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Seismic Noise Autocorrelations on Mars

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Key Points:

- Estimation of high-frequency reflection response using phase autocorrelations of seismic noise recorded on Mars at the InSight landing site.
- Presentation of a new data processing method that avoids aseismic signal bias and stability analysis of the reflection response.
- A signal at 10.6 s lag time is a possible candidate for a reflection from the base of the crust due to its strength, polarity, and stability.

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Abstract

Mars is the first extraterrestrial planet with seismometers (SEIS) deployed directly on its surface in the framework of the InSight (*Interior Exploration using Seismic Investigations, Geodesy and Heat Transport*) mission. The lack of strong Marsquakes, however, strengthens the need of seismic noise studies to additionally constrain the Martian structure. Seismic noise autocorrelations of single-station recordings permit the determination of the zero-offset reflection response underneath SEIS. We present a new autocorrelation study which employs state-of-the-art approaches to determine a robust reflection response by avoiding bias from aseismic signals which are recorded together with seismic waves due to unfavorable deployment and environmental conditions. Data selection and segmentation is performed in a data-adaptive manner which takes the data root-mean-square amplitude variability into account. We further use the amplitude-unbiased phase cross-correlation and work in the 1.2-8.9 Hz frequency band. The main target are crustal scale reflections, their robustness and convergence. The strongest signal appears at 10.6 s, and, if interpreted as P-wave reflection, would correspond to a discontinuity at about 24 km depth. This signal is a likely candidate for a reflection from the base of the Martian crust due to its strength, polarity, and stability. Additionally we identify, among the stable signals, a signal at about 6.85 s that can be interpreted as a P-wave reflection from the mid-crust at about 9.5 km depth.

1 Introduction

Since December 19, 2018, Mars is the first extraterrestrial planet with seismometers deployed directly on its surface. The seismometers are called SEIS (*Seismic Experiment for Interior Structure*) and have been brought by the InSight (*Interior Exploration using Seismic Investigations, Geodesy and Heat Transport*) mission (Lognonne et al., 2020). SEIS has been designed for planetary seismology (Lognonne et al., 2019) and consists of six axes to measure ground motion. It contains three very broad band (VBB) oblique axes which are sensitive to frequencies from tidal up to 10 Hz and three short period (SP) axes (one vertical, two horizontal) which are sensitive to frequencies from about 0.1 Hz to 50 Hz.

Before InSight, two SP seismometers were already landed on Mars with the 1976 Viking 1 and 2 missions (e.g., Anderson et al., 1977; Lognonné & Johnson, 2007). In contrast to InSight, both seismometers were mounted on the lander. While the Viking 1 seis-

62 mometer did not work properly, the Viking 2 seismometer picked up mostly vibrations
63 from the lander owing to operation and wind sensitivity. The lander vibrations and non-
64 ideal frequency-dependent sensitivity of the Viking SP sensor inhibited the detection of
65 marsquakes and Viking did therefore fail to provide unambiguous data for Martian seis-
66 mic activity and subsurface structure studies.

67 SEIS has been deployed on the ground of the Homestead hollow, 1.81 m south of
68 the closest lander foot (Stutzmann et al., 2021). Homestead hollow is a degraded impact
69 crater of about 27 m diameter in Elysium Planitia with a smooth sandy, granule- and
70 pebble-rich surface with few rocks (Golombek et al., 2020). After leveling and function-
71 ality checks SEIS has been covered with a wind and thermal shield (WTS) to further pro-
72 tect the sensors from environmental factors such as laminar and turbulent winds which
73 can reach about 20 m/s, atmospheric pressure changes of a few Pa, low atmospheric tem-
74 perature down to below -100°C and daily temperature variability in the order of 80°C
75 (Lognonne et al., 2020). In spite of these harsh conditions, 174 mostly small marsquakes
76 (Giardini et al., 2020) have been identified until 30 September 2019 thanks to the sen-
77 sitivity of SEIS and its careful deployment on the Martian surface.

78 Nevertheless, due to the unfavorable deployment conditions different aseismic sig-
79 nals are being recorded together with events of seismic origin (Ceylan et al., 2021; Lognonne
80 et al., 2020; Scholz et al., 2020; Stutzmann et al., 2021). That is, the seismic recordings
81 contain a wealth of features caused by operational activities at the lander, noise induced
82 by the lander due to atmospheric perturbations as laminar and turbulent winds, and ar-
83 tifacts caused by the response of the instruments to the variability of the severe climatic
84 factors as pressure and temperature. Data processing requires therefore special care and
85 adapted approaches to avoid any bias in the results and even misinterpretation of sig-
86 nals.

87 SEIS is a key instrument to reveal the internal Martian structure and to monitor
88 its seismic activity. However, the deployment of a seismometer at one single place lim-
89 its the ample spectrum of seismological imaging and monitoring strategies to single-station
90 approaches (e.g., Panning et al., 2015; van Driel et al., 2019; Drilleau et al., 2020). Promi-
91 nent single-station methodologies are P- and S-wave receiver functions (e.g., Phinney,
92 1964; Langston, 1979; Vinnik, 1977; Farra & Vinnik, 2000; Yuan et al., 2006), noise and
93 coda autocorrelation functions (e.g., Claerbout, 1968; Galetti & Curtis, 2012; Tibuleac

94 & von Seggern, 2012; Pham & Tkalčić, 2017; Tauzin et al., 2019; Buffoni et al., 2019),
 95 surface wave inversions (e.g., Drilleau et al., 2020) and Rayleigh wave ellipticity and spec-
 96 tral ratio analyses (e.g., Nakamura, 1989; Yano et al., 2009; Hobiger et al., 2013; Berbellini
 97 et al., 2019).

98 So far no unambiguous surface waves have been detected in SEIS data (Clinton et
 99 al., 2020; Giardini et al., 2020; Stutzmann et al., 2021). The very shallow structure down
 100 to 20 m depth at the InSight landing site has been probed using the travel time of mul-
 101 tiple hammer strokes of the HP³ (Heat Flow and Physical Properties Package) instru-
 102 ment and compliance observations (Kenda et al., 2020; Lognonne et al., 2020). The com-
 103 pliance approach employs seismic measurements of the surface deformation in response
 104 to pressure loading by dust-devils. First average crustal seismic attenuation and scat-
 105 tering results have been obtained from the body-wave coda shape of the best recorded
 106 marsquakes while first crustal layering has been inferred identifying body wave conver-
 107 sions in receiver functions (Lognonne et al., 2020). These results point to a crustal at-
 108 tenuation which is 3 times larger than on Moon and a highly variable upper crust layer
 109 of about 8 to 11 km thickness with S-wave velocities of 1.7 to 2.1 km/s. The exact thick-
 110 ness of the crust is still object of investigation, but receiver functions, event coda and
 111 noise autocorrelation results suggest that the crust is either about 15-26 or 27-47 km thick
 112 (Knapmeyer-Endrun et al., 2021). Deng and Levander (2020) have also computed noise
 113 autocorrelations for Mars and observe persistent signals which they interpret as Moho,
 114 upper-mantle transition and core-mantle boundary reflections. Their mantle signals have
 115 not yet been reproduced by other groups and can possibly be due to repeated glitches
 116 in the SEIS-data or interference of lander resonances (*Kim, Davis et al., in preparation*).
 117 High-frequency autocorrelations (5-7 Hz) have been presented by Suemoto et al. (2020)
 118 who showed robust signals which indicate the presence of two shallow reflectors in the
 119 first hundreds of meters. Noise and Marsquake autocorrelations have been also presented
 120 by Compaire et al. (2021), who find stable autocorrelations with signals related to crustal
 121 structure only during low-noise periods around 2.4 Hz

122 In this study we use the VBB SEIS data to further analyze noise autocorrelations
 123 through independent approaches. Special care is given to avoid imprints of aseismic sig-
 124 nals and artifacts on the autocorrelation results. The main objective is to extract a sta-
 125 ble and clean reflection response from the noise recordings. We focus on crustal scale sig-
 126 nals from vertical component recordings within the 1-9 Hz frequency band, and use dif-

127 ferently selected subsidiary data sets. The data selection strategy is novel and we show
 128 that a stable noise response is built up within a few Martian days of data and that it
 129 consists of several signals. Some of the signals are stable over a broad frequency band
 130 which makes them possible candidates for reflections. In any case, the autocorrelations
 131 are still difficult to interpret and possible ambiguities in the signal interpretations are
 132 discussed.

133 **2 Determination of P-Wave Reflection Response at SEIS**

134 On Earth, seismic ambient noise correlations have been successfully used to map
 135 crustal scale discontinuities (e.g., Ruigrok et al., 2011; Tibuleac & von Seggern, 2012;
 136 Gorbatov et al., 2013; Kennett et al., 2015; Taylor et al., 2016; Oren & Nowack, 2016;
 137 Saygin et al., 2017; Becker & Knapmeyer-Endrun, 2018; Romero & Schimmel, 2018; Buf-
 138 foni et al., 2019). Strictly, the cross-correlation of a diffuse wave field recorded at two
 139 sensors provides the Green’s function (GF) at one of the sensors for a virtual source placed
 140 at the other sensor (Lobkis & Weaver, 2001; Derode et al., 2003; Wapenaar, 2004; Snieder,
 141 2004, among others). When both recordings are the same then the cross-correlation be-
 142 comes an autocorrelation and provides a zero-offset GF. The high-frequency zero-offset
 143 GF is the reflection response which mainly consists of body wave primary reflections and
 144 multiples from seismic discontinuities beneath the station.

145 This principle has been presented already by Claerbout (1968) for one-dimensional
 146 (1-D) media as he demonstrated that the full reflection response can be obtained from
 147 the autocorrelation of a plane wave field which is transmitted from below the reflecting
 148 structure. Many years later, his finding has been extended to two-dimensional (2-D) and
 149 three-dimensional (3-D) acoustic and elastic media (e.g., Wapenaar, 2004).

150 The numerical determination of the zero-offset reflection response is based on the
 151 computation of autocorrelations. For this purpose the continuous noise recordings are
 152 cut into short segments to compute the autocorrelations. Finally, the autocorrelations
 153 of all segments are being stacked to provide the reflection response. In practice, wave
 154 fields are generally not diffuse and the exact GF is unknown or only partly reconstructed.
 155 We therefore now refer to empirical GF (EGF) or reflection response rather than GF to
 156 emphasize its approximate character.

157 Note that outliers in the amplitudes of the data can affect correlation results and
 158 it is therefore common to preprocess the data before computing autocorrelations (e.g.,
 159 Bensen et al., 2007; Schimmel et al., 2011). Different strategies exist to balance the am-
 160 plitudes in the time and frequency domain. One-bit normalization and spectral whiten-
 161 ing are often employed methods (Bensen et al., 2007). A disadvantage of these approaches
 162 is that they reduce the information content of the signal in a non-unique manner which
 163 can cause a less efficient EGF extraction as shown in Schimmel et al. (2018). Here, we
 164 avoid amplitude normalization strategies by replacing the conventional cross-correlation
 165 and linear stack with the amplitude unbiased phase cross-correlation (PCC, Schimmel
 166 (1999)) and time-frequency phase weighted stack (tf-PWS, Schimmel and Gallart (2007);
 167 Schimmel et al. (2011)).

168 In the following we highlight the main methods used to determine the reflection
 169 response at the InSight landing site and describe our data selection and processing.

170 2.1 Phase Cross-Correlation and Stacking

171 **Correlations.** The autocorrelation measures the self-similarity of a time series as
 172 function of lag time. It is a special case of the cross-correlation where both time series
 173 are the same. There exist different strategies to measure the self-similarity of time se-
 174 ries (e.g., Schimmel et al., 2018). Here, we employ the phase cross-correlation $c_{PCC}(\tau)$
 175 (PCC, Schimmel (1999)) which is based on the phase coherence of instantaneous phases
 176 as determined from analytic signal theory. PCC is expressed as:

$$c_{PCC}(\tau) = \frac{1}{2T} \sum_{t=1}^T \left| e^{i\Phi(t)} + e^{i\Psi(t+\tau)} \right|^\nu - \left| e^{i\Phi(t)} - e^{i\Psi(t+\tau)} \right|^\nu. \quad (1)$$

177 $\Phi(t)$ and $\Psi(t)$ are the instantaneous phases of the two input time series, τ is the
 178 lag time of the second time series with respect to the first one, T is the length of the time
 179 window, and ν a parameter which permits to tune the sensitivity of the PCC.

180 $e^{i\Phi(t)}$ is the envelope normalized analytic signal of the first time series. The ana-
 181 lytic signal can be build with the Hilbert Transform and is a unique representation of
 182 a real-valued time series in the complex number space. PCC benefits from the fact that
 183 thanks to the analytic signal theory a real time series can be decomposed into an instan-

184 taneous phase and amplitude (envelope) function. PCC uses only the instantaneous phases
 185 and is therefore explicitly signal amplitude unbiased.

186 The phase autocorrelation is obtained using $\Phi(t) = \Psi(t)$. Further, we use $\nu = 2$
 187 since it permits to simplify the equations for fast computations (Ventosa et al., 2019).
 188 $c_{PCC}(\tau)$ is, in analogy to a classical correlation, a real numbered functional with values
 189 ranging between -1 and 1. One of the main differences to the classical correlation is that
 190 waveform similarity is measured through the amount of phase-coherent samples rather
 191 than the sum of amplitude products.

192 **Stacking.** The obtained autocorrelations need to be averaged over larger time spans
 193 to achieve a stable noise response. Stacking data over larger time spans improves the az-
 194 imuthal coverage of the noise wavefield and the cancellation of cross terms (e.g., Snieder,
 195 2004; Medeiros et al., 2015). Both are necessary conditions in seismic interferometry. Here
 196 we employ linear stacks and time-frequency Phase Weighted Stacks (tf-PWS, Schimmel
 197 and Gallart (2007); Schimmel et al. (2011)). The tf-PWS are based on the instantaneous
 198 phase coherence (in analogy to PCC) which is being measured in the time-frequency do-
 199 main during stacking. The weights range between 0 and 1 to attenuate less coherent sig-
 200 nals in the time-frequency domain. Finally, linear stacks are weighted by the time-frequency
 201 phase coherence to build the tf-PWS.

202 The time-frequency representation of the data is obtained with the S-Transform
 203 by Stockwell et al. (1996) which is based on Fourier theory and frequency-dependent Gaussian-
 204 shaped windows. The obtained time-frequency representation can be made an analytic
 205 signal as shown in Schimmel and Gallart (2007) to enable the use of an instantaneous
 206 phase coherence measure which is the backbone of tf-PWS. Alternatively, tf-PWS can
 207 be presented using the wavelet transform (Ventosa et al., 2017) to reduce redundancies
 208 and to increase computational efficiency. This modification is based on the fact that the
 209 S-Transform with Gaussian-shaped windows can be derived from the Morlet wavelet trans-
 210 form (Ventosa et al., 2008). Both strategies provide exactly the same result.

211 **2.2 Data and Time Frame**

212 The VBB SEIS data are recorded on three oblique axes. Data from the three axes
 213 are needed to build the vertical and horizontal components (Lognonne et al., 2019). For
 214 this study we use vertical components, recorded from May 22, 2019 to June 30, 2020 at

215 20 samples-per-second and instrument corrected to ground velocity from 0.01 to 10 Hz.
 216 The correction is performed for the three oblique axes before rotation to the vertical and
 217 horizontal components. The late starting date has been chosen to avoid the initial de-
 218 ployment and testing phase. Key dates related to the seismic part of the mission are listed
 219 in Table 1.

220 As time frame, we employ the Local Mean Solar Time (LMST) throughout the en-
 221 tire study. The Martian day, called Sol, is about 40 min longer than a day on Earth with
 222 a Martian year being about 687 Earth days. Thus, using LMST is justified since the time
 223 on Mars differs from Earth time. The Martian dates, as usual in other missions, are de-
 224 fined as simple numerical counts using Sol 1 for the first significant Mars-day which for
 225 InSight corresponds to November 26, 2018. The data used here are from Sol 172 (2019-
 226 05-21 at 22:39:52.32) to Sol 567 (2020-06-30 at 19:16:53.76). Our initial database has been
 227 obtained cutting the instrument-corrected, vertical component records within every Sol
 228 into 7400 s segments which overlap by 600 s.

229 2.3 Data Segmentation and Selection

230 We filter the seismic recordings to a broad frequency band, 1.2 - 9.8 Hz, and de-
 231 termine the relative RMS variability for sliding data windows. A maximum RMS vari-
 232 ability threshold is then defined to obtain a mask and to extract data segments with RMS
 233 variability below the threshold through a minimum time duration. We use this proce-
 234 dure to build subsidiary data sets which contain less data problems such as glitches and
 235 outlying amplitude events. The approach and the subsidiary data sets are described in
 236 the following.

237 The moving window RMS r is determined for window i and length N using

$$r_i = \sqrt{\frac{1}{N} \sum_{n=i-N/2}^{i+N/2} a_n^2}, \quad (2)$$

238 where n stands for the time index and a_n for the seismic record. i marks the center sam-
 239 ple of the sliding window. In a next step the relative variance s^2 of the RMS amplitudes
 240 is computed during a second moving window analysis with window length $M > N$. The
 241 relative variance s^2 of window j is expressed as

$$s_j^2 = \frac{\left(\sum_{i=j-M/2}^{j+M/2} r_i - R_j\right)^2}{(M-1)R_j^2} \quad \text{with} \quad R_j = \frac{1}{M} \sum_{i=j-M/2}^{j+M/2} r_i, \quad (3)$$

242 where R_j is the non-zero mean RMS amplitude within the analysis window j . We de-
 243 fine the relative variance s^2 as the variance divided by the square of the mean to obtain
 244 a dimensionless (scale invariant) measurement of variability. This definition permits to
 245 compare data segments with variable RMS mean and to adjust to different seismic back-
 246 ground noise levels which may happen along the Sol.

247 In a next step, data segments are determined with $s_j^2 < S^2$, where S^2 is a cho-
 248 sen maximum RMS variability. A new subsidiary data base is then built accepting only
 249 data chunks with time duration larger than a minimum time duration, say t_{min} .

250 Thus, the free parameters of this data selection and segmentation approach are the
 251 window length (N and M of eqs. 2 and 3) and step intervals (i and j) for the two anal-
 252 ysis windows, the maximum RMS-variability S^2 and the minimum data segment length
 253 t_{min} .

254 On one hand, the analysis windows should be several times longer than the largest
 255 period as defined by the lowest corner frequency of the bandpass filter to warrant sta-
 256 tistical significance. On the other hand, the windows should not be too long to permit
 257 tracking RMS-variability changes with time. Throughout this study we used window length
 258 and step interval of 5 s and 0.1 s for the sliding-window RMS measurements (eq. 2) and
 259 20 s and 1 s for the RMS-variability determination (eq. 3). Further, the shortest admit-
 260 ted data segment length (t_{min}) is 300 s and the chosen RMS-variability thresholds (S^2)
 261 are 0.1 and 0.2. Using these parameters two subsidiary data sets have been set up which
 262 consist of data volumes of about 3% (RMS-variability threshold 0.1) and 30% (RMS-variability
 263 threshold 0.2) of the total data base. In the following, we will refer to these data sets
 264 as the total or 100%, 30%, and 3% data sets.

265 Different other parameters have been tested. The thresholds on data segment lengths
 266 and RMS-variability have a direct influence on the amount of selected data while vary-
 267 ing the analysis window parameters within reasonable bounds has a minor or insignif-
 268 icant impact on the subsidiary data base. In any case, there exists a trade-off between
 269 the selected amount of data and tolerance of RMS-variability changes. A fine tuning with
 270 the parameters may make sense for data sets where outlying noise is clearly separated
 271 from the rest of the data. In our case, aseismic noise exists at any amplitude level and
 272 therefore, it seems easiest to just analyze the results for more or less restrictive subsidiary
 273 data sets.

274 Examples of the data selection and segmentation procedure are shown in Fig. 1.
 275 The top traces of Figs 1a-c show seismic recordings with a duration of about 2 h. The
 276 start time of each trace is given in the figure. The second and third traces of each panel
 277 are the corresponding RMS (r_i) and RMS-variability (s_j , eqs 2 and 3). The horizontal
 278 red lines mark the RMS-variability threshold (0.2) to find the data segments with low
 279 RMS-variability. Segments with a duration larger than $t_{min} = 300$ s are drawn in red
 280 and form part of the 30% data set.

281 It can be seen from Fig. 1 that the selected red segments are data stretches with
 282 low-amplitude variability. I.e, outlying amplitude signals have been avoided by the ap-
 283 proach. Fig. 1c also shows that segments with different amplitudes are selected inher-
 284 ent to the use of relative variance s_j^2 . Further examples are shown in Fig. S1.

285 Fig. 2a shows the evolution of the relative RMS variability as function of Sol. Plot-
 286 ted are mean (red dots), one standard deviation uncertainty (gray bars), minimum and
 287 maximum value (black triangles) per Martian-day. All these values stay stable until about
 288 Sol 450. From about Sol 450 a slight but systematic increase of the maximum and mean
 289 RMS variability is being observed. A more rapid increase of the minimum RMS variabil-
 290 ity is evident from about Sol 500 to Sol 530. At the end of the analyzed period all val-
 291 ues are increased with respect to the beginning of the study period. The RMS variabil-
 292 ity increase correlates with a systematic raise of bad weather attributed to the entrance
 293 into local winter with more storms (Spiga et al., 2020). For example, Fig. 2b illustrates
 294 the measured mean wind speed (red dots), its one standard deviation uncertainty (gray
 295 bars), and minimum and maximum wind speed as function of sol. It can be seen that
 296 the minimum wind speed increases fast from about Sol 500 on, which is in concordance
 297 with the rise of the minimum RMS variability caused by the presence of winds at the
 298 lander site at all times. The highest wind speeds and standard deviation values decrease
 299 from about Sol 420 which reflects that the wind characteristics and distribution changed
 300 at the lander as also recorded by SEIS.

301 The just mentioned rise of RMS variability causes a decreased amount of selected
 302 data towards the last analyzed Sols as also documented in Fig. S2. This figure shows
 303 the LMST of the selected data segments as function of Sol for the 30% and 3% data sets.
 304 It can be seen that most of the selected data segments are from the evening and morn-
 305 ing hours. This is expected since lander and wind activity are low during the night. Still,

306 glitches and other aseismic abrupt signals may happen during night which makes our data
 307 adaptive selection and segmentation approach different from any time dependent (e.g.,
 308 day/night) selection. It is also seen that less data has been selected during the last 60
 309 Sols owing to the increase of bad weather during this period.

310 The data segment length distribution for the 30% subsidiary data set is shown in
 311 Fig. 3a. One third of the data segments has lengths smaller than 10 min. The number
 312 of segments decays quickly as function of segment length. Fig. 3b illustrates a normal-
 313 ized RMS amplitude distribution. The vertical axis now shows the total time duration
 314 rather than the number of individual segments. The gray histogram is for the 100% data
 315 set while the red histogram corresponds to the 30% data set. The RMS normalization
 316 is the same for both data sets. The absolute RMS amplitude is not important here, but
 317 the comparison of both histograms shows that the 30% data set consists mostly of small-
 318 amplitude segments. The 100 % data set RMS amplitudes have been obtained for 2-hour
 319 windows which consist typically of small and high RMS amplitude variability. Conversely,
 320 the 30% data set has a variable window length and does not include data stretches of
 321 high amplitude variability. This explains the increased total time duration for small RMS.

322 2.4 Phase Autocorrelation Spectra for Selected Data Sets

323 The Fourier Transform of the conventional autocorrelation of a time series equals
 324 its energy spectral density (ESD) for time series which have finite duration and are square
 325 integrable. In analogy to the ESD, we compute here the Fourier amplitude spectra of
 326 phase autocorrelations. The obtained spectra do generally not equal the ESD of the data
 327 as we use PCC to determine autocorrelations. Dissimilarities are often small and inher-
 328 ent to the different measure of signal coherence with each autocorrelation approach. How-
 329 ever, outlying amplitude signals do not bias PCC which permits a fast convergence to
 330 the EGF and stable autocorrelation spectra as shown in Schimmel et al. (2018).

331 Fig. 4 shows the Fourier amplitude spectra of the linear stack of the phase auto-
 332 correlations using the 100% (black line), 30% (red line) and 3% (blue line) data sets. The
 333 data have been band-pass filtered between 0.8 and 9.5 Hz before computation of the au-
 334 tocorrelations. Different spectral lines and bumps are visible in these spectra. The spec-
 335 tral lines at integer frequencies are related to the “tick noise“ which is an aseismic sig-
 336 nal caused by electrical coupling during the SEIS temperature acquisition at 1 sps (sam-

337 ple per second). The spectral amplitude bumps are related to lander modes and/or res-
 338 onance of the seismic subsurface structure (e.g., Ceylan et al., 2021). The main bumps
 339 have been labeled along the spectrum for the 100 % data set.

340 Bump 1 and spectral lines at integer frequencies appear to be enhanced in the data
 341 sets with less RMS amplitude variability, i.e., for the 30% and specially 3% data sets.
 342 This is partly due to the attenuation of other signals and noise with higher RMS am-
 343 plitude variability. The origin of bump 1 is still under investigation. It is centered at about
 344 2.4 Hz and could be caused by the superposition of lander and structural resonances. The
 345 corresponding lander modes at bump 1 are expected to arise as a response of the solar
 346 array oscillations during laminar wind flow, i.e., at wind speeds below about 3 m/s. This
 347 may explain why this bump 1 appears to be enhanced for the data sets with less RMS
 348 amplitude variability. Conversely, bumps 2-6 are systematically attenuated in the 30%
 349 and 3% data sets. These data sets consist mostly of seismic recordings during the local
 350 evening hours (Fig. S2) which is when there are less wind and less air pressure pertur-
 351 bations (e.g., Lognonne et al., 2020; Stutzmann et al., 2021). Bumps 2 to 6 correspond
 352 to resonances that are related to different lander modes which are mostly excited by tur-
 353 bulent winds above a threshold speed of about 3 m/s (Dahmen et al., 2021). In the fol-
 354 lowing we will work in the 1.2 - 8.9 Hz frequency band to avoid resonances at 1 and 9
 355 Hz.

356 2.5 Attenuation of Tick Noise, Lander and Shallow Structure Resonances

357 Fig. 5a shows vertical-component phase autocorrelations stacks as function of au-
 358 tocorrelation lag time and recording date. The entire data set has been used without any
 359 selection criteria, cut into 2-hour data segments and frequency band passed between 1.2-
 360 8.9 Hz before computation of the phase autocorrelations. The autocorrelations have been
 361 stacked linearly for recording dates within non-overlapping sliding 3-Sol data windows.
 362 In this figure, the positive amplitudes have been filled with red color and the positively
 363 correlated signals seen at every full second are tick noise (Fig. 5a). We have chosen a
 364 window at large lag time to avoid the interference with reflections from shallow discon-
 365 tinuities to permit a visual judgment on the tick noise attenuation.

366 The tick noise is caused by electro-magnetic coupling during the SEIS temperature
 367 acquisition at 1 sps with a recorded waveform which does not resemble an impulsive sig-

368 nal (Compaire et al., 2021). On vertical components and within the here considered fre-
 369 quency band, most of its energy is at 4, 7, and 2 Hz (Fig. 4).

370 Recorded tick noise and lander modes may interfere with seismic weak-amplitude
 371 reflections and should ideally be removed from the data to warrant the detection of weak
 372 amplitude reflections. Similarly, structural resonances should also be attenuated as their
 373 dominant signals may impede the detection of weak amplitude reflections. Structural res-
 374 onances are caused by seismic energy which is trapped in a shallow subsurface layer due
 375 to strong impedance contrasts at the limits of the layer. Only little energy leaks to deeper
 376 layers which therefore can inhibit the imaging of deeper structures with frequencies in
 377 the structural resonance band.

378 Here, we attenuate the tick noise together with other resonances using band-rejection
 379 filters. First, we try two band-rejection filters (3.9-4.4 Hz and 6.8-7.2 Hz) to remove the
 380 two strongest tick noise peaks at 4 and 7 Hz and neighboring lander modes (bumps 4
 381 and 6). Fig. 5b shows in full analogy to Fig. 5a the autocorrelations after the applica-
 382 tion of the two just mentioned band-rejection filters. Bump 3 has not been included into
 383 the first rejection band since this signal is already attenuated for the 30% data set (Fig.
 384 4, middle panel).

385 It can be seen from Fig. 5b that there exist still some lower-frequent tick noise which
 386 justifies employing a third band-rejection filter from 1.9 to 2.5 Hz. The resulting auto-
 387 correlation section Fig. 5c is finally not dominated by tick noise anymore. Besides, the
 388 data has been cleaned from other resonances (bumps 1, 4 and 6).

389 An alternative approach is to measure the tick waveform through stacking of 1 s
 390 data segments for subsequent subtraction from the data (Compaire et al., 2021). Here
 391 we chose a different and independent approach to further show stability in our results.

392 **3 Reflection Response and Interpretations**

393 Fig. 6 shows autocorrelations computed using PCC and stacked with the tf-PWS
 394 approach. The employed seismic recordings belong to the 30 % data set. We bandpass
 395 filtered these data from 1.2 to 8.9 Hz and applied the three band-rejection filters explained
 396 in the previous section. The autocorrelations have been stacked within non-overlapping
 397 3-Sol windows and negative amplitudes are plotted in blue. Note that P-wave reflections
 398 at seismic discontinuities with an impedance increase are expected to have negative am-

399 plitudes. The autocorrelation section of Fig. 6 has been split into three lag-time win-
 400 dows to apply an independent amplitude normalization in each window for visual pur-
 401 poses. The earliest lag time starts at 5 s as the first seconds are dominated by zero-lag
 402 autocorrelation sidelobes (e.g., Ruigrok & Wapenaar, 2012; Romero & Schimmel, 2018).
 403 The amount of stacked data is shown to the top of each autocorrelation. The maximum
 404 duration of the data used per autocorrelation is about 1 Sol rather than 3 Sol which is
 405 the length of the data window. This is because of the applied data selection which re-
 406 duced the data used here to about 30 %. The corresponding linearly stacked autocor-
 407 relation section is displayed in Fig. S4 of the Supplementary Material. As also shown
 408 further below, the tf-PWS approach provides cleaner results as incoherent signals and
 409 noise have been attenuated during the stacking.

410 The autocorrelation section of Fig. 6 contains signals repeated on most autocor-
 411 relations at specific lag times. These signals are stable as they show up for independent
 412 autocorrelations along the entire analyzed time interval. One of the most outstanding
 413 signals is seen at about 10.6 s. If we interpret this arrival as a P-wave reflection and as-
 414 sume an average crustal P-wave velocity of 4.5 km/s then the reflector is expected to be
 415 at about 24 km depth. Note that the assumed average P-wave velocity is slower than
 416 for Earth as indicated by receiver function inversions (Lognonne et al., 2020; Knapmeyer-
 417 Endrun et al., 2021).

418 As the raw data consists also of different other aseismic signals, an autocorrelation
 419 signal is not a synonym of a seismic reflection. Some of the signals are expected to be
 420 part of the seismic reflection response while other signals can be due to any coherent and
 421 repeated feature in the data or due to beating of resonating frequency components from
 422 the lander. Resonances with slightly different frequencies f_1 and $f_2 > f_1$ cause an in-
 423 terference pattern (wellknown in music) with beat frequency $f_b = f_2 - f_1$ (e.g., Kinsler
 424 et al., 1999). The beats of the interfering signals manifest in time-domain autocorre-
 425 lations as distinct and repeating signals of maximum amplitude at lag times $t_n = n/f_b$
 426 with $n \in N$. Similarly, glitches or other signals which are repeated systematically with
 427 the same time interval are expected to show up in autocorrelations at lag time which cor-
 428 responds to the time separation of the repeated features.

429 Indeed, the interpretation of autocorrelations without any further a priori infor-
 430 mation is difficult. However, receiver function studies of marsquakes (Knapmeyer-Endrun

431 et al., 2021; Lognonne et al., 2020) provide the first a priori information of the under-
 432 lying structure and expected crustal-scale P-wave reflections on Mars. In this respect,
 433 the strong arrival at 10.6 s lag time interpreted as a P-wave reflection seems to be con-
 434 sistent with P-to-s wave conversions observed with receiver functions (Knapmeyer-Endrun
 435 et al., 2021). Indeed, the 10.6 s signal is quite robust and a likely candidate for a P-wave
 436 reflection from the crust-mantle boundary. Note that Compaire et al. (2021) also report
 437 a signal at 10.6 s using a different approach.

438 The 10.6 s signal is discernible in linear and tf-PWSs of the three data sets as shown
 439 in Fig. 7. This figure contains the linear stacks in black and the tf-PWSs in red for all
 440 autocorrelations from the 100 % (top traces), 30 % (middle traces), and 3 % (bottom
 441 traces) data sets. The traces have been normalized by their RMS amplitudes measured
 442 between 8 and 20 s lag time. Further, amplitudes are clipped during the first seconds
 443 to favor the visibility of later arriving signals. It can be seen that the 10.6 s signal is vis-
 444 ible with amplitude of about twice the amplitude of neighboring signals and noise. Its
 445 shape resembles more a zero-phase wavelet than a wave train. The direct comparison
 446 of the stacks also shows that the tf-PWS approach provides cleaner autocorrelations through
 447 the attenuation of incoherent signals and noise.

448 3.1 Convergence

449 We now look at the convergence of autocorrelation stacks towards a stable seismic
 450 noise response. In seismic interferometry, the minimum amount of data needed is con-
 451 trolled by the cancellation of noise-cross terms (e.g., Snieder, 2004) and the abundance,
 452 distribution, quality and duration of signals to build up a stable EGF.

453 Under the assumption of stationarity and minimum frequency of 1 Hz, cross-terms
 454 cancel out within confidence level $\epsilon \approx 0.01$ after about 3 h (eq. 9 in Medeiros et al. (2015)).
 455 The SEIS data are highly variable and the assumption of stationarity is not valid. Nev-
 456 ertheless, the estimated 3 h can be taken as a guide value. This value is shorter than the
 457 used data length of each autocorrelation shown in the figures for the 30% and 100% data
 458 sets.

459 The total data length needed to extract a robust reflection response can be esti-
 460 mated by a convergence analysis. In this approach the evolution of autocorrelation stacks
 461 of random subsidiary data sets is being inspected as function of amount of data used for

462 the autocorrelations in each of the stacks. For this purpose the individual autocorrela-
 463 tion stacks are being compared with a reference waveform obtained by stacking all avail-
 464 able data. The waveform similarity of the two stacks can be determined with the zero-
 465 lag cross-correlation of the two time-series. Here, we employ PCC and the geometrically
 466 normalized cross-correlation (CCGN, e.g., Schimmel (1999)). The reference traces are
 467 those shown in Fig. 7.

468 There exist different data sampling strategies to draw the random autocorrelation
 469 stacks. We tested two strategies, random sampling without replacement and Bootstrap-
 470 ping which uses random sampling with replacement (Efron & Tibshirani, 1986). With-
 471 out replacement means that no autocorrelogram is used more than one time in a draw.
 472 We repeated the random drawing 40 times to enable the determination of mean and stan-
 473 dard deviation for the similarity to the reference waveform.

474 Figs 8 and S5 demonstrate our results using the Bootstrapping resampling and PCC
 475 and CCGN, respectively, to measure waveform similarity in moving windows of 0.5 s length.
 476 The 30 % data set has been used for Figs 8a,b. Fig 8a shows the waveform similarity
 477 while Fig. 8b contains the standard deviation of the similarity. The similarity (red line)
 478 and corresponding standard deviation (gray error bars) at 10.6 and 19.5 s are shown in
 479 the Figs 8c,d. 19.5 s has been chosen arbitrarily for comparison. A plateau in the sim-
 480 ilarity curve means that stacking more autocorrelations is not changing significantly the
 481 waveform similarity. The figures illustrate that the 10.6 s signal converges faster than
 482 a signal at 19.5 s lag time. Using CCGN (Fig. S5) an apparent overall faster waveform
 483 similarity is measured than using PCC. This is expected as PCC is the more waveform
 484 sensitive measure due to the employed instantaneous phase coherence.

485 From Figs 8a and S5a we also observe that signals at shorter lag time tend to con-
 486 verge faster than signals at larger lag time. For a P-wave reflection response a larger lag
 487 time means longer wave paths owing to a deeper discontinuity or multiple reverberation.
 488 Such signals may need more data to stabilize in the EGF since the corresponding waves
 489 are more susceptible to the different types of attenuation.

490 A comparison of the similarities for the 100 %, 30 %, and 3% data sets is shown
 491 in Figs 8e,f and S5e,f. It can be seen that slowest signal convergence is achieved using
 492 the 100 % data set (black curves). This means that a high amplitude variability is not
 493 contributing significantly to the extraction of the EGF. Note that this result does not

494 change when using only the data until Sol 410. I.e., the increasing RMS variability af-
 495 ter Sol 450 (Fig. 2) is not causing the slower convergence.

496 The 3 % and 30 % data sets seem to provide more similar results. The 3 % and
 497 30 % data sets have a total length of 151.8 h and 1557.1 h. The 3 % data set results are
 498 therefore obtained with a higher replacement rate. Drawing the random data sets with-
 499 out replacement (not shown here) illustrates that the similarity curves for the 3 % and
 500 30 % data are still more similar than for the 100 % data set.

501 **3.2 Stability of Reflection Response over Time**

502 The autocorrelations for the three data sets are shown in Fig. 9. The only differ-
 503 ences to Fig. 6 are the respective data sets (from left to right: 100 %, 30 %, and 3%)
 504 and the use of non-overlapping 30-Sol windows rather than 3-Sol windows. 30-Sol win-
 505 dows have been employed to reduce the number of autocorrelations to permit a compar-
 506 ison of the three autocorrelation sections at one glance. A welcomed side effects is that
 507 these autocorrelations are more robust owing to the increased amount of data used in
 508 each of the stacks. The corresponding linear stacks are demonstrated in Fig. S6 for com-
 509 pleteness.

510 The most striking observation is that the 100 % autocorrelations show systemat-
 511 ically changing noise responses, i.e., the autocorrelations from about Sol 450 towards the
 512 end of the section look different with respect to the autocorrelations obtained for the first
 513 Sols. This variability is likely due to changing climatic conditions with stronger storms
 514 and corresponding responses of the lander. In fact, the statistical properties of the seis-
 515 mic recordings start to change simultaneously at about Sol 450 as testified with the ob-
 516 served daily RMS variability shown in Fig. 2. In contrast to the 100 % data, the 30 %
 517 autocorrelations (middle panel of Fig. 9) show stable signals for all Sols. This is because
 518 the RMS variability threshold retained most of the seismic recordings with imprints of
 519 climate and lander response variability. This result reinforces that a thorough data se-
 520 lection is essential to warrant a minimum influence of aseismic signals which may bias
 521 any autocorrelation result. In this respect, a data adaptive approach is better than sim-
 522 ply selecting the data through LMST slots.

523 Amplitude spectra of the just discussed autocorrelations are shown in Fig. 10. The
 524 amplitudes have been normalized at 6 Hz for visual purposes. Spectra for linearly stacked

525 autocorrelations are shown in Fig. S7 for comparison. It can be seen from both figures
 526 that the 100 % data set suffers at about 3.8 Hz and Sols larger than 500 from energy which
 527 appears at the corner of one of the applied band-rejection filter. These signals are more
 528 pronounced in the spectra of the linear stacks and are likely lander resonances in response
 529 to the bad weather. Amplitude spectra for linearly stacked autocorrelations computed
 530 for data without application of band-rejection filters (Fig. S8) reveal that the strongest
 531 amplitude changes indeed occur around 4 Hz. Broader band-rejection filters could at-
 532 tenuate these signals, but unnecessarily reduce the band width of the autocorrelations
 533 for data recorded before Sol 450.

534 As expected from the time-domain autocorrelations of Fig. 9 the corresponding spec-
 535 tra (Fig. 10) for the 30 % and 3 % data sets show less variability than for the 100 % data
 536 set. The strongest resonances have still been attenuated by the data selection approach
 537 and three band-rejection filters.

538 **3.3 Stability of Reflection Signals over a Broad Frequency Band**

539 Finally, seismic signals related to structural discontinuities are expected to be de-
 540 tected for a rather broad than narrow frequency band, i.e., possible frequency-dependent
 541 reflectivity generally varies smoothly. Besides, at small lag time, sidelobes of the zero-
 542 lag autocorrelation peak may affect early structural arrivals. The autocorrelation side-
 543 lobes are caused by the convolution of a delta pulse with the effective noise source time
 544 function (e.g., Ruigrok & Wapenaar, 2012) and are expected to change faster with fre-
 545 quency than a reflection pulse (see Fig 6 in Romero and Schimmel (2018)).

546 We therefore inspect the signal stability across different frequency bands. The first
 547 three panels in Fig. 11 show autocorrelations for the 30 % data set and different one-
 548 octave frequency bands. From top to bottom these are 1.5-3.0 Hz, 2.4-4.8 Hz, and 3.6-
 549 7.2 Hz. The effective band width, nevertheless, is smaller than an octave owing to the
 550 employed band-rejection filters. The tf-PWS of all autocorrelations is illustrated in red
 551 while the black lines show tf-PWSs of 10 % randomly drawn autocorrelations. The fourth
 552 panel shows the red color stacks of the top three panels plotted on top of each other. The
 553 lowermost panel contains the tf-PWS (red line) and linear stack (blue line) for the wide
 554 1.2-8.9 Hz band.

555 It can be seen from this figure that some signals are persistent or in phase along
 556 different frequency bands. Labels *a-f* mark some of these signals at lag times of 6.15 s,
 557 6.85 s, 8.66 s, 10.6 s, 16.85 s, 23,8 s and 24.49 s. The dashed vertical lines have been added
 558 to aid the visual inspection. Signals *a* and *c* are not seen for the lowest frequency band
 559 and have therefore been marked at the base of the figure. None of the signals is being ob-
 560 served for only one frequency band. E.g., signal *b* is in phase for the three frequency bands
 561 while signal *d* is in phase for the two lower bands. The latter signal, however, appears
 562 only in the middle frequency band as a clear signal. It is seen from the top two panels
 563 that the amplitude maxima of signal *d* are not coherent while its minimum amplitude
 564 occurs at the same lag time to build up the observed negative polarity when filtering over
 565 a broader frequency band. Features *a* and *c* are in phase for the two higher frequency
 566 bands. Signals *e* and *f* are also in phase and show also up as slightly distinctive features
 567 in the 1.2-8.9 Hz correlations. *e* and *f* are less impulsive as *d*, i.e., in the 1.2-8.9 Hz cor-
 568 relations they seem to be part of a larger waveform. *f* has been marked twice, at the first
 569 minimum amplitude and 0.6 s later at the lowest minimum. We use only one letter, as
 570 it is not clear if this are several signals which arrive at a similar time.

571 In any case, a visible interference of zero-lag sidelobes or their misinterpretation
 572 is not expected owing to the stationarity of these signals over a broader frequency band
 573 (Romero & Schimmel, 2018).

574 **4 Discussion and Conclusion**

575 The 10.6 s signal, if interpreted as P-wave reflection, would point to a discontinu-
 576 ity at about 24 km depth considering expected Mars's crustal average seismic velocities
 577 of 4.5 km/s. We observe the 10.6 s signal robustly on the 100 %, 30 %, and 3 % data
 578 sets with amplitudes which can reach twice the amplitude of other nearby signals and
 579 noise. The shape of the waveform resembles more a zero-phase wavelet with negative po-
 580 larity than a wave train. The negative polarity is consistent with a reflection from a dis-
 581 continuity with a seismic impedance increase while the wavelet shape can be explained
 582 by a sharp discontinuity and lack of other interfering signals as reflections from strong
 583 nearby discontinuities.

584 Indeed, the 10.6 s signal is a likely candidate for a reflection from the base of the
 585 crust owing to its two-way travel time, negative polarity, strengths and robustness. En-

586 ergy at similar lag time has also been reported by Deng and Levander (2020) and Compaire
587 et al. (2021) and interpreted as P-wave Moho reflection. The 10.6 s signal seems to be
588 consistent with models obtained for receiver functions from marsquake data (Lognonne
589 et al., 2020; Knapmeyer-Endrun et al., 2021). Knapmeyer-Endrun et al. (2021) present
590 two model families resulting from receiver function inversions where the 10.6 s signal can
591 be explained either as a P-wave Moho or internal crustal discontinuity reflection. More
592 events from different distances or other geophysical constraints are needed to further limit
593 the model space and to aid the identification of autocorrelation signals. We prefer the
594 first model class which can explain the 10.6 s signal as a Moho reflection since we ob-
595 serve no other, at least equally-strong signal at a later time to explain a deeper Moho.
596 This is based on the assumption that the crust-mantle boundary is stronger than a mid-
597 crust discontinuity.

598 The seismic data acquisition conditions are harsh on Mars and there exist a wealth
599 of different aseismic signals (Lognonne et al., 2020; Ceylan et al., 2021; Scholz et al., 2020;
600 Stutzmann et al., 2021) which also may show up on autocorrelations. For instance, reg-
601 ularly repeated glitches (long duration pulses typically with frequencies below 1 Hz) and
602 donks (short duration pulses typically at frequencies above 8 Hz, Ceylan et al. (2021))
603 with similar waveforms can manifest, depending on their abundance and coherence, at
604 their repeat time. To attenuate the effect of glitches and donks, Deng and Levander (2020)
605 determine the absolute mean amplitude in moving data windows of 100 s length which
606 then are used to weight the seismic data (e.g., Bensen et al., 2007). Finally, they observe
607 at 11.5 s a signal which appears robustly on their Martian day-time and night-time data
608 and which they interpret as Moho P-wave reflection.

609 Conversely, Compaire et al. (2021) removed the tick noise and attenuated glitches
610 using an algorithm by Scholz et al. (2020). High-frequency components of glitches re-
611 main in the data and donks are not removed by the algorithm. All in all, they use data
612 recorded during the evening hours for which autocorrelations have the highest signal-
613 to-noise ratio (SNR) and find a signal at 10.6 s and at 21 s which they interpret as re-
614 flections from crustal layers. They also show that glitches can not interfere with these
615 reflections as they are separated by more than 30 s. The repeat time of donks, however,
616 can be much smaller with maximum at about 10 s around 17-18 h LMST (Compaire et
617 al., 2021). The authors argue that the observed stability of the 10.6 s signal with time

618 is not correlated with the overall distribution of donks which finally makes a donk ori-
619 gin of these reflections unlikely.

620 Here, we use a different data processing strategy. For instance, we do not de-glitch
621 the records as high frequency glitch signatures seem to remain in the cleaned data. Fur-
622 ther, we refrain from selecting data by choosing fixed time slots and design a data-adaptive
623 approach to segment and pick seismic records based on their RMS amplitude variabil-
624 ity. Our 30 % and 3 % data sets have been built selecting stretches of data with low RMS
625 variability which also led to an attenuation of most lander resonances as seen from the
626 spectra in Fig. 4. We further attenuated strong resonances using three band-rejection
627 filters (1.9-2.5 Hz, 3.9-4.4 Hz and 6.8-7.2 Hz). These band-rejection filters were also cho-
628 sen to remove jointly the strongest components of the tick noise.

629 Our data selection procedure is expected to avoid large amplitude donks and glitches
630 and should be less affected by aseismic features which are related to bad weather lan-
631 der and SEIS responses. However, small amplitude donks which do not affect the RMS
632 variability can still be present in the selected data. Concerning the 10.6 s signal, a donk
633 origin would require a sharp repeat time distribution of opposite polarity donks to ex-
634 plain the negative correlation peak and zero-phase shaped wavelet. A smooth distribu-
635 tion of donks is expected to either cancel out or to produce wave train shaped signals
636 at lag times which correspond to their repeat times. In any case, at present we are not
637 aware of hidden donks, but can also not rule out their existence.

638 Finally, large amplitude donks and glitches do not seem to have a dominant im-
639 print on the autocorrelations as can be seen by comparing the autocorrelation sections
640 for the 100 % and 30 % data sets (Fig. S9). This is because randomly distributed or in-
641 coherent glitches and donks, as well as other outlying signals and noise do not affect the
642 amplitude unbiased PCC. Therefore, PCC is an adequate approach for data from un-
643 favorable deployment and detection conditions as shown in Schimmel et al. (2018).

644 Another source of aseismic signals can be beats produced through interfering res-
645 onances (Kinsler et al., 1999). Beats can manifest in autocorrelations at lag time which
646 equals the inverse of the difference in frequency of the two resonances and multiples. I.e.,
647 a 10.6 s autocorrelation signal could be due to a 0.094 Hz beat. The 10.6 s signal does
648 not show a seasonal variability and would therefore require stable resonances through-
649 out the analyzed data. We believe that the autocorrelations are not dominated by strong

650 beats as the main lander resonances have been attenuated through rejection filters and
 651 data selection on frequency band pass filtered data. Still, the presence of weak ampli-
 652 tude beats in the data can not be ruled out.

653 Further, the fast convergence of the 10.6 s signal which can be extracted with about
 654 2 Sol of data is remarkable. There are no oceans on Mars, and all seismic energy is sup-
 655 posed to be released by weak magnitude events (the largest observed Marsquake has a
 656 magnitude of 4 Clinton et al. (2020)) and through atmospheric phenomena. In spite of
 657 the absence of strong sources, the low level of natural Martian noise (Lognonne et al.,
 658 2020) may favor the detectability of low-amplitude signals and therefore aid the conver-
 659 gence of the reflection response.

660 We focused the discussion on the 10.6 s signal, as it appears to be a likely candi-
 661 date for a reflection from the base of the crust. Nevertheless, the obtained reflection re-
 662 sponse contains also other signals which likely are reflections and multiples from other
 663 discontinuities. Some of them have been marked in Fig. 11 (labels a to g) owing to their
 664 appearance over a broader frequency band. The lag times are 6.15 s, 6.85 s, 8.66 s, 10.6
 665 s, 16.85 s, 23.8 s and 24.49 s. Specially for the earlier arrivals the frequency stability is
 666 an important criteria to avoid misinterpretations or interferences with zero-lag autocor-
 667 relation sidelobes as shown in Romero and Schimmel (2018).

668 Concerning inter-crustal discontinuities, receiver function studies (Lognonne et al.,
 669 2020; Knapmeyer-Endrun et al., 2021) provide stable estimates on a discontinuity at about
 670 8-11 km depths with S-wave velocities V_s of about 1.7-2.1 km/s. If we assume a mean
 671 discontinuity depth of 9.5 km and that our signal *a* at 6.15 s lag time (Fig. 11) is a re-
 672 flection from this discontinuity then the expected P-wave velocity V_p and V_p/V_s ratio
 673 for the 9.5 km layer are 3.1 km/s and 1.48-1.82 considering the V_s range. Under same
 674 assumptions, the close by signal *b* at 6.85 s lag time, would lead to $V_p=2.8\text{km/s}$ and V_p/V_s
 675 ratio of about 1.33-1.65. We believe that signal *a* provides a more realistic V_p/V_s ra-
 676 tio than signal *b* and could therefore likely be the reflection from the base of the upper
 677 crust layer. For comparison, the V_p/V_s ratio for the very shallow regolith layer has been
 678 estimated to 1.67 (Lognonne et al., 2020).

679 Finally, the estimated lag time dependent convergence of the autocorrelations shows
 680 that more data are needed to build the reflection response at later lag times. This makes
 681 sense as waves propagating over a longer time interval are more prone to scattering and

682 attenuation which needs to be compensated by stacking more autocorrelations. In any
 683 case, we see no reason for aseismic signals to show a systematic lag time dependent con-
 684 vergence.

685 **Data Availability Statement**

686 We acknowledge NASA, CNES, their partner agencies and Institutions (UKSA, SSO,
 687 DLR, JPL, IGP-CNRS, ETHZ, IC, MPS-MPG) and the flight operations team at JPL,
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 689 available at https://doi.org/10.18715/SEIS.INSIGHT.XB_2016. Processed data corre-
 690 sponding to this article are in Schimmel et al. (2021). PCC and tf-PWS software are avail-
 691 able at <http://diapiro.ictja.csic.es/gt/mschi/SCIENCE/tseries.html#software>. Figures
 692 have been done with SAC and GMT (Goldstein & Snoke, 2005; Wessel et al., 2019).

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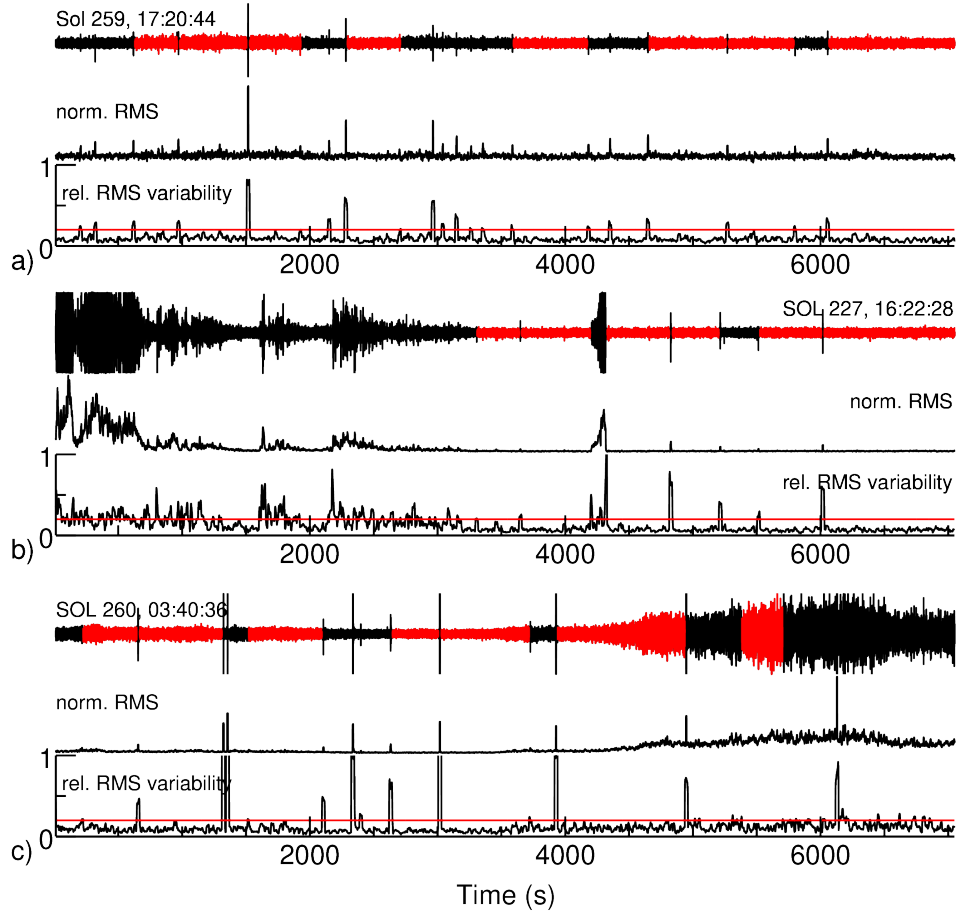
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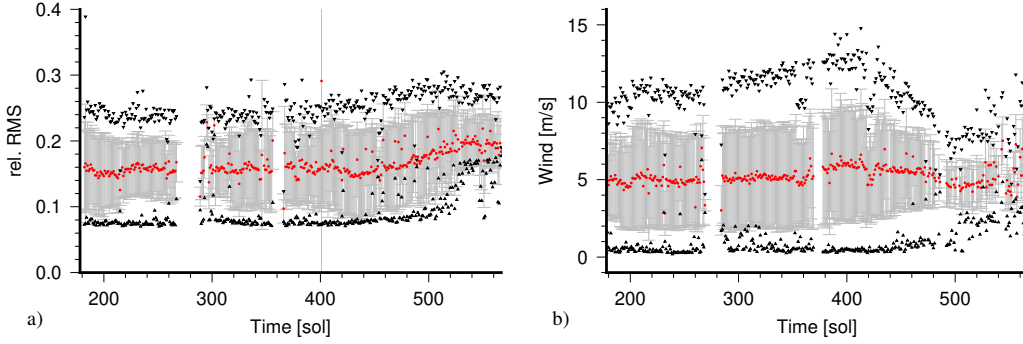
May 5, 2018	InSight launched from Vandenberg Air Force Base (California)
November 26, 2018 (SOL 0)	Landing near Elysium Planitia at $4.5024^{\circ}N, 135.6234^{\circ}E$
December 19, 2018 (SOL 22)	Deployment of SEIS on Martian ground
February 2, 2019 (SOL 66)	SEIS is covered by Wind and Thermal Shield (WTS)
May 19, 2019 (SOL 169)	SEIS heating system has been switched on
August 28, 2019 (SOL 267)	Start of Mars Solar conjunction, i.e., no data transmission
September, 19, 2019 (SOL 289)	End of Mars Solar conjunction, i.e., start of data transmission

886

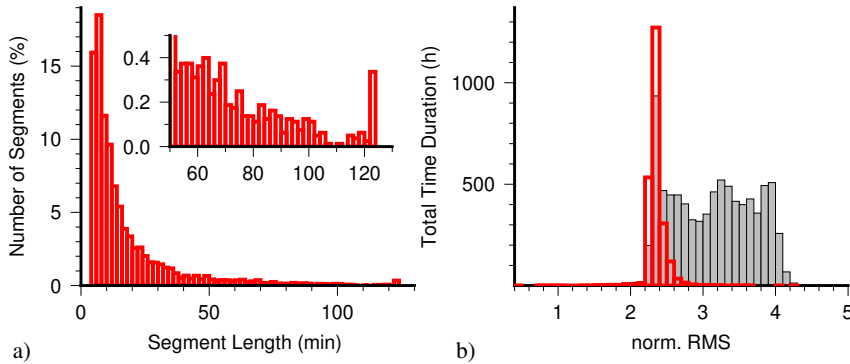
Table 1. Summary of key dates and works related to SEIS deployment and operation on Mars.



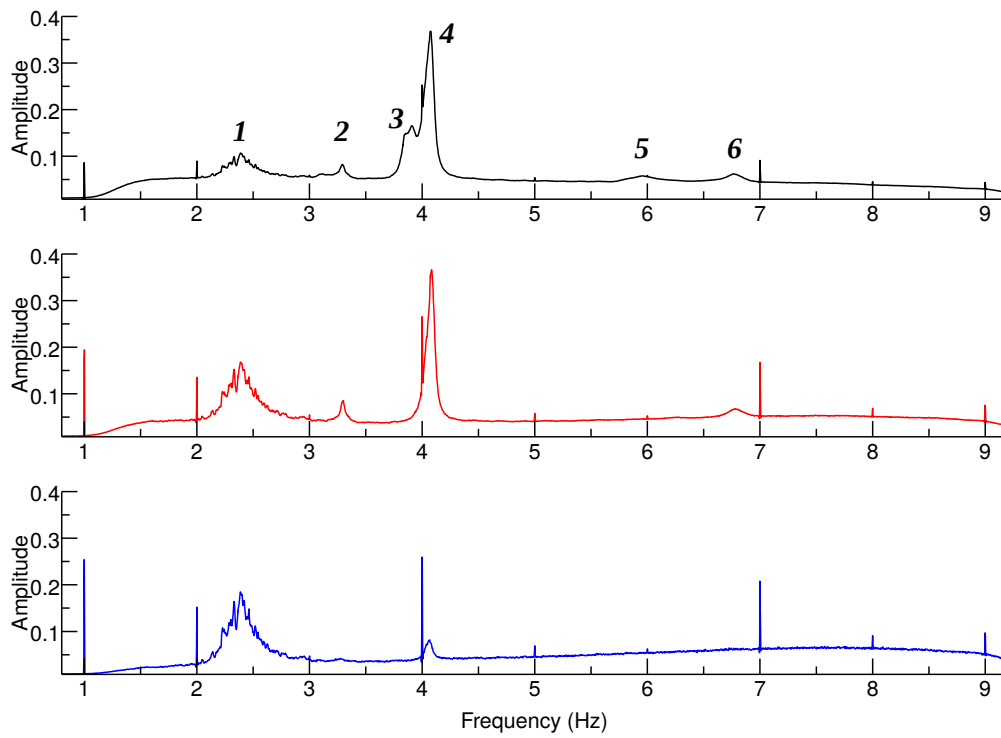
887 **Figure 1.** Three data selection and segmentation examples. a) The top trace shows the
 888 vertical component record with the selected segments in red. The two bottom traces are the nor-
 889 malized RMS and the relative RMS variability. The horizontal red line marks the threshold RMS
 890 variability used for the segment selection. The begin time (LMST) of the time series is written
 891 to the top left. b) and c) show the same as a), but for different time records. More examples are
 892 shown in Fig. S1 of the Supplementary Section.



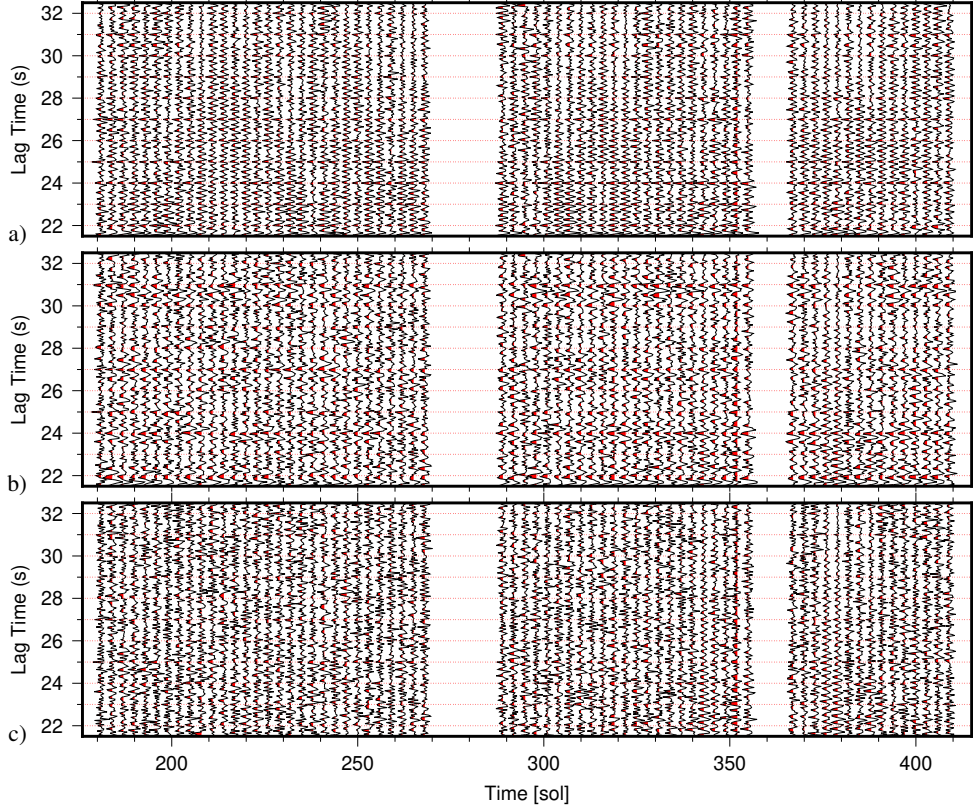
893 **Figure 2.** a) Evolution of seismic signal RMS variability as function of Sol measured on
 894 Z-component filtered from 1.2-9.5 Hz. Red dots and gray error bars mark the mean and one
 895 standard deviation uncertainty per Sol. Black triangles point to the minimum and maximum
 896 RMS variability encountered per Sol. b) Wind speed as function of Sol. In analogy to the seismic
 897 signal RMS variability plot, red dots and gray bars mark the mean and one standard deviation
 898 uncertainty while black triangles point to the minimum and maximum RMS variability encoun-
 899 tered per Sol.



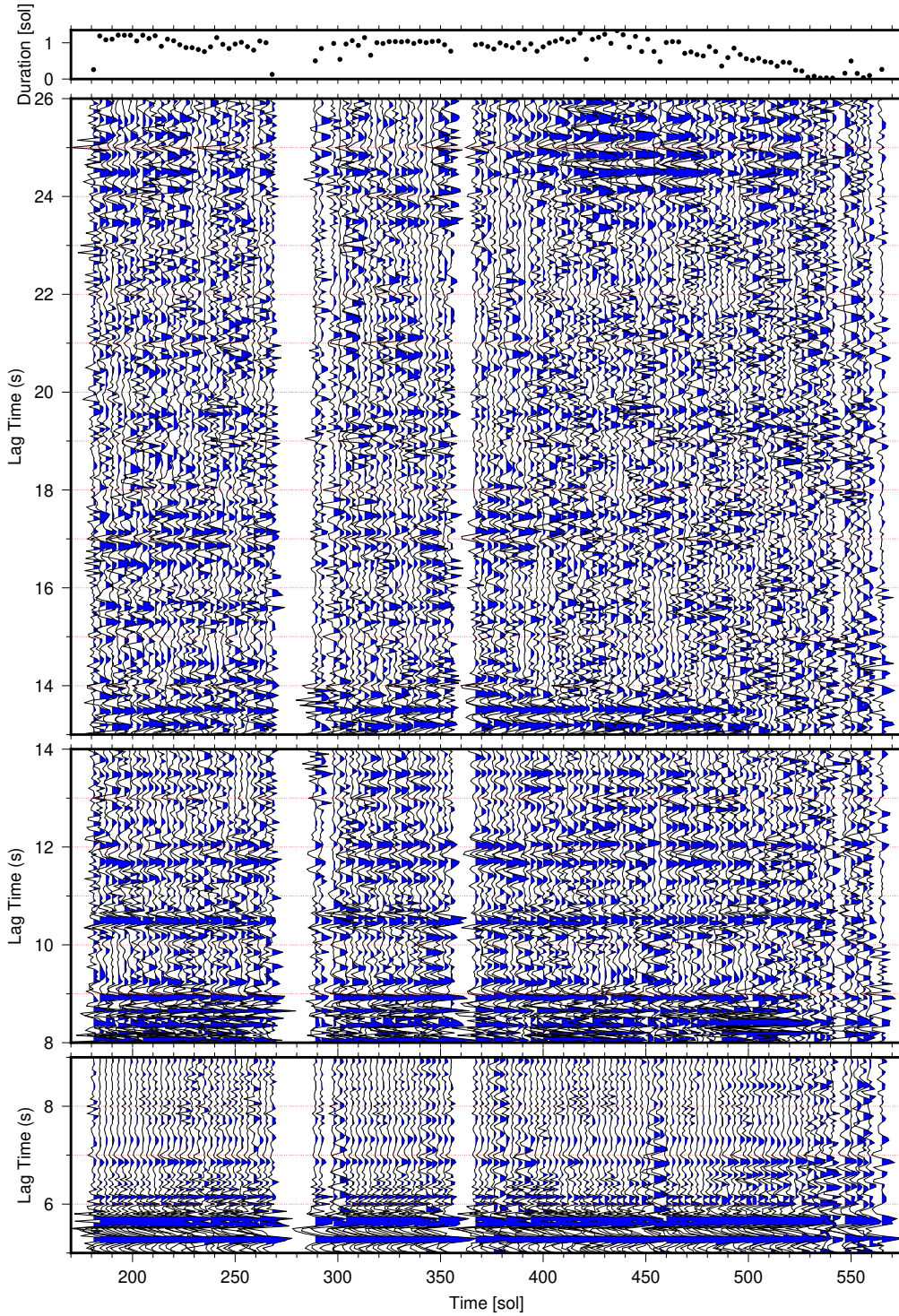
900 **Figure 3.** a) Histogram of segment length distribution for the 30% subsidiary data set. The
 901 inset is a zoom for segment length between 30 and 130 min. Vertical axis contains the number of
 902 segments in percentage while horizontal axis shows the segment length in minutes. b) Histogram
 903 of normalized RMS distribution for the 100 % (gray) and 30 % (red) data sets. Vertical axis is
 904 cumulative time in hours and horizontal axis is the base 10 logarithm of the normalized RMS
 905 distribution. The increase of cumulative time for the subsidiary data set with respect to the total
 906 data bases is due to the RMS variability and data segmentation.



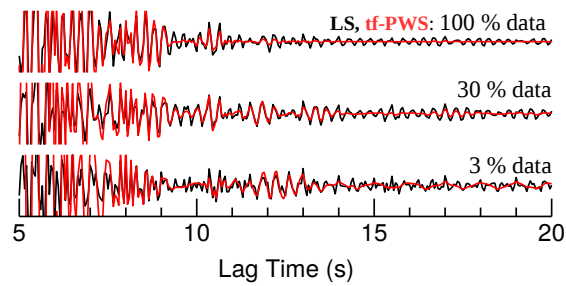
907 **Figure 4.** Normalized Fourier amplitude spectra of autocorrelation stacks based on PCC and
908 linear stacking. Black, red and blue lines show the spectra for the total data set, the 30% and 3%
909 subsidiary data sets, respectively. Italic numbers 1-6 mark features discussed in the main text.



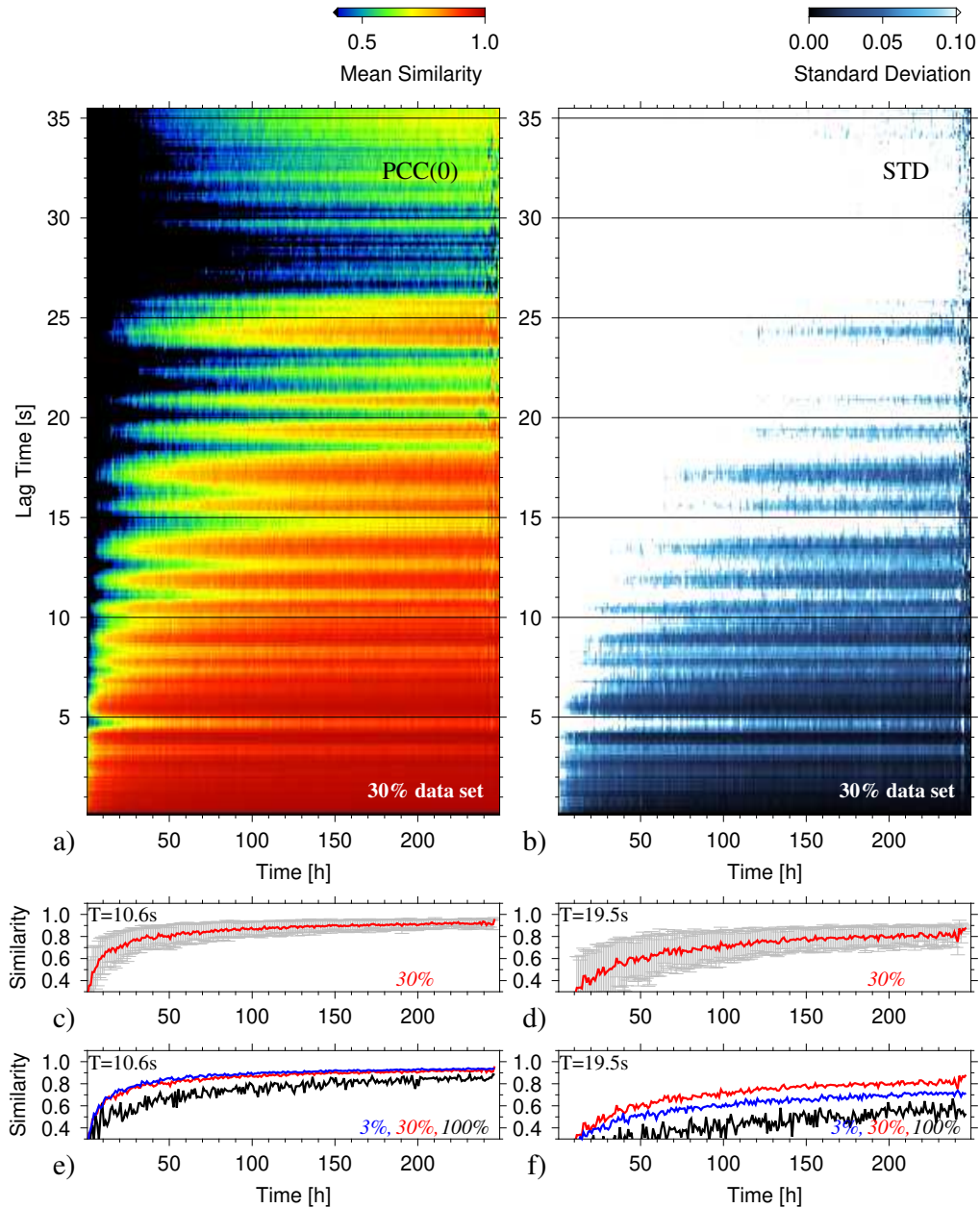
910 **Figure 5.** a) Vertical-component autocorrelation stacks for sliding 3-Sol data windows. The
 911 frequency band is 1.2-8.9 Hz, data windows do not overlap, and positive amplitudes are in red.
 912 Shown are linear stacks of phase autocorrelations for the entire data set at lag time without re-
 913 flections from shallow discontinuities. The tick noise are the positive amplitude signals at every
 914 full second. b) Same as a), but two band-rejection filters, 3.9-4.4 Hz and 6.8-7.2 Hz have been
 915 applied before computation of the phase autocorrelations. c) Same as b), but the data has been
 916 filtered with a third band rejection filter 1.9-2.5 Hz. See Fig. S3 for another example employing
 917 the 3 % data set and tf-PWS.



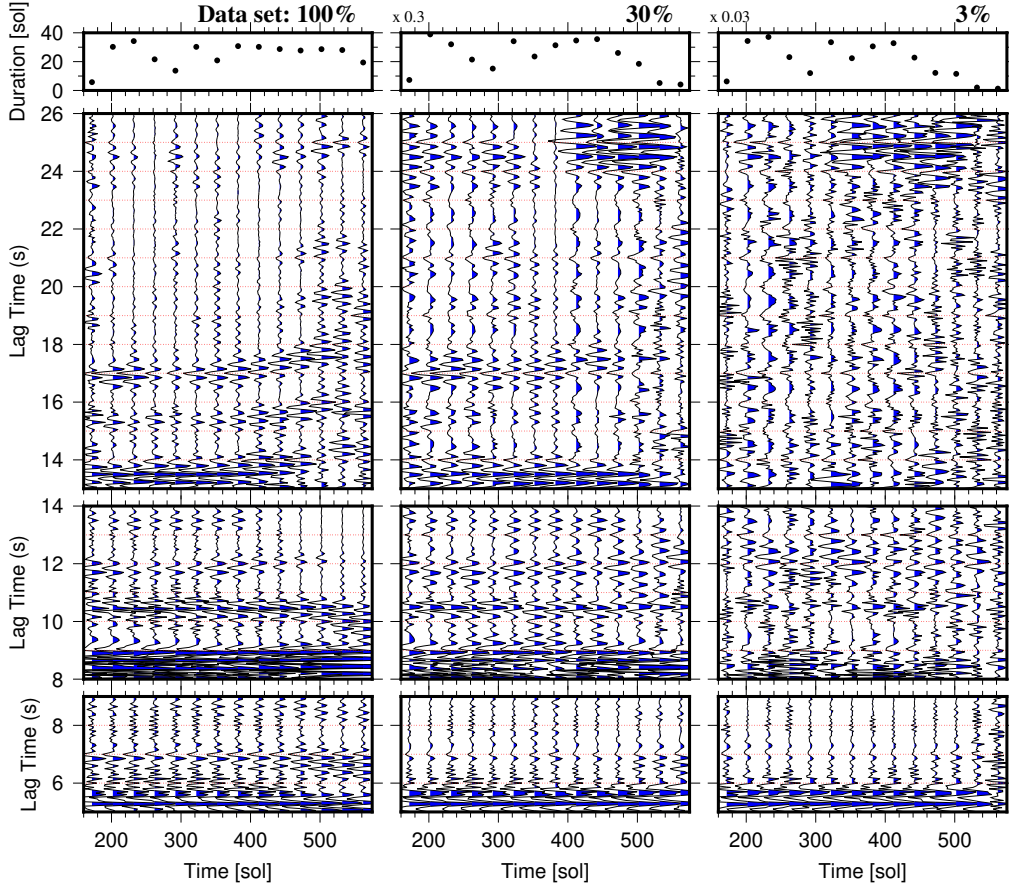
918 **Figure 6.** Vertical-component autocorrelation stacks for sliding 3-Sol data windows. The fre-
 919 quency band is 1.2-8.9 Hz and data windows do not overlap. Shown are tf-PWSs of phase auto-
 920 correlations computed for the 30 % data set. Blue marks negative amplitudes. The three lag-time
 921 windows have been used to improve the visibility through independent amplitude normalization.
 922 Top panel shows the total duration of the selected data used to compute autocorrelations within
 923 each of the 3-Sol data windows. Linear stacks for the same data are shown in Fig. S4.



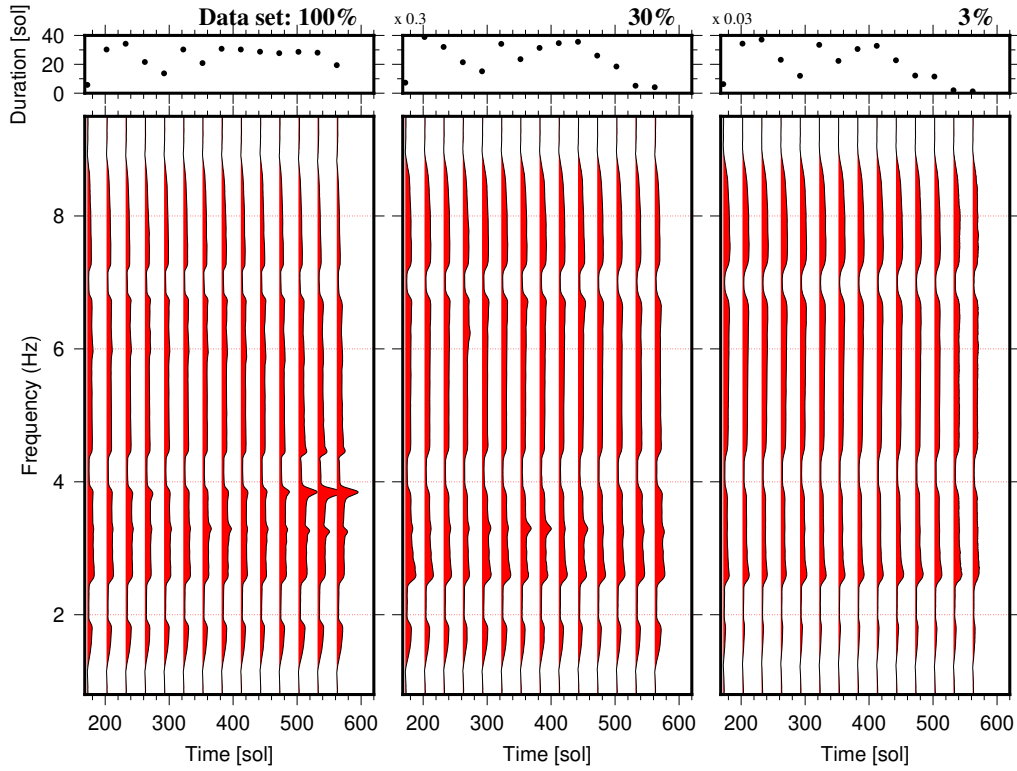
924 **Figure 7.** This figure shows the stacked autocorrelations for the 100 % data (top panel), 30
925 % data (middle panel), and 3 % data (bottom panel). The linear stacks are plotted in black and
926 the corresponding tf-PWS in red. The amplitudes of each stack have been normalized for visual
927 purposes. The 10.6 s signal appears with in impulsive shape for the three data sets and stands
928 out from its immediate surroundings.



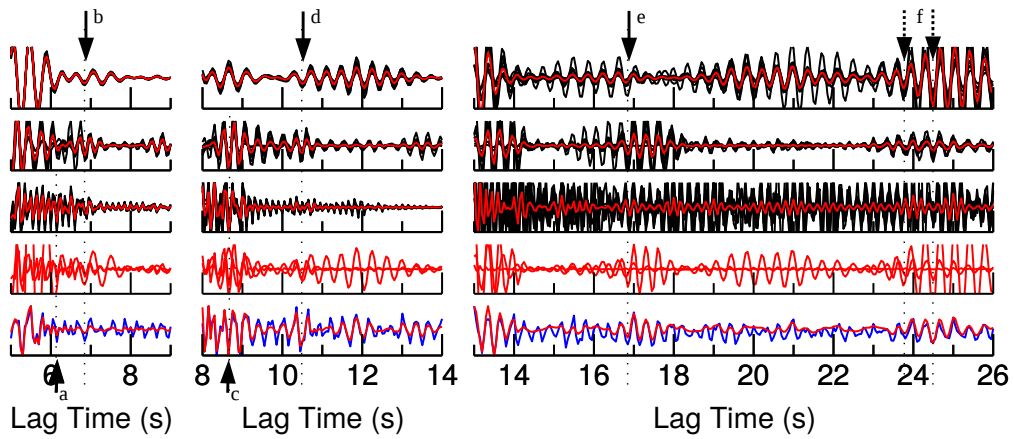
929 **Figure 8.** a) Autocorrelation waveform convergence as function of lag time and total length of
 930 data using the 30% data set. Colors are used to contour the mean similarity of randomly stacked
 931 autocorrelations with the reference trace. The reference trace is the linear stack of all autocor-
 932 relations from the 30% data set (black trace, middle panel of Fig. 7). The total data length is
 933 2350.2 h. b) Standard deviation of the similarity shown in a). c) Similarity (red) and standard
 934 deviation (gray) of the 10.6 s signal for the 30 % data set. d) Same as c) but for a signal at 19.5
 935 s lag time. e) Same as c) but showing also the results for the 3 % (blue) and 100% data sets
 936 (black). The reference traces are based on a total data length of 201.2 h and 8355.6 h for the 3 %
 937 and 100 % data sets, respectively. f) Same as e) but for the 19.5 s signal.



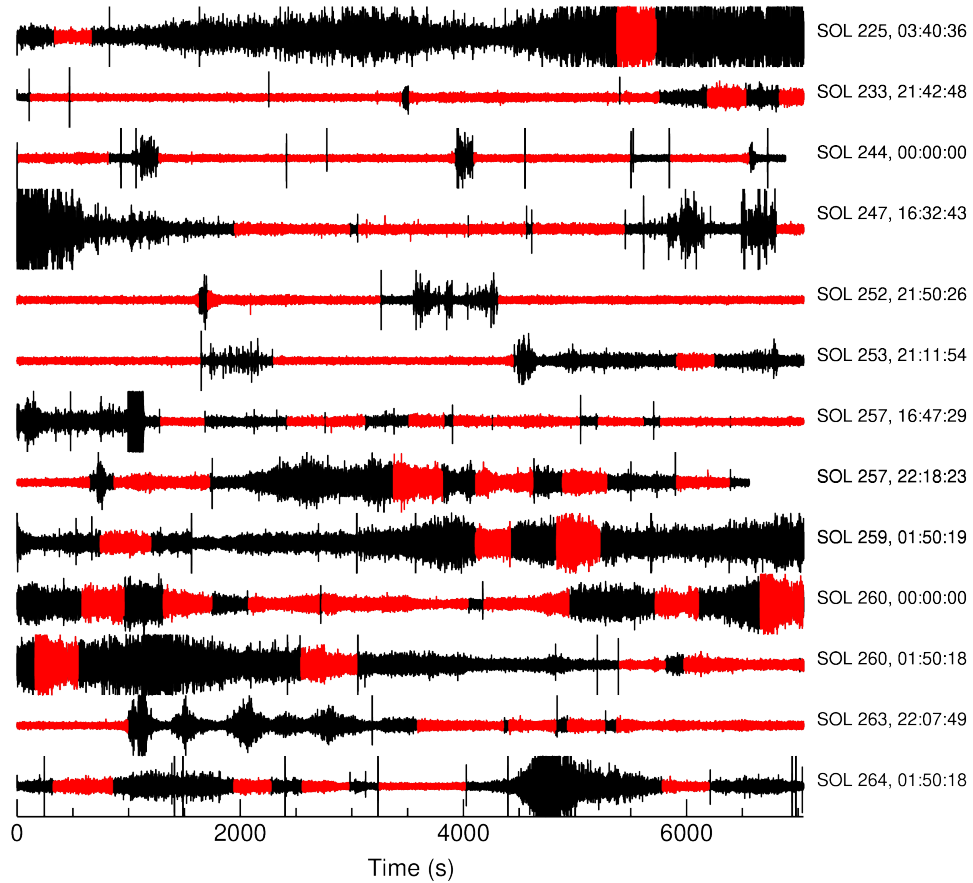
938 **Figure 9.** Vertical-component noise autocorrelation stacks for sliding 30-Sol data windows.
 939 The frequency band is 1.2-8.9 Hz and data windows do not overlap. Shown are time-frequency
 940 phase weighted stacks of phase autocorrelations. Blue marks negative amplitudes. The three
 941 lag-time windows have been used to improve the visibility through independent amplitude nor-
 942 malization. The top panel shows the total duration of the selected data used to compute autocor-
 943 relations within each of the 30-Sol data windows. The axis for the duration of the 30 % and 3 %
 944 data set are scaled by the number to the top left. Linear stacks for the same data are shown in
 945 Fig. S6.



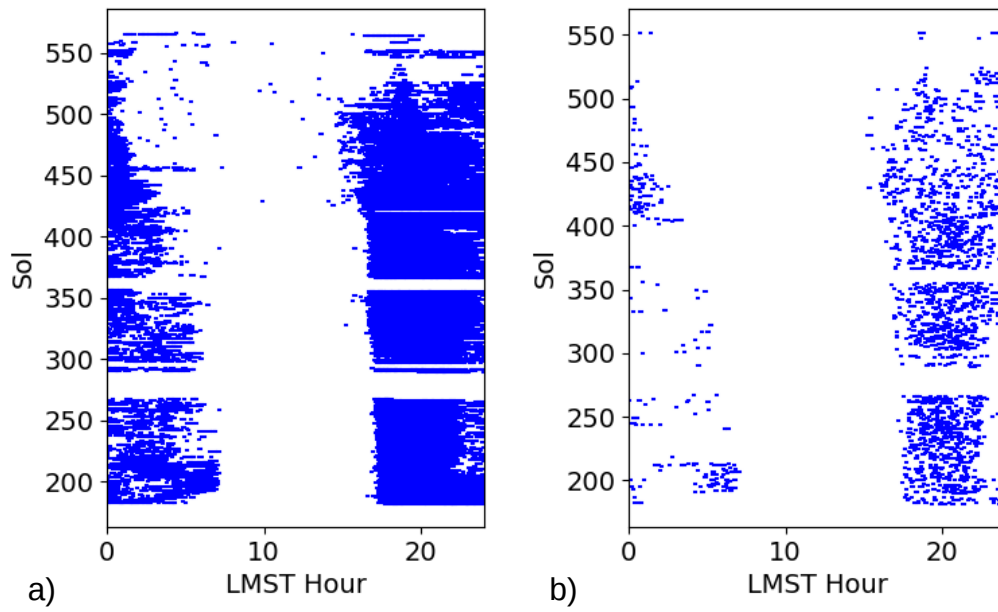
946 **Figure 10.** Amplitude spectra of tf-PWS autocorrelations shown in Fig. 9 as function of Sol
 947 for the 100 % (left panel), 30 % (middle panel), and 3 % (right panel) data sets. Each amplitude
 948 spectrum is placed at its window center time and has been normalized at 6 Hz. Spectra of linear
 949 stacks are shown in Fig S7.



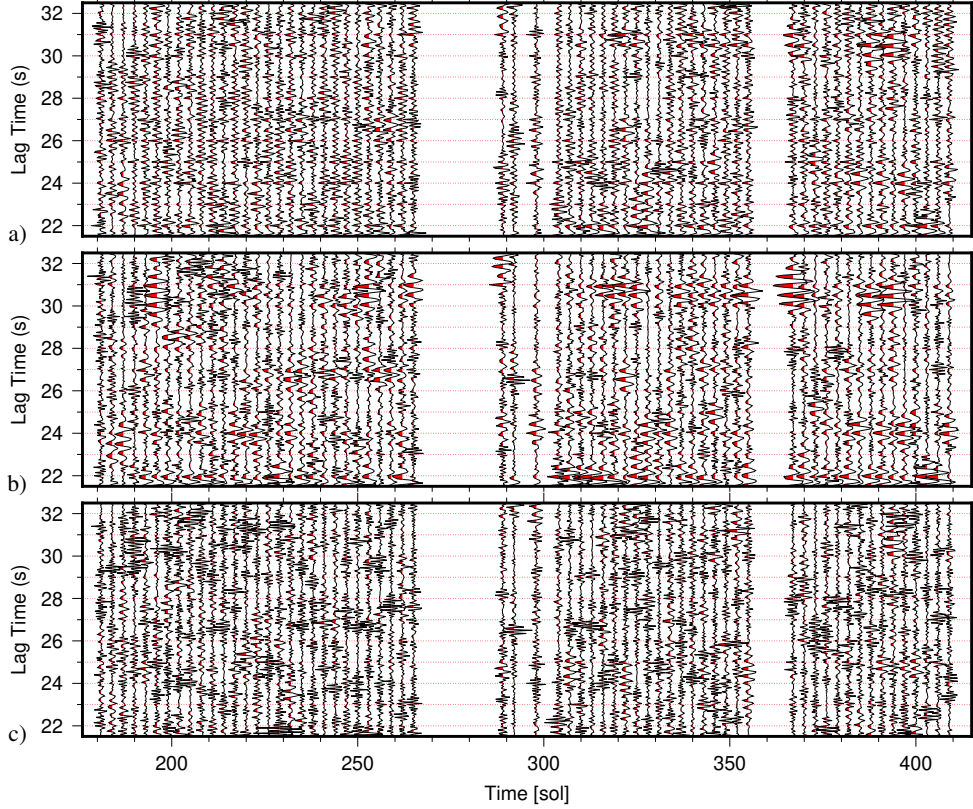
950 **Figure 11.** Vertical-component noise autocorrelation stacks for the 30 % data set. tf-PWSs
 951 are shown in red and black. Red traces are based on the entire 30 % data set while black traces
 952 mark stacks for only 10% of the data. Lag-time windows correspond to those of Fig. 6 and have
 953 been chosen to improve signal visibility. The first three panels are for 1.5-3.0 Hz, 2.4-4.8 Hz, and
 954 3.6-7.2 Hz band-passed filtered noise. The fourth panel compares the stacks from the top three
 955 panels. The lowermost panel shows the linear stack (blue line) and tf-PWS (red line) for the
 956 frequency band 1.2-8.9 Hz. Arrows mark signals mentioned in the text.



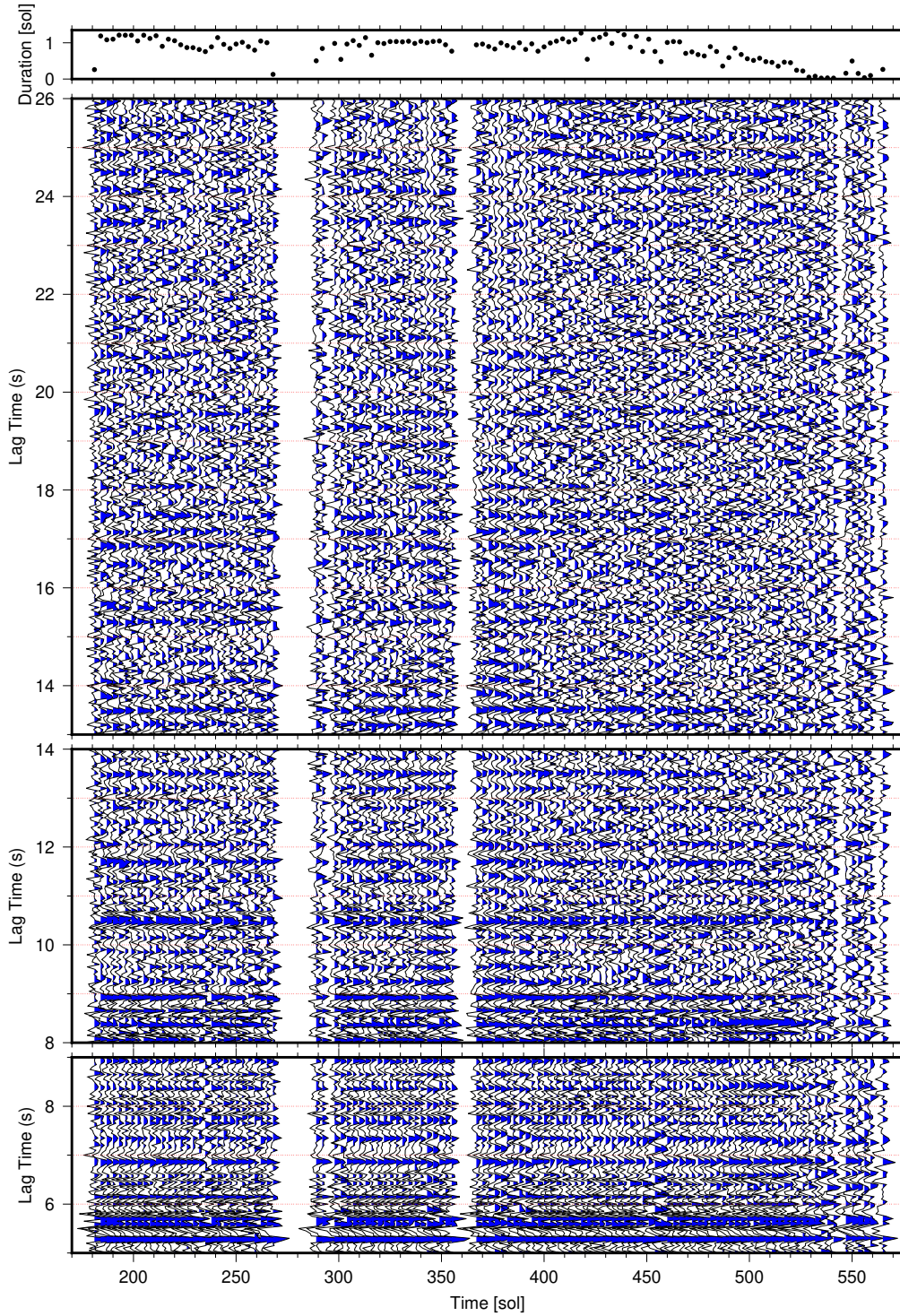
957 **Figure S1.** Data selection and segmentation examples. The selected segments are marked in
958 red. The start time of each trace is given in LMST to the right of each record.



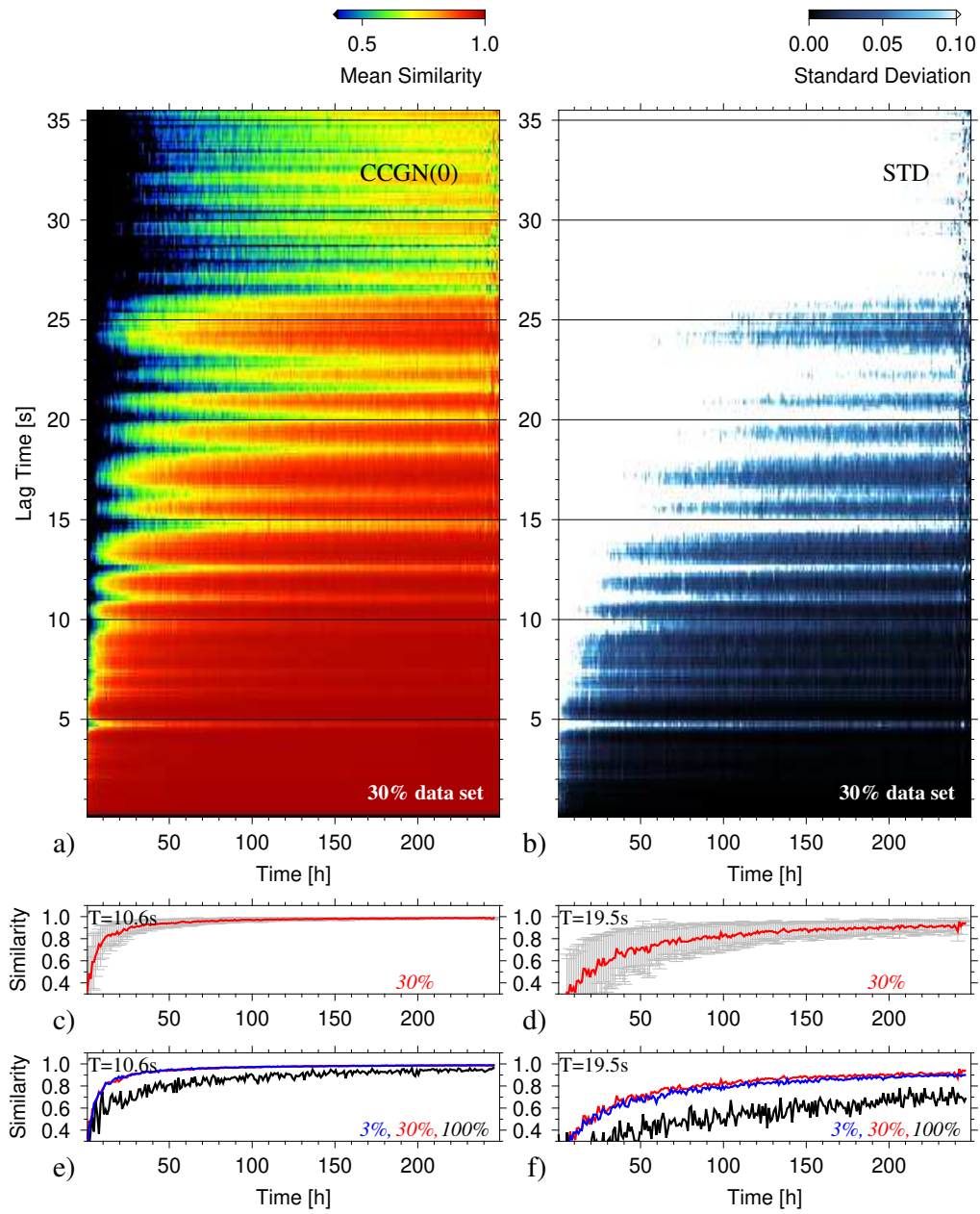
959 **Figure S2.** Selected data windows as function of Sol and LMST for the 30% (a) and 3% (b)
960 subsidiary data sets. Very short time windows are not well resolved. Nevertheless, this figure
961 shows that most of the selected time segments with low RMS variability are from the evening
962 when wind activity is low.



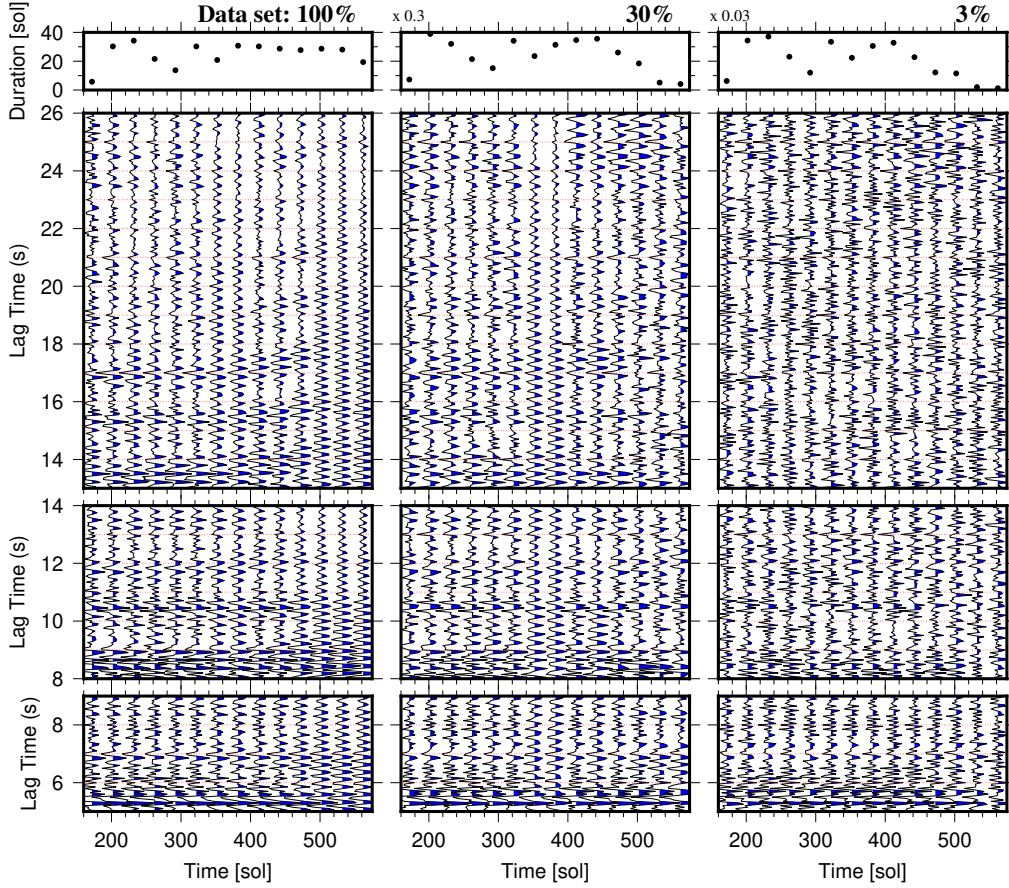
963 **Figure S3.** Same as Fig. 5, but using tf-PWS and the 3 % data set rather than the linear
 964 stack and the 100 % data set: a) Vertical-component noise autocorrelation stacks (tf-PWS) for
 965 sliding 3-Sol data windows. The frequency band is 1.2-8.9 Hz, data windows do not overlap, and
 966 positive amplitudes are in red. Phase autocorrelations are for a subsidiary data set of about 3%
 967 of the total data volume, i.e., containing the traces with the lowest RMS amplitude variability.
 968 The lag time window is large to avoid reflections from shallow discontinuities. The tick noise are
 969 the positive amplitude signals at every full second. b) Same as a), but two band-rejection filters,
 970 3.9-4.4 Hz and 6.8-7.2 Hz have been applied before computation of the phase autocorrelations. c)
 971 Same as b), but the data has been filtered with a third band rejection filter 1.9-2.5 Hz.



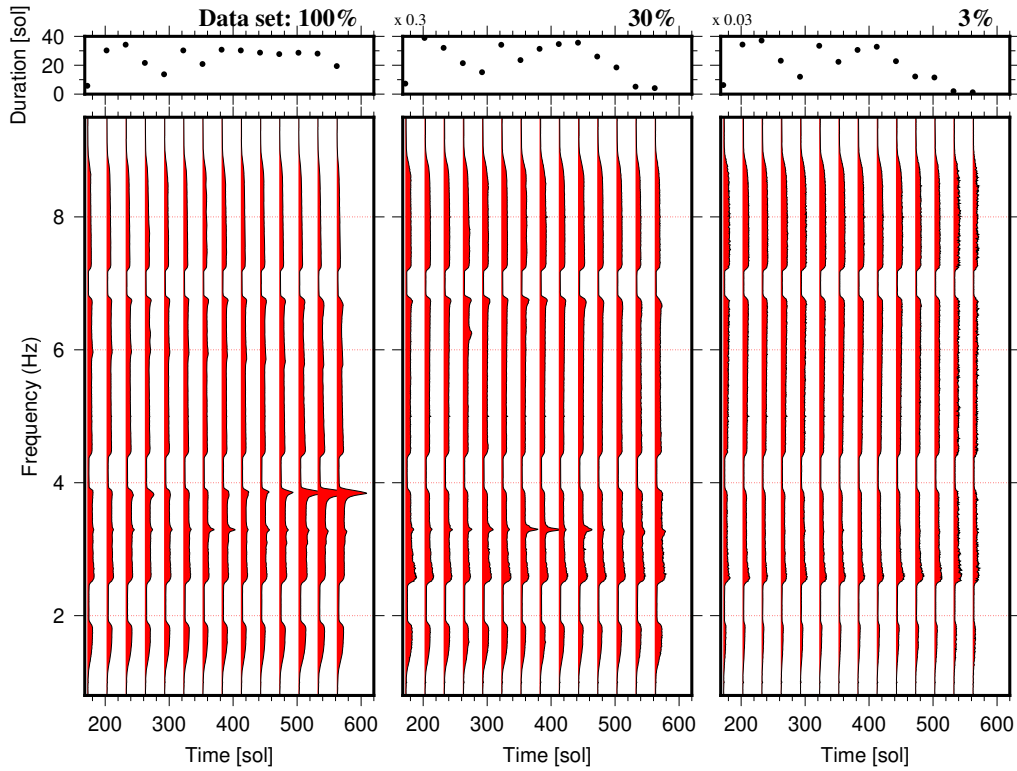
972 **Figure S4.** Same as Fig. 9, but employing the linear stack rather than the tf-PWS: Vertical-
 973 component noise autocorrelation stacks for sliding 30-Sol data windows. The frequency band is
 974 1.2-8.9 Hz and data windows do not overlap. Shown are linear stacks of phase autocorrelations.
 975 Blue marks negative amplitudes. The three lag-time windows have been used to improve the
 976 visibility through independent amplitude normalization. The top panel shows the total duration
 977 of the selected data used to compute autocorrelations within each of the 30-Sol data windows.
 978 The axis for the duration of the 30 % and 3 % data set are scaled by the number to the top left.



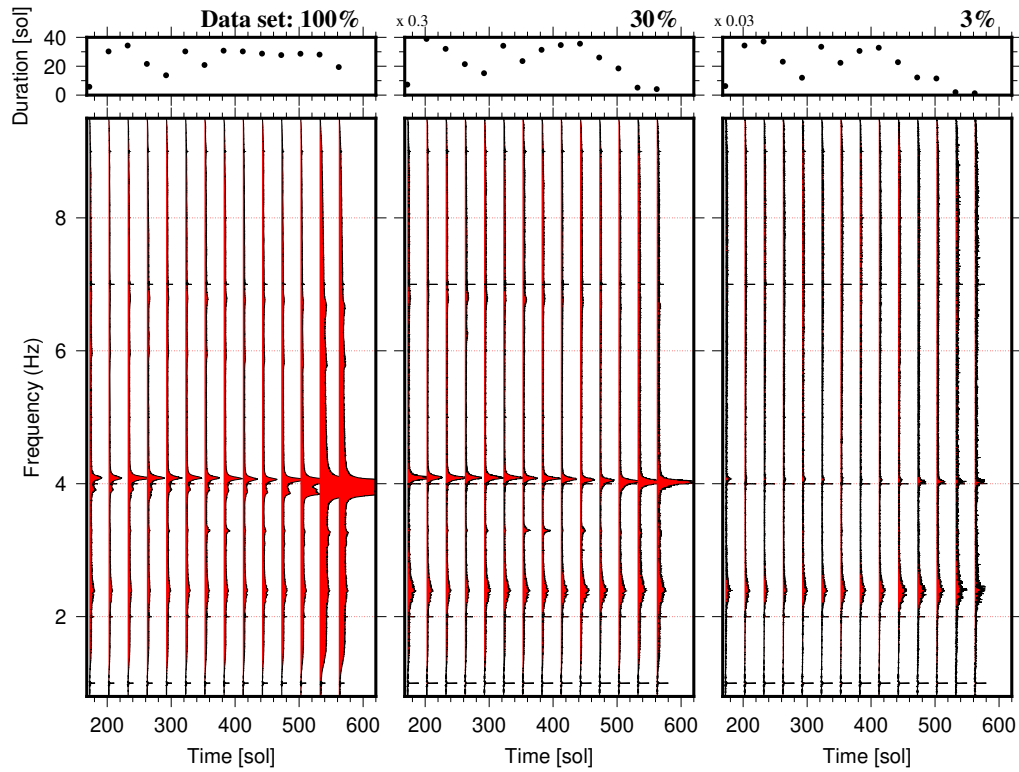
979 **Figure S5.** Same as Fig. 8, but using zero-lag CCGN rather than PCC to measure the wave-
 980 form similarity. This figure shows a faster waveform convergence as PCC is the more waveform
 981 sensitive measure.



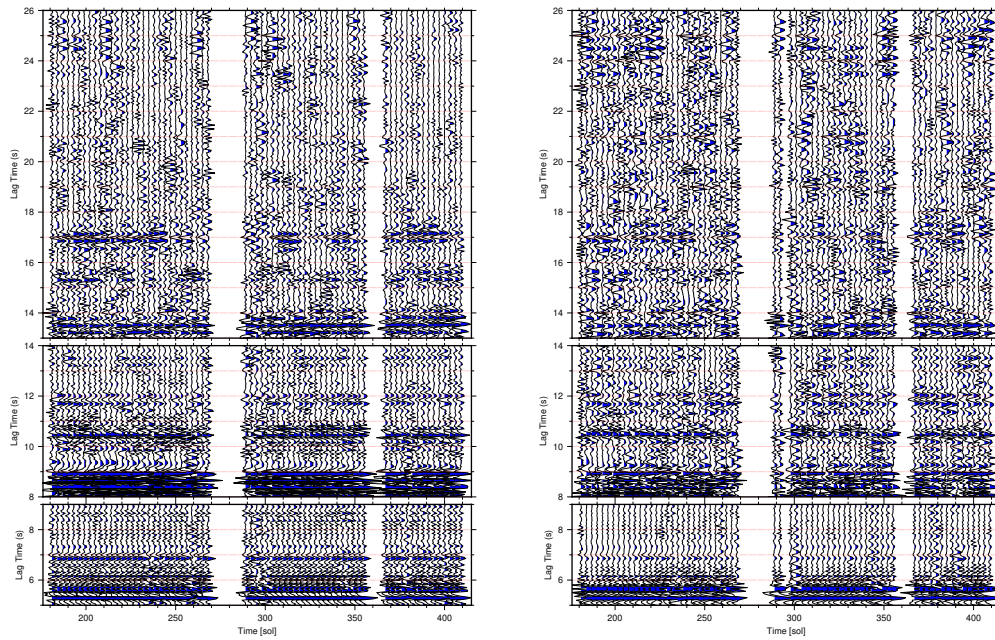
982 **Figure S6.** Same as Fig. 9, but employing the linear stack rather than tf-PWS: Vertical-
 983 component noise autocorrelation stacks for sliding 30-Sol data windows. The frequency band is
 984 1.2-8.9 Hz and data windows do not overlap. Shown are linear stacks of phase autocorrelations.
 985 Blue marks negative amplitudes. The three lag-time windows have been used to improve the
 986 visibility through independent amplitude normalization. The top panel shows the total duration
 987 of the selected data used to compute autocorrelations within each of the 30-Sol data windows.
 988 The axis for the duration of the 30 % and 3 % data set are scaled by the number to the top left.



989 **Figure S7.** Same as Fig. 10, but using linear stacks: Amplitude spectra of linearly stacked
 990 autocorrelations as function of Sol for the 100 % (left panel), 30 % (middle panel), and 3 % (right
 991 panel) data sets. Stacks are build using all available autocorrelations within non-overlapping
 992 30-Sol data windows. Each amplitude spectrum is placed at its window center time and has been
 993 normalized at 6 Hz. The total duration of data used to compute the autocorrelations within
 994 each 30-Sol window is plotted to the top. The numbers to the top left are factors to reduce the
 995 duration axes of the 30 % and 3 % data sets.



996 **Figure S8.** Same as Fig. S7, but using a slightly broader frequency band (0.8-9.5 Hz) and no
 997 band-rejection filters. Spectra are normalized at 1 Hz and amplitudes have been multiplied by 0.5
 998 for the 100 % data set (left panel).



999 **Figure S9.** Vertical-component autocorrelation stacks for sliding 3-Sol data windows. The
 1000 frequency band is 1.2-8.9 Hz and data windows do not overlap. Shown are tf-PWSs of phase au-
 1001 tuncorrelations computed for the 100 % (left panel) and 30 % data set up to Sol 410. Most of the
 1002 signals appear for both data sets. This further testifies that PCC is a robust approach as data
 1003 problems, glitches and donks present in the 100 % data set do not bury the signals shown with
 1004 the 30 % data set.