

# Seismic velocity variations at TCDP are controlled by MJO driven precipitation pattern and high fluid discharge properties

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## Abstract

Using seismic noise based monitoring techniques we find that seismic velocity variations ( $dv/v$ ) observed with the borehole array of the Taiwan Chelungpu-fault Drilling Project (TCDP) are controlled by strong precipitation events associated with the Madden-Julian Oscillation (MJO), a dynamic intraseasonal atmospheric pattern in the tropical atmosphere. High-frequency noise ( $>1$  Hz) excited by steady anthropogenic activity in the vicinity of the TCDP allows daily resolution of  $dv/v$  time series. Relatively large fluid discharge properties control the equilibration of the ground water table and hence seismic velocities on time scales smaller than the average precipitation recurrence interval. This leads to the observed synchronous 50–80 day periodicity in  $dv/v$  and rainfall records in addition to the dominant annual component. Further evidence for the governing role of hydraulic properties is inferred from the similarity of observed  $dv/v$  timing, amplitude, and recovery properties with  $dv/v$  synthetics generated by a combined model of ground water table changes and diffusive propagation of seismic energy. The lapse time ( $\tau$ ) dependent increase of  $dv/v$  amplitudes is controlled by the sensitivity

of the diffuse wave field sampled at 1100 m depth to shallower water level fluctuations. The significant vertical offset between stations and water level explains the direct  $\tau$  dependence which is opposite to the trend previously inferred from measurements at the surface.

*Keywords:* Ambient noise, Monitoring, Madden-Julian Oscillation, Borehole Seismology, Ground Water Table

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## 1. Introduction

Interactions of atmospheric dynamics with solid Earth processes are many-fold (Tanimoto and Artru-Lambin, 2007). It includes triggering of slow earthquakes through low pressure systems (Liu et al., 2009), velocity changes in the upper crust by pressure fluctuations (Niu et al., 2008), and the excitation of seismic waves by nonlinear coupling of atmospheric disturbances with solid Earth through the ocean water column (Longuet-Higgins, 1950; Hasselmann, 1963). Reversely, ground motion excited by volcanic eruptions (Fee and Matoza, 2013) or earthquakes (Mutschlecner and Whitaker, 2005; Le Pichon et al., 2005) can propagate as pressure disturbances in the atmosphere. Through thermoelastic effects (Berger, 1975), temperature changes can cause seasonal variations in subsurface deformation (Prawirodirdjo et al., 2006) and in high-frequency noise excitation (Hillers and Ben-Zion, 2011). Precipitation triggers shallow seismicity and slope instabilities (Husen et al., 2007; Helmstetter and Garambois, 2010), and modulates regional seismic activity (Bettinelli et al., 2008) and seismic wave speeds (Meier et al., 2010) through variable water content in sedimentary basins. In general these variations are characterized by an annual periodicity gov-

19 ernerred by the orbit of Earth and associated hemispheric weather pattern.  
20 Other repeat intervals of crustal processes in response to external forcing—  
21 i.e., neglecting phenomena governed by plate tectonics—are associated with  
22 tidal deformation, which are known to modulate volcanic and tectonic tremor  
23 activity (Custodio et al., 2003; Rubinstein et al., 2008), seismicity (Stroup  
24 et al., 2007), and subsurface wave speeds (Reasenber and Aki, 1974).  
25 In contrast to wave speed measurements based on intermittent explosive  
26 sources, methods based on the ubiquitous ambient seismic wave field consti-  
27 tute a powerful tool for continuous monitoring of seismic velocities (Campillo  
28 et al., 2011, and references therein). Noise based techniques are now routinely  
29 used to quantify fluctuations of crustal properties associated with volcanic  
30 activity (Brenquier et al., 2008b; Obermann et al., 2013a), earthquake de-  
31 formation (Brenquier et al., 2008a; Rivet et al., 2011), water content and  
32 hydraulics (Sens-Schönfelder and Wegler, 2006; Meier et al., 2010; Froment  
33 et al., 2013), and tidal deformation (Hillers et al., 2013b). The temporal  
34 resolution of these methods is governed by the convergence rate of the noise  
35 correlation function, and is therefore frequency dependent (e.g., Larose et al.,  
36 2007); in the microseism frequency range resolution is usually on the order  
37 of days, but it can be improved using advanced data processing techniques  
38 (Baig et al., 2009; Hadziioannou et al., 2011).  
39 Here we study seismic velocity changes ( $dv/v$ ) using short period ( $>1$  Hz)  
40 data recorded by the borehole array of the Taiwan Chelungpu-fault Drilling  
41 Project (TCDP, Fig. 1), which pierces the east dipping rupture plane of the  
42 1999 M7.6 Chi-Chi thrust earthquake. The construction of daily high-SNR  
43 (signal-to-noise ratio) noise correlation functions benefits from steady noise

44 excitation through anthropogenic activity in the densely populated lowlands  
45 in western Taiwan (Hillers et al., 2012).  
46 Knowledge of the system response to various loading mechanisms is essential  
47 for the assessment of potential earthquake triggering mechanisms in this ac-  
48 tive tectonic collision zone. Beyond the well documented seasonal periodicity  
49 we find that velocity variations are characterized by a significant intrasea-  
50 sonal 50–80 day spectral component. Analysis of meteorological data reveals  
51 that this pattern is controlled by strong precipitation events associated with  
52 the Madden-Julian Oscillation (MJO), a large-scale atmospheric circulation  
53 pattern in the tropic parts of the Indian and Pacific oceans (Zhang, 2005).  
54 We use the resulting  $dv/v$  time series to invert for hydraulic properties of  
55 the crust using a model of ground water level changes based on Darcy’s law  
56 coupled to a diffusion model of scattered wave propagation (Sens-Schönfelder  
57 and Wegler, 2006, hereafter referred to as SSW06). Inversion results indicate  
58 that a relatively high drainage rate in the low- $Q$  medium (Wang et al., 2010)  
59 hosting the Chi-Chi earthquake governs fast equilibration of the ground wa-  
60 ter table after strong precipitation events, which leads to the observed syn-  
61 chronous periodicity of  $dv/v$  and rainfall time series. We discuss that the  
62 experimental configuration, i.e., the vertical offset of the deep array from  
63 shallow water level variations, allows conclusions on the lapse time ( $\tau$ ) de-  
64 pendent sensitivity of the scattered wave field. The agreement between the  
65 observed  $\tau$  dependence of  $dv/v$  amplitudes and the predicted  $\tau$  dependence  
66 of depth-integrated sensitivity kernels verifies the accuracy of the diffusion  
67 model; the compatibility further indicates the possibility to constrain esti-  
68 mates of the scattering mean free path.

## 69 **2. Velocity Variations**

### 70 *2.1. Data Processing*

71 We process 3-component data from 6 TCDP short period (4.5 Hz) sensors  
72 installed between 946 m and 1274 m depth. For a detailed description of the  
73 recording environment and ambient wave field properties we refer the reader  
74 to Hillers et al. (2012). We compute daily correlation functions for all 9  
75 components of the correlation tensor in two frequency ( $f$ ) bands above 1 Hz  
76 for 2008 and 2009 using processing by Poli et al. (2012) to reduce the effects  
77 of transients. Different  $dv/v$  time series are created by constructing ‘daily’  
78 correlations consisting of sub-stacks of  $d$  days ( $\pm(d-1)/2$  days), where the  
79 choice of  $d$  affects SNR and temporal resolution. The best SNR is found for  
80 1–4 Hz correlations (Hillers et al., 2012), which indicates sufficient sensitivity  
81 of the short period sensors below 4 Hz.

82 Noise based monitoring targets the lapse time ( $\tau$ ) dependent accumulation  
83 of arrival time changes ( $d\tau$ ) of correlation coda phases associated with ho-  
84 mogeneous relative velocity variations ( $dv/v$ ) in a scattering medium, i.e.,  
85  $dv/v = -d\tau/\tau$ . Hillers et al. (2012) discussed that the obtained correlations  
86 are poor estimates of the inter-sensor Green’s functions (GF). This is a re-  
87 sult of the proximity of the TCDP to the noise excitation region, and the  
88 associated directionality of the incident wave field. Evidence for coda phase  
89 sensitivity to medium properties was demonstrated by re-correlation of the  
90 coda wave field, which leads to improved GF estimates.

91 Noise source dependent fluctuations in wave field properties can lead to spu-  
92 rious  $dv/v$  signals that are not associated with targeted changes in the prop-  
93 agation medium (Zhan et al., 2013). We therefore analyzed variations of

94 the spectral content, SNR, incidence angle, and rectilinearity (Hillers et al.,  
95 2012) for the two-year observation period. The stability of these auxiliary  
96 time series, and the sub-stack coherency with the reference stack (*cc*; Fig.  
97 2a) discussed below, do not indicate a bias associated with excitation varia-  
98 tions. We conclude that the correlation functions, though not fully converged  
99 GF, are sufficiently stable to facilitate wave speed monitoring (Hadziioannou  
100 et al., 2009).

101 For each of the 9 components, all correlations are stacked to create reference  
102 functions. We apply a time- and a frequency-domain technique (‘stretching’  
103 and ‘doublet’ method) for daily estimates of  $dv/v$ . This allows a further  
104 assessment of the robustness of the results, because the methods perform  
105 different in the presence of pseudo-noise or wave field fluctuations (Hadzi-  
106 ioannou et al., 2009, 2011). At each datum, the  $dv/v$  estimates obtained with  
107 the stretching method (Lobkis and Weaver, 2003) are averaged over the 15  
108 inter-station times 9 inter-component results. Errors are estimated using the  
109 approach by Weaver et al. (2011) and scaled by the number of measurements  
110 (Hadziioannou et al., 2011). Weights associated with the two phase- and  
111 time-domain regressions constituting the doublet method (Poupinet et al.,  
112 1984; Clarke et al., 2011) allow a simultaneous inversion of all data, leading  
113 to results characterized by reduced daily fluctuations (estimated, e.g., during  
114 01/2009) and error estimates. We perform the analysis for three sub-stack  
115 choices ( $d = 1, 3, 7$  days) and three coda windows of 4 s duration defined by  
116 their average lapse time  $\tau = 4, 8, 12$  s. We focus on the 1–4 Hz range because  
117 the noise intensity is proportional to  $1/f$  (Hillers et al., 2012); at 2–8 Hz,  
118  $dv/v$  amplitudes and the similarity of daily correlations to the reference stack

119 are significantly reduced.

## 120 *2.2. Properties of Velocity Change Time Series*

121 Overall,  $dv/v$  time series obtained with the two techniques are remark-  
122 ably similar, yielding high confidence in the significance of the variations.  
123 The records are characterized by sudden velocity reductions during summer  
124 months in both years with peak amplitudes between 0.1–0.3%, which are  
125 followed by a recovery over days to tens of days to the background level. The  
126 lapse time  $\tau$  controls peak  $dv/v$  estimates during velocity reduction episodes  
127 (Fig. 2b) and the overall coherency level. The  $\tau$  dependence of the  $dv/v$  am-  
128 plitude is robust considering the  $cc$  dependent (stretching) error estimates  
129 between  $1.3 \times 10^{-4}$  and  $1.2 \times 10^{-4}$  for  $\tau = 4, 12$  s.

130 We analyze the spectral content of the  $dv/v$  time series in Figure 2 using two  
131 approaches. First, we apply a Lomb-Scargle (LS) algorithm to the incomplete  
132 time series (5% gaps; mostly associated with acquisition problems coincident  
133 with taifuns). Second, we interpolate the gaps and perform a standard DFT  
134 analysis. The results mutually support each other. Amplitude spectra are  
135 dominated by an annual signal (Fig. 3a); peaks with decreasing amplitude  
136 towards shorter periods are associated with overtones. However, peaks be-  
137 tween 50–80 days (Fig. 3b) are not compatible with the decaying overtone  
138 pattern. The significance of this ridge is verified by estimating the spectra  
139 of a ‘high-pass’ time series, which is the residual between the original and a  
140 tens-of-day smoothed ‘low-pass’ time series.

141 A weak 7-day spectral component is the footprint of anthropogenic excitation  
142 (Hillers et al., 2012). Its  $\tau$  dependent decrease indicates that randomization  
143 through scattering causes a progressive decay of characteristics inherited from

144 the source process (Paul et al., 2005).

### 145 *2.3. Meteorological Data*

146 Spectra of meteorological records (pressure P, temperature T, rainfall R;  
147 neglect of wind data) recorded 10 km west of the TCDP site (Fig. 1) are  
148 dominated by an annual periodicity (Fig. 3c). The rainfall spectrogram is  
149 characterized by a second significant peak of scaled amplitude 0.8 around  
150 50–80 days (Fig. 3d), which resembles the  $dv/v$  pattern in Figure 3b. In  
151 comparison, corresponding P and T spectral amplitudes of  $\sim 1/10$  of the an-  
152 nual signal are significantly smaller.

153 The analysis shows that atmospheric dynamics in Taiwan are controlled  
154 by the Madden-Julian Oscillation (MJO), “the dominant component of the  
155 intraseasonal (30–90 days) variability in the tropical atmosphere” (Zhang,  
156 2005). which is associated with a pattern of eastward propagating low pres-  
157 sure systems originating in the warm Indian and Pacific oceans. The MJO  
158 thus mostly affects precipitation rates, and the small intraseasonal P and T  
159 components correspond to pressure and temperature drops associated with  
160 rainfall events. Cross-correlation of hourly sampled high-pass P-R and T-R  
161 time series shows that pressure decreases  $\sim 20$ –30 hours before rainfall, and  
162 temperature falls almost simultaneously with the onset of precipitation.

163 The coincidence of seismic velocity reductions with strong MJO driven pre-  
164 cipitation events (Fig. 4), and the similarity of  $dv/v$  and R spectrograms  
165 imply that seismic wave speed changes are controlled by fluctuations of the  
166 water content in the upper crust. Similarly important for the emergence of  
167 the MJO spectral footprint in the  $dv/v$  data is the observed recovery on time  
168 scales smaller than the average large-precipitation periodicity.



### 169 3. Inversion for Hydraulic Parameters

#### 170 3.1. The Model

171 We use the model of SSW06 (Sens-Schönfelder and Wegler, 2006) to val-  
172 idate the hypothesis of precipitation driven velocity changes and to estimate  
173 average hydraulic properties from the  $dv/v$  measurements. We briefly repro-  
174 duce the four model building blocks which couple seismic velocity variations  
175 to precipitation rates and drainage properties; see Sens-Schönfelder and We-  
176 gler (2011) for a more detailed description.

177 (1) Darcy’s law controls the exponential drainage of the water table through  
178 an aquifer after a rain event. Convolution of the precipitation rate  $p$  with this  
179 exponential decrease yields the ground water level  $GWL$  at time  $t_i$  measured  
180 in days,

$$GWL(t_i) = GWL_0 - \sum_{n=0}^i \phi^{-1} p(t_n) \exp[-(t_i - t_n)a], \quad (1)$$

181 which depends on some unknown asymptotic level  $GWL_0$ , the porosity  $\phi$   
182 controlling the amplitude of the  $GWL$  variation in response to  $p(t)$ , and the  
183 decay parameter  $a$ ; Helmstetter and Garambois (2010) use a similar formu-  
184 lation for the modeling of precipitation induced landslide triggering.

185 (2) The relative velocity perturbation  $V(t_i, z)$  at depth  $z$  depends on the  
186 predicted  $GWL(t_i)$ , a reference water level  $GWL_{\text{ref}}$ , and  $\delta v$ , the relative ve-  
187 locity difference between drained and undrained states, i.e.,  $V(t_i, z) = \delta v$  for  
188  $GWL(t_i) < z < GWL_{\text{ref}}$ ,  $V(t_i, z) = -\delta v$  for  $GWL_{\text{ref}} < z < GWL(t_i)$ , and  
189  $V(t_i, z) = 0$  elsewhere. The reference level is chosen to be the mean level  
190 over the period for the reference correlation stack for the  $dv/v$  analysis, i.e.,  
191 the average over the two year analysis period.

192 (3) Energy propagation of the scattered coda wave field is modeled as a diffu-  
 193 sion process (Pacheco and Snieder, 2005). Considering network dimensions  
 194 and wavelength, we use a 3-D sensitivity kernel under the assumption of  
 195 coincident source and receiver,  $K_{3D}(\mathbf{x}, \tau) = (2\pi Dr)^{-1} \exp[-r^2/(D\tau)]$ . The  
 196 distance between source/receiver and a point in space  $\mathbf{x}$  is  $r$ , and  $D$  is the  
 197 diffusion constant of seismic energy. Centered on the observation depth  $z_0$   
 198  $K_{3D}(\mathbf{x}, \tau)$  is integrated across the horizontal domain yielding  $K(z, \tau)$ .  $K$  is  
 199 normalized by  $\tau$  to ensure  $\int K dz = 1$ .

200 (4) The three components are combined to compute the delay time  $d\tau$  at  
 201 lapse time  $\tau$  by integrating the velocity perturbation  $V$  weighted by the  
 202 nonlinear kernel  $K$ :

$$d\tau_i(\tau) = d\tau(t_i, \tau) = \int_{z=0}^{\infty} \frac{K(z, \tau)}{V(t_i, z)} dz. \quad (2)$$

203 The model allows an assessment of timing, amplitude, and recovery proper-  
 204 ties of the observed relative velocity variations by estimating  $GWL_0$ ,  $\phi$ ,  $a$ ,  
 205 and  $\delta v$ . This is done by minimizing the residual  $P$  between the synthetic  
 206  $(dv_i/v)_s = -d\tau_i/\tau$  (Eq. 2) and the observed  $(dv_i/v)_o$  time series,  $P = \sum_i \rho_i$ ,  
 207 with  $\rho_i = [(dv_i/v)_s - (dv_i/v)_o]^2$ . Note the trade-off between  $\phi$  and  $\delta v$ , i.e.  
 208  $\delta s/\phi$  with  $\delta s = \delta v^{-1}$ . Small slowness perturbations associated with large  
 209  $GWL$  amplitudes (small  $\phi$ ) can not be resolved from large  $\delta s$  changes meet-  
 210 ing small  $GWL$  fluctuations (large  $\phi$ ). Following SSW06 we use a genetic  
 211 algorithm (GA) for the minimization of  $P$ . We analyze distributions of 150  
 212 independent estimates, because the rough fitness landscape is characterized  
 213 by many local minima.

214 We consider two types of inversions. Separate lapse time dependent inver-  
 215 sions are motivated by the observation that some drainage episodes show a

216  $\tau$  dependence of the decay behavior (e.g., 08/2008, 08/2009, Fig. 2b). In  
217 contrast, a joint inversion minimizes the residuals simultaneously for joint  
218 constraints of  $GWL_0$ ,  $a$ , and  $\delta s/\phi$ .

## 219 3.2. Inversion Results

### 220 3.2.1. Timing

221 The similarity between  $(dv_i/v)_o$  and  $(dv_i/v)_s$  with respect to the timing  
222 of the  $dv/v$  drops (Fig. 4) supports the hypothesis of precipitation driven  
223 velocity variations. Performing separate inversions, we observe a  $\tau$  dependent  
224 increase of the residual  $P$ , which is associated with the lapse time dependent  
225 increase in remnant coda fluctuations. This also causes larger  $P$  associated  
226 with  $d = 1$  day  $dv/v$  time series for all  $\tau$  compared to  $d = 3$  and 7 days.  
227 Visual inspection of  $\rho_i$  time series reveals a  $d$  dependence of the misfit at  
228 large amplitude velocity drops. It implies that the disadvantage of small- $d$   
229 time series associated with small SNR is compensated by the better temporal  
230 resolution in response to rainfall, and indicates that the system response delay  
231 does not exceed one day. Yet better resolution can be obtained if fluctuations  
232 associated with diurnal excitation changes (Hillers et al., 2012) are mitigated  
233 (Baig et al., 2009; Hadziioannou et al., 2011). In the remainder of this work  
234 we use  $d = 3$  days to balance the trade-off between temporal resolution and  
235 SNR.

### 236 3.2.2. Amplitude and Decay

237 The consistency between precipitation driven synthetic and observed  $dv/v$   
238 levels indicates the applicability of the model for estimates of average hy-  
239 draulic properties controlling  $GWL$  amplitude and decay. Amplitude refers

240 to the reduced  $dv/v$  value in response to rainfall (Fig. 4), and decay rates  
 241 to the recovery speed controlled by drainage properties of the model aquifer.  
 242 Amplitude estimates are sensitive to properties of  $K(z, \tau)$  and therefore de-  
 243 pend critically on the diffusion constant  $D = lv/3$ , which is proportional to  
 244 wave velocity  $v$  and the scattering or elastic mean free path  $l$ . The mean free  
 245 path describes the average distance between two scattering events and is con-  
 246 sequently controlled by the medium heterogeneity (Aki and Richards, 1980).  
 247 A direct estimate of  $l$  from spectral properties of  $v(z)$  (Hillers et al., 2013a)  
 248 is inhibited by the limited extension of the velocity log (Fig. 5a). However,  
 249 the lower limit of  $D$  is constrained considering that  $l$  must be larger than the  
 250 wavelength  $\lambda = v/f$ . We assume the 9-component average to be controlled  
 251 by  $S$ -wave sensitivities ( $v = v_S$ ), and that frequencies at the high- $f$  edge of  
 252 the 1–4 Hz range dominate the  $dv/v$  estimates (Hillers et al., 2012). With  
 253  $f = 4$  Hz,  $l/\lambda > 1$  for  $D > 2 - 3 \times 10^5 \text{ m}^2\text{s}^{-1}$  (Fig. 5b), where we assume that  
 254  $l/\lambda$  tends to increase towards shallower depths. With an average  $v_S$  value  
 255 this translates into  $l > \lambda \approx 450$  m.  
 256 Using  $D = 3 \times 10^5 \text{ m}^2\text{s}^{-1}$  in the separate inversions (Fig. 6), the  $a$  distri-  
 257 butions confirm the visually inferred intermittent  $\tau$  dependence in the  $dv/v$   
 258 time series. Lapse time independent  $GWL_0$  distributions cluster around the  
 259 peak- $K$  level at  $z_0$ , so that the observed amplitudes are reproduced by the  
 260  $\tau$  dependence of  $\delta s/\phi$ . This, however, implies different water levels fluctua-  
 261 tions, which is not compatible with a single-aquifer model.  
 262 The depth range of the observed direct  $\tau$  dependence is limited by the depth  
 263  $z_\times$  at which the  $K(z, \tau)$ -functions intersect (Figs. 5c–e). This behavior is  
 264 utilized in a joint inversion (Fig. 7), where the three  $\tau$  dependent measure-

265 ments constrain the asymptotic water level to  $0 < z < z_{\times}$  and resolve the  
266  $GWL_0$ - $\delta s/\phi$  trade-off. Consequently, the average depth of a resulting  $GWL_0$   
267 distribution is compatible with the associated  $D$  dependent  $z_{\times}$  estimate.

268 Larger diffusion constants flatten the kernels and cause a reduction of (peak)  
269  $K$  values. The  $GWL_0$  sensitivity of  $\delta s/\phi$  thus follows from the constraint  
270 of a constant  $d\tau$  amplitude (Eq. 2). The role of  $\phi$  as a tuning parameter  
271 becomes evident if we assume that  $\delta s$  is independent of depth. It explains  
272 why associated  $\phi$  estimates are smaller compared to porosity measurements  
273 from TCDP rock samples (Wang et al., 2009).

274 It should be noted that the TCDP  $dv/v$  variations are an order of magnitude  
275 smaller compared to the  $\sim 2\%$  reported by SSW06. We attribute this to the  
276 shorter distance between stations at the surface and the inferred  $GWL$  level  
277 above 40 m at Mt. Merapi. Water table changes occur near the  $K$ -peak, and  
278 this effect is amplified by the smaller diffusion constant  $D = 5 \times 10^4 \text{ m}^2\text{s}^{-1}$   
279 (note that  $K$  values in Fig. 7 in Sens-Schönfelder and Wegler (2011) are  
280 erroneous).

281 Properties governing the drainage rate ( $0.02$ – $0.03 \text{ d}^{-1}$ ) are independent of  
282 these amplitude controlling factors. The 2–3 times larger estimate compared  
283 to the experiment at Mt. Merapi ( $0.008 \text{ d}^{-1}$ ) indicates that the crust hosting  
284 the Chi-Chi earthquake is characterized by a more efficient fluid percolation  
285 network.

#### 286 4. Discussion and Conclusions

287 Our high-frequency noise based monitoring analysis shows that seismic  
288 velocity variations ( $dv/v$ ) measured with a borehole array of the Taiwan

289 Chelungpu-fault Drilling Project (TCDP) are characterized by a significant  
290 intraseasonal periodicity in addition to the annual spectral component fre-  
291 quently observed in  $dv/v$  studies (Meier et al., 2010; Froment et al., 2013).  
292 We find that the 50–80 day period matches properties of the precipitation  
293 pattern in Taiwan which is driven by the dynamics of the Madden-Julian  
294 Oscillation (MJO). Further evidence for the governing role of hydraulic prop-  
295 erties is inferred from the similarity of averaged  $dv/v$  timing, amplitude, and  
296 recovery properties with  $dv/v$  synthetics. The adopted model synthesizes  
297  $dv/v$  changes based on ground water level ( $GWL$ ) fluctuations controlled by  
298 precipitation data and Darcy’s law coupled to the sensitivity  $K$  of the scat-  
299 tered seismic wave field (Sens-Schönfelder and Wegler, 2006, abr. “SSW06”).  
300 The plausibility of this model is demonstrated by the remarkable consis-  
301 tency between multiple model components and observations in response to  
302  $K$ -controlling variations of the diffusion constant  $D$ . Estimates of hydraulic  
303 parameters that govern the velocity response function to precipitation indi-  
304 cate a relatively large fluid mobility compared to estimates from a usually  
305 highly fractured volcanic environment (SSW06). High drainage properties  
306 facilitate the  $GWL$  equilibration on time scales shorter than the average  
307 precipitation interval, and thus constitute a necessary condition for the  $dv/v$   
308 pattern to follow the MJO rhythm. Efficient drainage properties are com-  
309 patible with observations of low  $Q$  values (Wang et al., 2010), which are  
310 likely associated with widespread damage induced by the 1999 M7.6 Chi-Chi  
311 earthquake.

312 Residual time series  $\rho_i$  indicate the difficulty to match amplitude and recov-  
313 ery properties associated with individual precipitation events using average

314 estimates of the model parameters (Fig. 4a). The intermittently observed  
315 lapse time dependence of  $a$  implies spatially variable hydraulic conditions  
316 and is thus incompatible with the assumption of a laterally homogeneous 1-D  
317 aquifer. Resolution of such second-order inconsistencies requires deciphering  
318 the complex hydraulic situation associated with subsurface fluid percolation  
319 properties and the spatio-temporal variation of precipitation. While the uti-  
320 lized rainfall time series  $p(t)$  is characterized by high temporal resolution,  
321 it constitutes only a proxy of the actual rainfall pattern over the area that  
322 controls  $dv/v$  estimates (Bell, 1987). Figure 1 illustrates estimates of precip-  
323 itation distributions observed from space. The large variability is indicated  
324 by the 60% contours of cumulative rainfall during days defined by the 10  
325 largest daily amounts of precipitation recorded at the meteorologic station.  
326 The contours indicate that maximum precipitation occurs mostly in areas  
327 that do not include the rain gauge. The crustal structure in the tectonic  
328 collision zone is characterized by a dipping geology. Together with strong  $Q$   
329 discontinuities across the Chelungpu fault (Wang et al., 2012), the implied  
330 variable drainage properties further contribute to the difficulties in repro-  
331 ducing the observed  $dv/v$  time series using average model parameters. It  
332 also challenges the assumption of isotropic propagation of the scattered wave  
333 field, which underpins the construction of  $K$ .

334 The range of 0.1–0.3% velocity reduction in response to significant precip-  
335 itation is comparable to or somewhat larger than peak values reported for  
336  $dv/v$  in response to rainfall (0.1%, Meier et al., 2010) and deformation due to  
337 earthquakes (0.5%, <0.1%, 0.2%, Wegler and Sens-Schönfelder, 2007; Bren-  
338 guier et al., 2008a; Froment et al., 2013), volcanic activity (<0.1%, Brenguier

339 et al., 2008b), and slow slip events (0.2%, Rivet et al., 2011). However, our  
 340 estimates are an order of magnitude smaller than the 2% variations at Mt.  
 341 Merapi (SSW06). We attribute this to different  $K$  sensitivities associated  
 342 with variable diffusion constants and different distances between the obser-  
 343 vation depth  $z_0$  and the level of  $GWL$  changes. In addition to the direct  
 344 poroelastic effect where the presence of water slows seismic wave propaga-  
 345 tion (Grêt et al., 2006), a loading effect can alter wave speeds. Similar to  
 346 atmospheric pressure changes (Silver et al., 2007; Niu et al., 2008), water  
 347 table fluctuations induce variable loads on the rock matrix below  $GWL$ —or  
 348 at least below some impermeable layer such as the  $\sim 300$  m thick dipping  
 349 formation that hosts the Chelungpu fault. However, this direct effect causes  
 350 a  $dv/v$  fluctuation of opposite sign in the far field of an observation borehole.  
 351 It may therefore contribute to the observed  $dv/v$  values by counterbalancing  
 352 the poroelastic effect, but it does not dominate the wave speed variations.  
 353 We do not find evidence that atmospheric pressure or temperature changes  
 354 bias the discussed first order properties of the  $dv/v$  time series associated  
 355 with timing, amplitude, and decay properties, either through surface loading  
 356 effects or through perturbations of the conditions in the borehole.  
 357 The precipitation driven  $dv/v$  inverse amplitude dependence (smaller nega-  
 358 tive values) on lapse time reported by SSW06 is opposite to our observation  
 359 showing a direct  $\tau$  dependence (larger negative values; Fig. 2b). The effect  
 360 is controlled by the relative position of  $z_0$  and the water table change with  
 361 respect to the intersection level  $z_\times$  of the kernels  $K(z, \tau)$  (Figs. 5c–e). In  
 362 addition to constraining the equilibrium level  $GWL_0$ , this behavior allows  
 363 estimates of the scattering mean free path  $l = 3D/v_S$ . The lower limit is



364 imposed by the wavelength,  $l > \lambda \approx 450$  m, and the direct  $\tau$  dependence of  
 365 the  $dv/v$  amplitudes constrains together with the inverse  $\tau$  dependence for  
 366 all  $z < z_0$  for  $D > 5 \times 10^5$  m<sup>2</sup>s<sup>-1</sup> (Fig. 5e) the upper limit to  $l < 850$  m.  
 367 Estimates of  $l$  are likely to decrease towards shallower depth considering the  
 368 velocity gradient above 600 m and the mountain topography. However, depth  
 369 variable scattering properties are not considered in the 3-D isotropic wave  
 370 propagation model underlying the analytic expression of  $K(\mathbf{x}, \tau)$ .  
 371 SSW06 conclude that the coda wave field at Mt. Merapi consists of body  
 372 waves instead of surface waves. For primary sources located at the surface,  
 373 the dominance of body waves implies a short mean free time (Obermann  
 374 et al., 2013b), which is compatible with the small diffusion constant. TCDP  
 375 noise at 1100 m depth is similarly dominated by body waves (Hillers et al.,  
 376 2012), indicating that our analysis is not biased by the neglected conversions  
 377 between surface and body waves.  
 378 Application of the 1-D joint inversion to situations in which the data quality  
 379 is inferior, or where the signal is weaker, can benefit from a range of potential  
 380 improvements. These include but are not limited to the denoising of noise  
 381 correlation coda (Stehly et al., 2008; Baig et al., 2009); the construction of  
 382 spatially averaged rainfall time series; the construction of kernels consider-  
 383 ing wave conversions; the application of kernels based on radiative transfer  
 384 theory (Planes et al., 2014, and references therein), which have different sen-  
 385 sitivities at early lapse times and short distances compared to the diffusion  
 386 approximation (Obermann et al., 2013b); and the application of weighted  
 387 misfit functions  $\rho_i$ . With these optimizations, the approach has the potential  
 388 to constrain water level changes associated with anthropogenic activity such

389 as impoundment, ground water depletion, or the injection and extraction of  
390 fluids in the context of reservoir engineering.

391 Precipitation can trigger seismicity (Husen et al., 2007; Bettinelli et al., 2008;  
392 Helmstetter and Garambois, 2010; Hainzl et al., 2013). From an earthquake  
393 source physics point of view it is interesting to isolate the mechanism that  
394 controls variations in the nucleation rate, e.g., fault lubrication or pressuriza-  
395 tion, or changes in the loading rate caused by underground accumulation of  
396 water. We analyzed a regional earthquake catalog for correlations between  
397 daily rainfall and seismic event rates (Helmstetter and Garambois, 2010) us-  
398 ing a systematic grid search over variable spatial and magnitude bins. The  
399 method detects a few coincidences, but the lack of systematic triggering in  
400 the associated space and magnitude intervals does not indicate a relevant  
401 physical mechanism.

402 We conclude by iterating the beneficial role steady anthropogenic activity  
403 plays in the construction of daily high-frequency correlation functions. Con-  
404 sidering the additional information contained in decorrelation time series  
405 (Larose et al., 2010; Obermann et al., 2013a) we emphasize the relative sta-  
406 bility of coherency measurements compared to  $dv/v$  fluctuations (Fig. 2a).  
407 It implies that the scattering properties do not change. This can be differ-  
408 ent for extended network geometries that contain areas impacted by strong  
409 rainfall events. In such a situation, analyses of  $dv/v$  and decorrelation data  
410 can target the interaction of the ambient wave field with evolving hydraulic  
411 situations.

412

413 **Acknowledgments** This work was supported by the European Research

414 Council (Advanced grant Whisper L27507). GH acknowledges support through  
415 a Heisenberg fellowship from the German Research Foundation. Figures were  
416 made using GMT (Wessel and Smith, 1991). Data used in this study were  
417 produced with the Giovanni online data system, developed and maintained  
418 by the NASA GES DISC. We acknowledge the helpful comments of C. Sens-  
419 Schönfelder and an anonymous reviewer.

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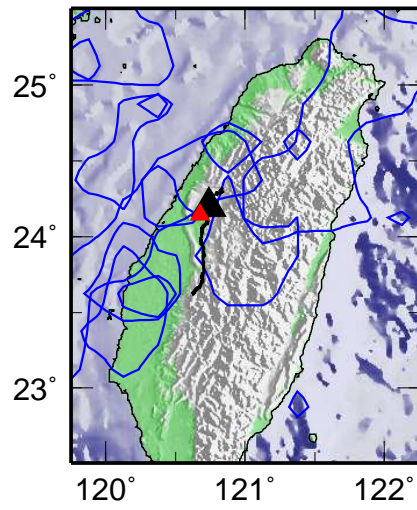


Figure 1: The map of the study area indicates locations of the TCDP site (black triangle) and the meteorologic station (red triangle). Anthropogenic seismic noise is excited in the green indicated lowland southwest of the TCDP (Hillers et al., 2012). The black line beneath the TCDP is the surface trace of the east dipping Chelungpu fault. Blue lines indicate precipitation distributions observed from space. Each line represents the 60% contour of cumulative rainfall during the 10 days in 2008 and 2009 defined by peak precipitation events.

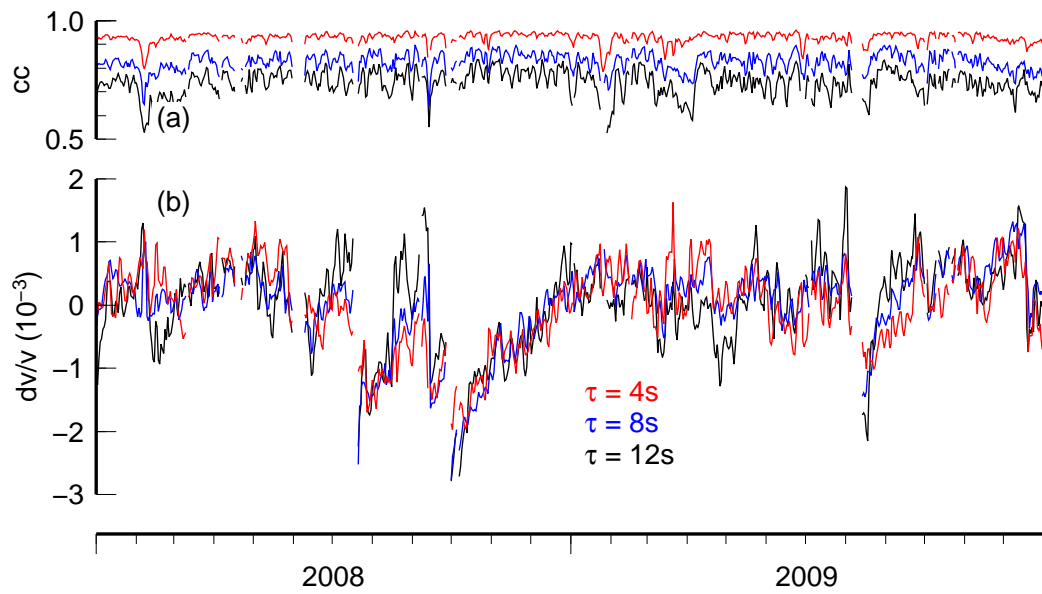


Figure 2: (a) Coherency estimates associated with (b) relative velocity changes ( $dv/v$ ) measured with the stretching technique using three different coda lapse time windows. The frequency range is 1–4 Hz, and  $d = 3$ .

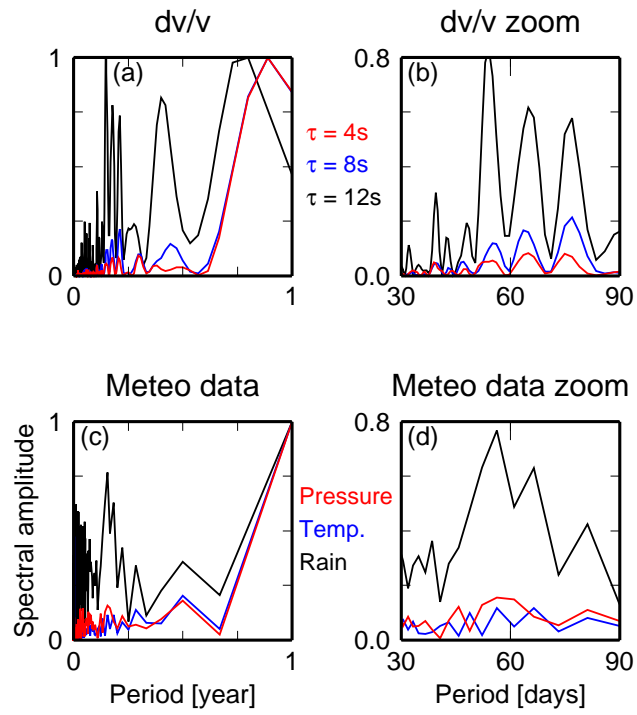


Figure 3: (a) Spectral amplitudes of lapse time ( $\tau$ ) dependent  $dv/v$  observations. Colors as in Figure 2. Amplitudes are scaled to the annual component. (b) Zoom on the MJO pattern. (c) Spectral amplitudes of rainfall, temperature, and atmospheric pressure records. Amplitudes are scaled to the annual component. (d) Zoom on the MJO pattern.

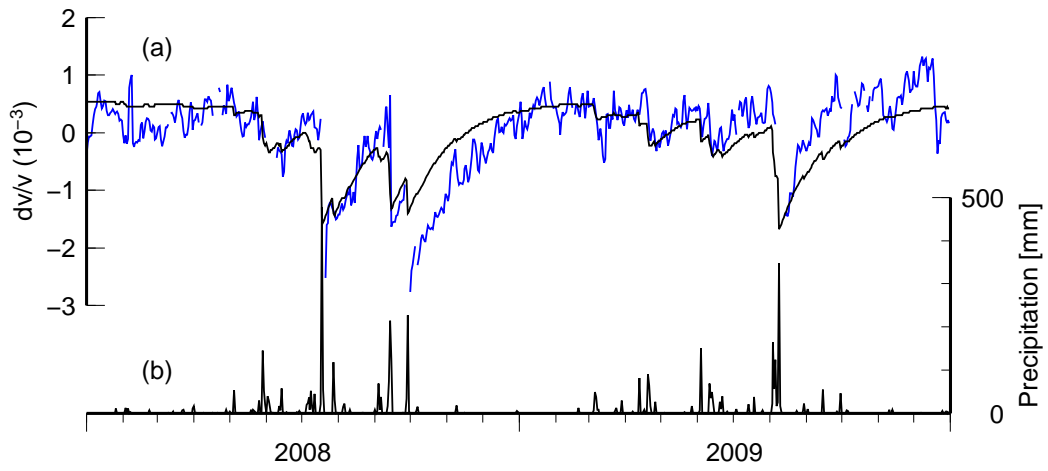


Figure 4: (a) Blue: Observed  $dv/v$  time series ( $\tau = 8$  s). Black: Synthetic  $dv/v$  estimates based on the model described in Section 3. The consistency indicates that the model can explain first order characteristics of the measurements associated with timing, amplitude, and drainage. Resolution of the  $dv/v$  synthetics (vertical discretization of the black curve) is controlled by the vertical resolution  $dz$  of the kernel  $K$ . (b) The model ground water level (Eq. 1) is driven by daily precipitation records collected 8 km southwest of the TCDP site (Fig. 1).

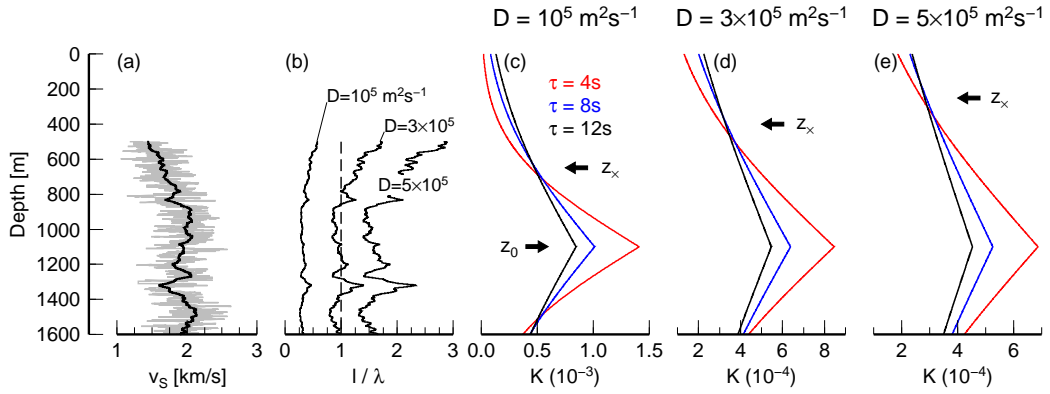


Figure 5: (a) Section of the shear wave velocity log (gray; data are available between 500 m and 1850 m; Wu et al., 2007) and its 50 m average (black). (b) The ratio of scattering mean free path ( $l = 3D/v_S$ ) and wavelength ( $\lambda = v_S/f$ ) using an average  $v_S$  profile,  $f = 4$  Hz, and a range of diffusion constants  $D$ . It should be noted that  $D$  cannot be defined on scales indicated by the vertical  $l/\lambda$  resolution. However, the distributions illustrate the range of plausible  $D$  values for which  $l > \lambda$ . (c)–(e):  $D$  dependent distributions of the kernel  $K(z, \tau)$  associated with the observation depth  $z_0 = 1100$  m. The  $\tau$  dependence of velocity change amplitudes is controlled by the water level relative to the intersection depth  $z_x$ .

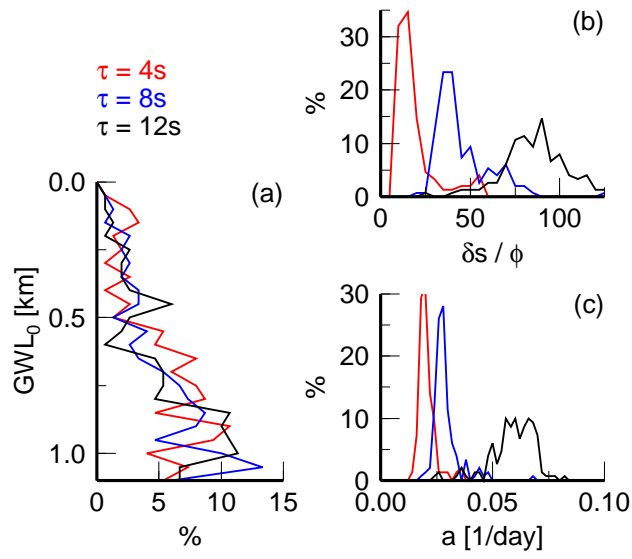


Figure 6: Distributions of the hydraulic parameters (Eq. 1) obtained from 150 separate inversions using  $D = 3 \times 10^5 \text{ m}^2\text{s}^{-1}$ . Colors indicate lapse time. (a) Equilibrium ground water table  $GWL_0$  (bin width 50 m). The search range is limited to  $z < z_0$ . (b) Slowness sensitivity  $\delta s / \phi$  (bin width 5). (c) Decay rate  $a$  (bin width 0.002 1/day). The residual  $R$  is uniformly distributed across the parameter space.



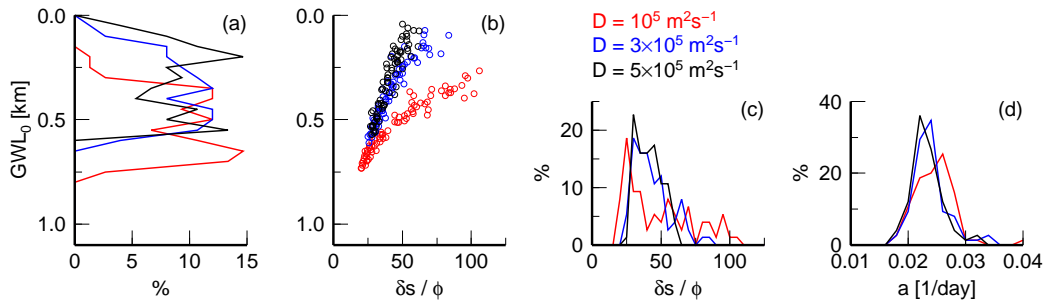


Figure 7: Distributions of the hydraulic parameters (Eq. 1) associated with 150 joint inversions. We show the best 50% because the residual  $R$  is sensitive to  $GLW_0$ . Colors indicate the diffusion constant which controls the depth sensitivity of the kernel  $K$ . We used a range of  $D$  values to illustrate the sensitivity of the solutions to the crossing depth  $z_x$  (Figs. 5c–e), although  $D < 2 \times 10^5 \text{ m}^2\text{s}^{-1}$  might be unphysical (Fig. 5b). (a) Equilibrium ground water table  $GLW_0$  (bin width 50 m). (b) Dependence of  $\delta s / \phi$  on  $GLW_0$ . (c) Slowness sensitivity  $\delta s / \phi$  (bin width 5). (d) Decay rate  $a$  (bin width 0.002 1/day). There is no dependence of  $a$  on  $GLW_0$ .