 displacement or throw. There is greater uncertainty in areas of low throw, especially when  
805 close to or below the limit of separability. When a large proportion of the deformation is  
806 taken up by folding (Figure 14b), uncertainties are higher due to challenges in interpreting  
807 continuous cut-offs. These challenges are related to the variability of the horizon dip, the  
808 distance to the inflection point and the variability and magnitude of fault dip. Finally,  
809 uncertainties were particularly evident in complex fault zones (Figure 14c), where the image  
810 quality may be more degraded and there may be challenges in interpreting deformation  
811 across multiple nearby fault strands. The factors shown in Figure 14 indicate why there are  
812 along-strike and down-dip variations in the uncertainties, and therefore highlights that  
813 there may be local geometric variations in fault geometry that merit additional care and  
814 quantification of uncertainties.

## 815 **6. Conclusions**

816 Our study demonstrated that fault properties extracted from seismic reflection datasets are  
817 prone to three types of uncertainty: interpretation repeatability, measurement obliquity,  
818 and interpreted cut-off type. Obliquity related errors varies depending on the horizon and  
819 fault interpreted, the magnitude of obliquity, and the fault property measured. High errors  
820 occurred when obliquity exceeded  $\pm 20^\circ$ , with throw showing lower percentage errors  
821 compared to heave across all datasets. Heave errors caused uncertainties in displacement  
822 and dip extraction, particularly in areas of low displacement. Repeatability errors were  
823  $\sim \pm 10\%$  for throw, and 13-23% for heave, with higher errors in areas of structural complexity  
824 or low seismic image quality. Measurement obliquity was not found to compound

825 repeatability errors; however, interpreting continuous cut-offs increased uncertainty and  
826 error in extracted fault properties.

827 Measurement obliquity and interpretation repeatability can have a minor effect on the  
828 calculation of shale gouge ratio (SGR), but local fault plane patches showed significant  
829 errors. Average SGR values were generally insensitive to errors, but resevoirs near the  
830 sealing threshold might experience unexpected local cross-fault fluid flow, potentially  
831 affecting compliance with legislation for carbon capture and storage facilities. Slip-rate  
832 extraction, which utilises continuous cut-offs, was strongly affected by both obliquity and  
833 repeatability errors. This could lead to over- or underestimation of slip-rate and differences  
834 in the interpreted slip-rate profile. This could significantly impact fault-based seismic  
835 hazard assessments, especially in low seismicity areas, and therefore the suitability of  
836 nuclear waste disposal sites. These examples underline the importance of considering and  
837 mitigating obliquity and repeatbility errors when extracting fault data from seismic  
838 reflection datasets.

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1064 **Supplementary data**

1065 **Supplementary 1 : data tables**

1066 **S1.1 Repeatability statistics**

Parameter	SF2				SF3				SF4				SF5				All faults			
	Equivalent datasets	% equivalent datasets	Mean Abs difference	% Absolute difference	Equivalent datasets	% equivalent datasets	Mean Abs difference	% Absolute difference	Equivalent datasets	% equivalent datasets	Mean Abs difference	% Absolute difference	Equivalent datasets	% equivalent datasets	Mean Abs difference	% Absolute difference	Equivalent datasets	% equivalent datasets	Mean Abs difference	% Absolute difference
Td: HDF1	9	82%	7.5	7%	9	82%	5.5	6%	7	64%	1.7	6%	25	76%	5.0	7%	9	9%	23.2	38%
Td: HDF 0.1	11	100%	3.2	2%	11	100%	3.2	2%	9	82%	4.7	6%	9	82%	1	3%	30	91%	3.0	4%
Td	20	91%	5.55	5%	19	86%	5.1	7%	16	73%	1.35	5%	55	83%	4.0	5%	55	83%	4.0	5%
Tl: HDF1	3	27%	1.8	14%	8	73%	13.1	7%	10	91%	5.6	5%	2	18%	4.3	9%	23	52%	6.2	9%
Tl: HDF 0.1	3	27%	2	16%	6	55%	12.7	6%	4	36%	5.9	6%	2	18%	2.7	6%	15	34%	5.8	9%
Tl	6	27%	1.9	15%	14	64%	12.9	7%	14	64%	5.75	6%	14	64%	3.5	8%	48	55%	6.0	9%
Throw	6	27%	1.9	15%	34	77%	9.2	6%	33	75%	5.4	6%	30	68%	2.425	6%	103	69%	5.0	7%
Hd: HDF1	0	0%	30.0	26%	0	0%	26.5	37%	3	27%	13.2	52%	5	9%	9%	23.2	38%	9%	23.2	38%
Hd: HDF 0.1	9	82%	10.8	7%	5	45%	22.5	19%	5	45%	11.1	25%	19	58%	14.8	17%	19	58%	14.8	17%
Hd	9	41%	20.4	17%	5	23%	24.5	28%	8	36%	12.15	29%	22	33%	19.0	28%	22	33%	19.0	28%
Hl: HDF1	2	18%	8.9	42%	7	64%	25	12%	2	18%	31.1	37%	2	18%	12.3	33%	13	30%	19.3	31%
Hl: HDF 0.1	4	36%	8.6	41%	8	73%	14.1	9%	5	45%	20.1	16%	6	55%	12	19%	23	52%	13.7	21%
Hl	6	27%	8.8	42%	15	68%	19.6	13%	7	32%	25.6	27%	8	36%	12.2	26%	36	41%	16.5	26%
Move	6	27%	8.8	42%	24	55%	20.0	14%	12	27%	25.1	27%	16	36%	12.2	32%	58	37%	17.8	27%
Dd: HDF 1	0	0%	27.1	16%	3	27%	21.9	21%	4	36%	10.7	29%	7	21%	19.9	22%	7	21%	19.9	22%
Dd: HDF 0.1	10	91%	10.1	4%	9	82%	22	15%	6	55%	8.6	15%	25	76%	13.6	11%	25	76%	13.6	11%
Dd	10	45%	18.6	10%	12	55%	21.95	18%	8	36%	9.65	22%	30	45%	16.7	17%	30	45%	16.7	17%
Dl: HDF 1	2	18%	8.7	34%	5	45%	26.2	9%	4	36%	14	9%	5	45%	7.5	12%	16	36%	14.1	16%
Dl: HDF 0.1	4	36%	7.1	27%	8	73%	17.4	7%	6	55%	21.5	13%	8	73%	7.8	10%	26	59%	13.5	14%
Dl	6	27%	7.9	31%	13	59%	21.8	8%	10	45%	17.8	11%	13	59%	7.7	11%	42	48%	13.8	15%
Displacement	6	27%	7.9	31%	36	52%	20.2	9%	32	50%	19.9	15%	21	48%	8.7	17%	72	47%	15.3	16%
Dipd: HDF 1	0	0%	5.2	12%	0	0%	9.3	20%	3	27%	12.9	27%	3	9%	9.1	20%	3	9%	9.1	20%
Dipd: HDF 0.1	8	73%	2.1	4%	3	27%	4	11%	6	55%	6.4	18%	17	52%	4.2	11%	17	52%	4.2	11%
Dipd	8	36%	3.65	8%	3	14%	6.65	16%	9	41%	8.65	23%	20	30%	6.7	15%	20	30%	6.7	15%
Dipt: HDF 1	4	36%	9.9	28%	1	9%	4.7	10%	0	0%	9.2	19%	4	36%	8.7	17%	9	20%	8.1	19%
Dipt: HDF 0.1	5	45%	8.4	25%	8	73%	2.1	4%	4	36%	2.8	7%	4	36%	5.8	16%	21	48%	4.8	13%
Dipt	9	41%	9.2	27%	9	41%	3.4	7%	4	18%	6.0	13%	8	36%	7.3	17%	30	34%	6.5	16%
Dip	9	41%	9.2	27%	17	39%	3.5	8%	7	16%	6.3	14%	17	39%	8.5	20%	50	32%	6.6	16%
All Discontinuous Parameters: HDF 1	9	20%		15%	12	27%		22%	17	39%		29%	38	29%		22%				
All Discontinuous Parameters: HDF 0.1	38	86%		4%	27	61%		15%	26	59%		15%	91	69%		11%				
All Discontinuous Parameters	47	53%		10%	39	44%		17%	41	47%		22%	127	48%		16%				
Continuous: HDF 1	11	25%		30%	21	48%		10%	16	36%		18%	61	35%		19%				
Continuous: HDF 0.1	16	36%		27%	30	68%		7%	19	43%		11%	20	45%		14%				
Continuous	27	31%		28%	51	58%		8%	35	40%		14%	43	49%		15%	156	44%	16%	16%
Average: All parameters	27	31%		28%	111	56%		9%	84	42%		16%	84	48%		19%	283	46.2%	16%	16%

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1068 **Table S1: Repeatability statistics**

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1070 **S1.2 Obliquity statistics**

Horizon	Td		Hd		Dipd		Dispd		Tl		Hl		Dipt		Dipst		Overall		Discontinuous parameter		Continuous parameters	
	% difference	% equal datasets	% difference	% equal datasets	% difference	% equal datasets	% difference	% equal datasets	% difference	% equal datasets	% difference	% equal datasets	% difference	% equal datasets	% difference	% equal datasets	% difference	% equal datasets	% difference	% equal datasets	% difference	% equal datasets
H1	13%	60%	32%	40%	13%	35%	22%	50%	20%	50%	52%	47%	18%	47%	30%	57%	26%	49%	20%	46%	30%	50%
H2	11%	87%	31%	70%	14%	57%	22%	77%	13%	70%	65%	28%	19%	28%	43%	33%	28%	54%	19%	73%	35%	39%
H3	6%	97%	20%	73%	11%	53%	14%	77%	12%	65%	25%	55%	12%	38%	18%	63%	13%	63%	13%	75%	17%	54%
H4	6%	87%	25%	57%	12%	50%	16%	70%	16%	75%	28%	50%	1%	43%	18%	58%	16%	60%	15%	65%	16%	56%
H5	5%	90%	26%	45%	11%	40%	18%	45%	6%	73%	34%	100%	13%	40%	20%	57%	17%	53%	15%	55%	18%	52%
H6	6%	97%	25%	57%	12%	43%	16%	70%	6%	85%	37%	45%	14%	40%	22%	60%	17%	61%	15%	67%	20%	58%
H7	6%	97%	26%	57%	11%	50%	13%	73%	8%	80%	49%	28%	18%	21%	58%	20%	56%	14%	69%	24%	46%	
TM	4%	100%	44%	50%	14%	33%	15%	73%	7%	90%	34%	40%	27%	45%	16%	70%	18%	63%	19%	64%	17%	61%
H8	5%	97%	29%	47%	12%	33%	17%	63%	11%	78%	39%	45%	15%	30%	25%	43%	20%	54%	16%	60%	23%	49%
H9	1%	100%	53%	20%	25%	10%	28%	20%	7%	70%	42%	30%	17%	30%	25%	40%	24%	41%	27%	38%	23%	43%
IMC	8%	100%	37%	33%	15%	37%	23%	47%	10%	75%	35%	43%	13%	38%	22%	53%	20%	53%	21%	54%	20%	52%
H10a	13%	80%	23%	80%	14%	50%	12%	90%	12%	90%	37%	60%	15%	50%	20%	70%	18%	71%	15%	75%	21%	68%
H11	8%	80%	34%	50%	13%	40%	14%	55%	6%	100%	40%	30%	14%	20%	16%	60%	18%	54%	17%	56%	19%	53%
H12	4%	100%	25%	70%	10%	40%	13%	80%	5%	100%	66%	10%	25%	10%	36%	20%	23%	54%	13%	73%	33%	35%
H14	8%	90%	38%	55%	12%	45%	11%	70%	9%	70%	64%	30%	20%	20%	25%	40%	23%	54%	17%	65%	30%	40%
Total	7%	91%	31%	54%	13%	43%	17%	65%	10%	76%	41%	40%	15%	34%	15%	53%	20%	56%	17%	63%	22%	51%

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1072 **Table S2: Obliquity statistics split by the horizon the data is collected from.**

Obliquity	SF2			SF3			SF4			SF5			ALL FAULTS		
	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	mean abs difference	% difference	% equal datasets
-50	2.95	24%	36%	9.19	7%	83%	4.79	6%	92%	5.87	18%	75%	6.11	12%	78%
-40	1.92	15%	55%	12.39	10%	58%	4.87	6%	92%	3.4	11%	90%	6.33	10%	77%
-30	1.86	14%	64%	9.65	9%	58%	2.98	4%	88%	2.86	9%	95%	4.77	8%	78%
-20	0.69	6%	100%	10.02	8%	83%	3.11	4%	100%	2.83	9%	95%	4.76	7%	94%
-10	0.77	6%	91%	5.52	5%	88%	2.69	4%	92%	2.35	7%	100%	3.18	5%	93%
10	1.2	10%	82%	10.86	9%	54%	2.16	3%	100%	3.06	10%	85%	4.83	7%	80%
20	1.61	13%	64%	5.19	5%	92%	2.56	3%	92%	3.15	9%	90%	3.36	6%	88%
30	0.72	16%	55%	10.01	9%	63%	3.61	4%	92%	4.2	12%	95%	5.42	9%	79%
40	1.64	13%	64%	9.1	7%	79%	4.07	5%	92%	3.99	12%	95%	5.22	8%	85%
50	1.86	15%	64%	14.08	14%	75%	8.06	10%	73%	4.41	13%	95%	8.1	13%	78%
<b>Total</b>	<b>1.64</b>	<b>13%</b>	<b>67%</b>	<b>9.6</b>	<b>8%</b>	<b>73%</b>	<b>3.89</b>	<b>5%</b>	<b>92%</b>	<b>3.61</b>	<b>11%</b>	<b>92%</b>	<b>5.21</b>	<b>9%</b>	<b>83%</b>

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1074 **Table S3: Obliquity statistics for Throw**

Obliquity	SF2			SF3			SF4			SF5			ALL FAULTS		
	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	mean abs difference	% difference	% equal datasets
-50	15.01	128%	18%	64.51	55%	13%	60.69	76%	8%	20.37	65%	45%	45.66	74%	20%
-40	5.45	45%	27%	61.78	49%	4%	40.62	51%	19%	12.01	40%	55%	35.05	47%	25%
-30	2.72	24%	45%	30.31	25%	29%	26.08	33%	38%	7.35	26%	75%	19.54	28%	46%
-20	2.65	24%	27%	17.69	15%	67%	10.36	13%	69%	5.09	18%	85%	10.18	16%	67%
-10	3.16	29%	82%	8.86	7%	79%	4.34	6%	96%	4.59	15%	95%	5.58	12%	89%
10	2.06	20%	82%	18.83	17%	54%	13.6	18%	54%	4.76	16%	90%	11.4	18%	67%
20	3.43	32%	64%	10.13	9%	88%	17.09	22%	46%	5.73	23%	80%	10.37	20%	69%
30	7.32	69%	36%	30.29	27%	21%	23.5	30%	19%	8.4	32%	85%	19.59	35%	38%
40	4.3	37%	45%	52.59	42%	4%	37.15	48%	8%	12.69	55%	45%	31.22	46%	21%
50	9.77	83%	9%	97.07	79%	8%	65.75	82%	8%	12.39	44%	45%	54.25	72%	17%
<b>Total</b>	<b>5.59</b>	<b>49%</b>	<b>44%</b>	<b>39.21</b>	<b>33%</b>	<b>37%</b>	<b>29.92</b>	<b>38%</b>	<b>37%</b>	<b>9.34</b>	<b>33%</b>	<b>70%</b>	<b>24.28</b>	<b>37%</b>	<b>46%</b>

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1076 **Table S4: Obliquity statistics for Heave**

Obliquity	SF2			SF3			SF4			SF5			ALL FAULTS		
	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	mean abs difference	% difference	% equal datasets
-50	15.56	88%	9%	51.03	28%	17%	48.78	41%	15%	19.29	41%	50%	37.65	44%	23%
-40	4.84	27%	55%	54.65	28%	8%	33.74	28%	31%	10.41	23%	65%	30.25	27%	36%
-30	3	17%	73%	27.03	16%	33%	20.28	17%	50%	7.27	17%	80%	16.72	17%	56%
-20	1.89	11%	91%	19.88	11%	71%	8.76	7%	77%	5.49	13%	95%	10.31	10%	81%
-10	2.76	17%	82%	10.04	6%	79%	4.14	4%	96%	4.69	10%	100%	5.84	8%	90%
10	1.34	8%	91%	17.53	10%	58%	10.47	9%	62%	4.62	10%	95%	9.88	10%	73%
20	2.27	13%	91%	10.29	6%	83%	13.94	12%	54%	5.32	12%	95%	9.15	11%	78%
30	5.6	34%	45%	24.51	14%	50%	19.61	17%	54%	7.05	16%	95%	16.06	18%	62%
40	3.27	18%	73%	43.68	23%	33%	30.37	27%	23%	8.75	24%	85%	25.25	24%	48%
50	7.72	43%	45%	81.3	44%	8%	55.81	48%	8%	8.34	19%	95%	45.11	39%	35%
<b>Total</b>	<b>4.38</b>	<b>28%</b>	<b>65%</b>	<b>34</b>	<b>19%</b>	<b>44%</b>	<b>24.59</b>	<b>21%</b>	<b>47%</b>	<b>8.11</b>	<b>18%</b>	<b>86%</b>	<b>20.62</b>	<b>21%</b>	<b>58%</b>

1077

1078 **Table S5: Obliquity statistics for Displacement**

Obliquity	SF2			SF3			SF4			SF5			All faults		
	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	Abs difference	% difference	% equal datasets	mean abs difference	% difference	% equal datasets
-50	8.95	18%	18%	10.09	21%	0%	13.9	29%	0%	8.41	17%	45%	10.74	22%	14%
-40	7.7	15%	45%	8.05	18%	4%	9.36	20%	8%	6.77	14%	45%	8.12	17%	21%
-30	5.5	11%	64%	4.73	10%	29%	7.03	15%	4%	3.91	8%	80%	5.37	11%	38%
-20	5.79	12%	73%	2.44	6%	67%	3.34	7%	50%	3.53	7%	75%	3.45	7%	64%
-10	5.74	12%	64%	1.73	4%	92%	1.55	3%	81%	2.71	6%	85%	2.45	5%	83%
10	6.46	13%	36%	3.17	6%	67%	4.64	10%	50%	3.41	7%	75%	4.15	8%	59%
20	9.07	18%	27%	1.95	4%	88%	4.95	10%	31%	5.5	11%	75%	4.75	10%	58%
30	11.05	22%	18%	5.14	11%	17%	6.17	13%	4%	5.81	11%	75%	6.44	13%	27%
40	7.96	16%	45%	7.2	16%	4%	9.5	20%	0%	12.19	25%	5%	9.27	19%	9%
50	15.13	30%	0%	11.95	25%	0%	13.84	29%	0%	11.53	24%	20%	12.88	27%	5%
<b>Total</b>	<b>8.33</b>	<b>16%</b>	<b>39%</b>	<b>5.64</b>	<b>12%</b>	<b>37%</b>	<b>7.43</b>	<b>16%</b>	<b>23%</b>	<b>6.38</b>	<b>13%</b>	<b>58%</b>	<b>6.76</b>	<b>14%</b>	<b>38%</b>

1079

1080 **Table S6: Obliquity statistics for Dip**

Obliquity	Fault						All faults	
	SF3		SF4		SF5		% er	% equal datasets
	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets		
-50	7%	83%	8%	92%	11%	90%	9%	89%
-40	9%	75%	5%	100%	8%	100%	7%	91%
-30	10%	50%	4%	92%	10%	100%	8%	80%
-20	6%	92%	4%	100%	11%	90%	7%	94%
-10	4%	92%	3%	100%	8%	100%	6%	97%
10	9%	58%	3%	100%	12%	80%	7%	80%
20	4%	92%	2%	100%	7%	100%	4%	97%
30	8%	83%	2%	100%	11%	100%	7%	94%
40	4%	100%	4%	100%	11%	90%	6%	97%
50	7%	92%	6%	100%	17%	90%	9%	94%
<b>Total</b>	<b>7%</b>	<b>82%</b>	<b>4%</b>	<b>85%</b>	<b>11%</b>	<b>94%</b>	<b>7%</b>	<b>91%</b>

1081

1082 **Table S7: Obliquity data for discontinuous throw**

Obliquity	Fault								All faults	
	SF2		SF3		SF4		SF5		% er	% equal datasets
	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets		
-50	24%	36%	6%	83%	5%	92%	24%	60%	14%	70%
-40	15%	55%	12%	42%	7%	85%	13%	80%	11%	65%
-30	14%	64%	8%	67%	4%	85%	9%	90%	9%	76%
-20	6%	100%	10%	75%	4%	100%	8%	100%	7%	93%
-10	6%	91%	4%	83%	4%	85%	7%	100%	5%	89%
10	10%	82%	9%	50%	3%	100%	7%	90%	7%	80%
20	13%	64%	6%	92%	4%	85%	10%	80%	8%	80%
30	16%	55%	9%	42%	6%	85%	13%	90%	11%	67%
40	13%	64%	10%	58%	7%	85%	13%	100%	10%	76%
50	15%	64%	21%	58%	14%	46%	10%	100%	15%	65%
<b>Total</b>	<b>13%</b>	<b>67%</b>	<b>9%</b>	<b>65%</b>	<b>6%</b>	<b>85%</b>	<b>11%</b>	<b>89%</b>	<b>11%</b>	<b>76%</b>

1083

1084 **Table S8: Obliquity data for total throw**

Obliquity	Fault						All faults	
	SF3		SF4		SF5		% er	% equal datasets
	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets		
-50	61%	17%	60%	15%	45%	70%	56%	2%
-40	46%	8%	37%	23%	34%	70%	39%	24%
-30	29%	25%	22%	77%	22%	90%	24%	48%
-20	11%	83%	4%	100%	13%	100%	9%	72%
-10	8%	67%	5%	100%	13%	90%	9%	65%
10	22%	50%	10%	77%	16%	90%	16%	54%
20	10%	83%	14%	77%	23%	70%	15%	59%
30	33%	17%	25%	23%	37%	80%	31%	28%
40	39%	0%	42%	15%	70%	50%	49%	15%
50	67%	17%	60%	15%	44%	50%	58%	20%
<b>Total</b>	<b>33%</b>	<b>82%</b>	<b>28%</b>	<b>52%</b>	<b>32%</b>	<b>76%</b>	<b>31%</b>	<b>41%</b>

1085

1086 Table S9: Obliquity data for discontinuous heave

Obliquity	Fault								All faults	
	SF2		SF3		SF4		SF5			
	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets
-50	128%	18%	50%	83%	92%	0%	85%	20%	88%	11%
-40	45%	27%	53%	42%	65%	15%	47%	40%	53%	20%
-30	24%	45%	22%	67%	43%	0%	29%	60%	30%	33%
-20	24%	27%	19%	75%	21%	38%	23%	70%	22%	46%
-10	29%	82%	6%	83%	6%	92%	16%	100%	14%	91%
10	20%	82%	12%	50%	26%	31%	17%	90%	19%	63%
20	32%	64%	8%	92%	30%	15%	22%	90%	23%	63%
30	69%	36%	22%	42%	34%	15%	27%	90%	38%	39%
40	37%	45%	45%	58%	53%	0%	39%	40%	44%	22%
50	83%	9%	91%	58%	104%	0%	44%	40%	83%	11%
<b>Total</b>	<b>49%</b>	<b>44%</b>	<b>33%</b>	<b>37%</b>	<b>48%</b>	<b>85%</b>	<b>35%</b>	<b>64%</b>	<b>41%</b>	<b>40%</b>

1087

1088 Table S10: Obliquity data for total heave

Obliquity	Fault						All faults	
	SF3		SF4		SF5			
	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets
-50	31%	17%	31%	31%	29%	80%	31%	30%
-40	26%	8%	20%	46%	18%	80%	21%	33%
-30	18%	25%	11%	85%	15%	90%	15%	50%
-20	8%	83%	3%	100%	12%	100%	7%	72%
-10	7%	75%	4%	100%	10%	100%	7%	70%
10	12%	50%	6%	77%	11%	100%	10%	57%
20	6%	83%	8%	77%	12%	90%	8%	63%
30	17%	33%	14%	69%	17%	100%	16%	50%
40	1%	50%	24%	46%	32%	80%	25%	43%
50	33%	17%	34%	15%	19%	90%	29%	28%
<b>All obliquities</b>	<b>18%</b>	<b>44%</b>	<b>16%</b>	<b>65%</b>	<b>17%</b>	<b>91%</b>	<b>17%</b>	<b>50%</b>

1089

1090 Table S11: Obliquity data for discontinuous displacement

Obliquity	Fault								All faults	
	SF2		SF3		SF4		SF5			
	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets
-50	88%	9%	24%	17%	51%	0%	53%	20%	53%	11%
-40	27%	55%	31%	8%	37%	15%	27%	50%	31%	30%
-30	17%	73%	14%	42%	23%	15%	18%	100%	18%	48%
-20	11%	91%	14%	58%	12%	54%	13%	90%	13%	72%
-10	17%	82%	5%	83%	4%	92%	10%	100%	9%	89%
10	8%	91%	7%	67%	13%	46%	9%	90%	9%	72%
20	13%	91%	6%	83%	16%	31%	13%	100%	12%	74%
30	34%	45%	11%	67%	20%	38%	15%	90%	20%	59%
40	18%	73%	25%	17%	30%	0%	16%	90%	23%	41%
50	43%	45%	55%	0%	62%	0%	18%	100%	46%	33%
<b>Total</b>	<b>28%</b>	<b>65%</b>	<b>19%</b>	<b>44%</b>	<b>27%</b>	<b>14%</b>	<b>19%</b>	<b>80%</b>	<b>23%</b>	<b>53%</b>

1091



1092 **Table S12: Obliquity data for total displacement**

Obliquity	Fault						All faults	
	SF3		SF4		SF5		% er	% equal datasets
	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets		
-50	22%	0%	26%	0%	15%	60%	21%	13%
-40	18%	8%	16%	8%	12%	40%	39%	13%
-30	11%	17%	11%	8%	6%	90%	10%	26%
-20	6%	75%	4%	85%	7%	90%	6%	63%
-10	4%	83%	3%	85%	6%	90%	9%	65%
10	6%	75%	6%	77%	6%	90%	6%	61%
20	5%	83%	8%	46%	10%	80%	8%	52%
30	11%	8%	13%	8%	13%	80%	12%	22%
40	16%	8%	19%	0%	28%	0%	20%	2%
50	26%	0%	25%	0%	24%	30%	25%	7%
<b>Total</b>	<b>13%</b>	<b>36%</b>	<b>13%</b>	<b>52%</b>	<b>13%</b>	<b>76%</b>	<b>13%</b>	<b>32%</b>

1093

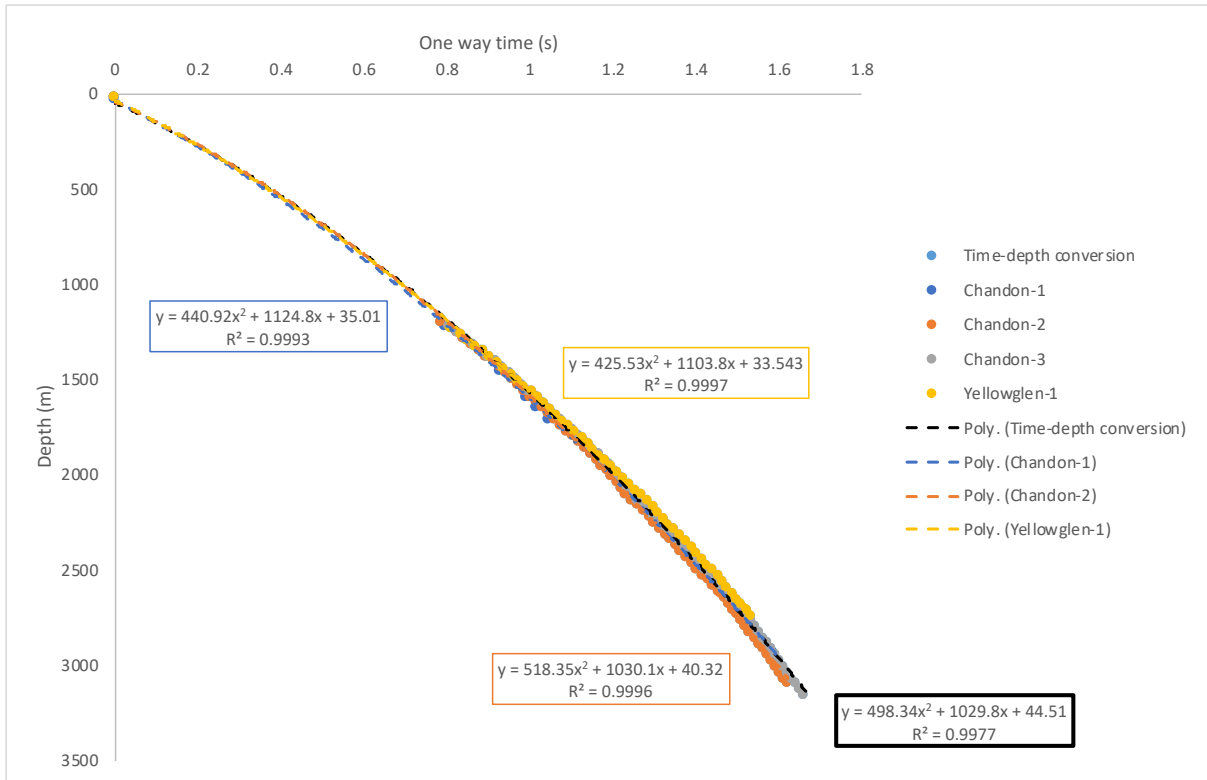
1094 **Table S13: Obliquity data for discontinuous dip**

Obliquity	Fault								All faults	
	SF2		SF3		SF4		SF5		% er	% equal datasets
	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets	% er	% equal datasets		
-50	18%	18%	21%	0%	33%	0%	20%	30%	23%	11%
-40	37%	45%	17%	0%	24%	8%	15%	50%	18%	24%
-30	11%	64%	9%	42%	19%	0%	9%	70%	12%	41%
-20	12%	73%	5%	58%	10%	15%	7%	60%	9%	50%
-10	12%	64%	4%	100%	3%	77%	5%	80%	6%	80%
10	13%	36%	6%	58%	13%	23%	7%	60%	10%	43%
20	18%	27%	3%	92%	13%	15%	12%	70%	11%	50%
30	22%	18%	10%	25%	14%	0%	9%	70%	38%	26%
40	16%	45%	15%	0%	22%	0%	21%	10%	19%	13%
50	30%	0%	24%	0%	33%	0%	23%	10%	28%	2%
<b>Total</b>	<b>16%</b>	<b>39%</b>	<b>11%</b>	<b>37%</b>	<b>18%</b>	<b>14%</b>	<b>13%</b>	<b>64%</b>	<b>15%</b>	<b>34%</b>

1095

1096 **Table S14: Obliquity data for total dip**

1097 **Supplementary 2: Time-depth conversion**



1098

1099 **Figure S2.1: Checkshot data and best fit polynomial. The combined dataset (black) is used**  
 1100 **to convert cut-off data from time to depth.**

1101 **Supplementary 8: Statistical approach used to analyse the obliquity and repeatability**  
 1102 **datasets.**

1103 **Repeatability datasets:**

1104 *Individual picks:* The presentation of individual pick data enables us to investigate the along-  
 1105 strike and down-dip variability in fault parameters as well where errors differ from  
 1106 population values. We report the differences as (*pick 1 – pick 2*) and hypothesise that  
 1107 picks undertaken at the same location on the fault should be identical; therefore, the  
 1108 difference between picks should be zero. To enable datasets to be compared across fault  
 1109 parameters we also report the % difference of individual picks (i.e., (*pick 1 –*  
 1110 *pick 2*)/( $\frac{pick\ 1 + pick\ 2}{2}$ ))  $\times 100$ ). Because the picks are independent on each other, we  
 1111 report differences and % difference as absolute values.

1112 *Dataset statistics:* The appropriate statistical test depends on a) whether the groups are  
 1113 dependent on each other; and b) whether the data is normally distributed. Because repeat  
 1114 measurements are undertaken at the same location, they can be considered dependent. In  
 1115 this case, we first test whether the difference between picks for a given dataset can be  
 1116 considered as normally distributed using the Shapiro-Wilk's test (Shapiro and Wilk, 1965;  
 1117 Royston, 1995), which is widely used to test the univariate normality of populations (Thode,  
 1118 2002). In this study, we use the amended version of the test which enables it to be used on  
 1119 datasets which range in size from  $3 \leq n \leq 5000$ , with our datasets ranging from 14 to 80.

1120 Where the null hypothesis is met for the Shapiro-Wilk test (i.e., there is a 95% probability (p-  
1121 value > 0.05) that *pick 1* – *pick 2* follows a normal distribution), we calculate population  
1122 statistics and undertake a paired t-test to test whether the datasets may be considered  
1123 statistically equivalent. The null hypothesis for the paired t-test ( $H_0$ ) is that the difference in  
1124 population means between pick 1 and pick 2 are zero (i.e., the repeat picks can be  
1125 considered equivalent). Because the repeat dataset may have a mean that is either higher  
1126 or lower than the original pick, we use a two tailed t-test with an alternative hypothesis ( $H_1$ )  
1127 of *pick 1*  $\neq$  *pick 2*. Where the alternative hypothesis is met for the Shapiro-Wilk test (i.e.,  
1128 there is a 95% probability (p-value < 0.05) that *pick 1* – *pick 2* does **not** follow a normal  
1129 distribution), we use the Mann-Whitney U test, also termed the Wilcoxon Rank Sum Test.  
1130 This is widely considered the nonparametric alternative to the 2-sample t-test. We use the  
1131 same null and alternative hypothesis as the paired t-test.

1132 To enable datasets to be compared based on certain parameters (e.g., obliquity, fault,  
1133 horizon, measurement type), we report the average difference between population means,  
1134 the average % difference, and the proportion of datasets that can be considered equivalent.  
1135 An example of the latter is if 8 out of 10 horizons had a p-value greater than 0.05 for  
1136 discontinuous throw, we would report that the % of datasets that can be considered equal is  
1137 80%). The reporting of aggregated dataset statistics enables parameters that have a  
1138 different number of datasets (e.g., discontinuous, and continuous throw) to be directly  
1139 compared.

#### 1140 **Measurement obliquity datasets:**

1141 *Individual picks:* For measurement obliquity datasets, the measurement location is not  
1142 located at the exact same place along the fault (Figure 1a). Therefore, where values are  
1143 directly compared (e.g., strike projections), the along-strike profiles are extrapolated using a  
1144 linear extrapolation and resampled to the same pick spacing. Absolute differences are not  
1145 reported but used to calculate % error. For the obliquity datasets, we assume that the  
1146 dataset extracted from an orthogonally orientated transect represents the ‘correct’  
1147 distribution. Due to the obliquity datasets not being measured at the same along-strike  
1148 location, we first take the resampled datasets of both the oblique and orientated picks. We  
1149 then calculate the % error for each resampled location using the following equation:

$$1150 \left( \frac{\text{Oblique pick} - \text{Orientated pick}}{\text{Orientated pick}} \right) \times 100$$

1151 *Dataset statistics:* The sample locations for oblique picks are not equal, and therefore the  
1152 datasets cannot be considered as dependant (i.e., they are an unpaired dataset). We  
1153 therefore use the Mann-Whitney U test to test whether the oblique dataset may be  
1154 considered statistically equivalent to the orientated dataset ( $H_0$ ) or whether they are  
1155 statistically different ( $H_1$ ). Similarly, to the repeatability datasets, we report the absolute  
1156 difference between population mean/medians, the % difference between population  
1157 mean/median and the proportion of datasets that may be considered equal for data.

#### 1158 **Comparing interpreted deformation style datasets:**

1159 To enable the effect of deformation type to be isolated, we initially combine and discuss the  
1160 obliquity and repeatability statistics of each fault parameter for each deformation type (i.e.,  
1161 take the average values for absolute difference, % difference, and % of equal datasets of the  
1162 discontinuous and continuous datasets). Following this, we then compare discontinuous and  
1163 continuous obliquity and repeatability datasets in the same manner as described above.

1164