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**Normalized Microwave Reflection Index:**

**A Vegetation Measurement derived from GPS Networks**

Kristine M. Larson

Department of Aerospace Engineering Sciences, University of Colorado

Eric E. Small

Department of Geological Sciences, University of Colorado

**Corresponding Author:**

Kristine M. Larson

UCB 429

University of Colorado

Boulder, CO 80309

[Kristinem.larson@gmail.com](mailto:Kristinem.larson@gmail.com)

303 492 6583 (phone)

303 492 7881 (fax)

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**Abstract**

Measurements of vegetation state are required both for modeling and satellite validation. Reflected GPS signals recorded by the Plate Boundary Observatory network provide a source of new information about vegetation state in the western United States and Alaska. The GPS ground stations were installed between 2005-2008 to measure plate boundary deformation. They operate continuously and transmit their data to a public facility at least once/day. However, they also act as bi-static radars by recording the interference between a direct GPS signal (transmitted at 1.5 GHz) and a reflected GPS signal. This frequency of this interference pattern primarily depends on the vertical distance between the antenna and the ground reflector. As a L-band sensor, the amplitude of the interference pattern depends on vegetation water content. A daily vegetation metric that depends on reflection amplitudes, NMRI (Normalized Microwave Reflection Index), is defined. A method for removing outliers caused by snow and rain is described. The footprint of NMRI depends on the antenna height and local terrain. The minimum footprint is 1,000 m<sup>2</sup>. A database of more than 300 station NMRI time series have been compiled; these data span the period 2007-2013. Comparisons between NMRI and *in situ* sampling of vegetation state are the subject of a companion paper.

36

## 37 **1. Introduction**

38 The amount of water stored in vegetation canopies is an important biophysical parameter for  
39 both climate studies and drought monitoring. For example, the productivity of natural and  
40 agricultural ecosystems is strongly controlled by plant water status [1]. Knowledge of the  
41 amount of biomass and its water content can guide fire management practices [2]. Quantifying  
42 the amount of water in plants is also critical for retrieval of hydrologic variables from remote  
43 sensing data - as both passive and active remote sensing of soil moisture requires knowledge of  
44 vegetation water content (VWC) [3,4]. Accordingly, remote sensing methods have been  
45 developed to estimate water in vegetation, using both optical and radar data.

46

47 There is a long history of using optical remote sensing to estimate biophysical parameters. The  
48 Normalized Difference Vegetation Index [5], and similar indices [6], has been calculated from  
49 operational satellite data for decades. NDVI is largely considered a measure of plant greenness,  
50 and has been used to infer biomass, leaf area index (LAI), fractional vegetation cover and other  
51 variables [7,8,9]. VWC has also been estimated from NDVI, although a cause-effect relationship  
52 does not exist between the two variables [10]. Factors such as plant type, plant-water status, and  
53 hydroclimatic conditions affect VWC and “greenness” differently, thus the relationship between  
54 NDVI and VWC is not expected to be strong [11].

55

56 An optical remote sensing index to more directly quantify the amount of water in vegetation is  
57 known as Normalized Difference Water Index (NDWI) [12]. It is calculated using reflectance in

58 two near infrared (NIR) channels. Similar indices have been proposed that use reflectance at  
59 other NIR wavelengths, either tuned for different satellite channels or to capitalize on other water  
60 absorption bands [2,13,14,15,10]. Validation of these indices by comparison to *in situ*  
61 observations demonstrates a range of performance, depending upon vegetation type, sensor  
62 configuration, and other factors. Reflection from the underlying soil complicates the use of  
63 NDWI and related indices in areas with fractional vegetation cover or low LAI [12,13,10].

64

65 Both passive and active microwave remote sensing have been used to estimate water stored in  
66 vegetation [16]. The dielectric constant of water is roughly ten times higher than for dry  
67 vegetation. Therefore, the amount of water stored in plant material directly affects how  
68 microwave radiation interacts with vegetation canopies, including changes in scattering,  
69 polarization, and absorption. The amount of water in vegetation affects the emissivity of the  
70 canopy, and thus the brightness temperature sensed remotely [17]. Water in vegetation also  
71 absorbs microwave radiation emitted by the soil surface, thus vegetation water content hinders  
72 retrieval of soil moisture via passive radar sensing [3]. Vegetation optical depth (VOD) can be  
73 retrieved from brightness temperature measurements. Comparisons between the seasonal  
74 evolution of VOD and NDVI show that there are both similarities and differences between these  
75 microwave and optical measures [18].

76

77 Active microwave experiments have shown that VWC and other biophysical parameters affect  
78 the scattering coefficient and polarization of signals from vegetation canopies. Various sensor  
79 configurations have been evaluated, including a range of wavelengths, polarizations, and  
80 incidence angles [19,20,21,22]. In general, the scattering coefficient increases as VWC and

81 biomass increase, with the greatest sensitivity at incidence angles of ~20-40 degrees off nadir.  
82 At L-band, radar backscatter is sensitive across a wide range of VWC (0-5 kg/m<sup>2</sup>) [23]. L-band  
83 signals penetrate all but the thickest vegetation canopies (e.g., tropical forests), and therefore  
84 they are also affected by soil moisture [4]. In addition to soil moisture, the VWC-backscatter  
85 relationship is complicated by vegetation structure and soil surface roughness. The influence of  
86 these factors may be minimized by using the Radar Vegetation Index (RVI), which incorporates  
87 both cross- and co-polarized measurements [23,24].

88

89 A relatively new L-band remote sensing technique with relevance for measuring vegetation state  
90 uses reflected GPS (and more generally GNSS, Global Navigation Satellite Systems, signals).  
91 Reflected GPS signals were first proposed in 1993 as a method to measure sea level from space  
92 [25]. This idea has since been expanded and tested on a variety of ground, aircraft, and space  
93 based platforms for studies of soil moisture [26,27], altimetry [28,29], ocean winds [30], sea ice  
94 [31], oil slicks [32], ocean tides [33,34], and snow [35]. Most relevant to this study are the GPS  
95 reflection studies of [36,37,38] where the technique is applied to vegetation. These investigators  
96 showed that GPS signal power levels could be used to detect vegetation changes for a variety of  
97 agricultural crops, including corn, sorghum, wheat, barley, sunflowers, and leaves in walnut  
98 trees. Good agreement was shown between the GPS retrievals and field observations of  
99 vegetation height and VWC.

100

101 In this paper, we describe an alternative way to use GPS to measure VWC. An index is derived  
102 from these data, Normalized Microwave Reflection Index (NMRI). As with [36,37,38], a  
103 bistatic-radar geometry is used. L-band signals transmitted by GPS satellites are reflected by the

104 land surface and received by geodetic-quality GPS antennas a few meters above the ground. A  
105 limited number of comparisons between these types of GPS reflections and *in situ* observations  
106 of plant biophysical parameters were first presented by [39]; they also compared time series of  
107 GPS reflections and NDVI from several sites in the western United States. In this paper we  
108 summarize the theory that explains the reflected GPS signals, present a method to quantify  
109 reflections from the GPS observations, describe the data editing required for a useful metric, and  
110 provide a first-order normalization to correct for terrain effects. Validation of the NMRI method  
111 by comparison with *in situ* measurements of VWC is covered in a companion paper [40,  
112 hereafter paper II].

## 113 **2. Overview of the Global Positioning System**

114 NMRI is based on reflection effects (paper.) recorded in GPS ranging data, known as  
115 pseudoranges and carrier phases. The goal of this section is to first provide a description of the  
116 GPS system needed to define NMRI. This will be followed by a theoretical description of  
117 multipath geometry and how it can be observed in GPS measurements known as pseudoranges.

### 118 **2.1 Satellites**

119 GPS is a constellation of satellites (currently 31) at an altitude of ~20,000 km above the surface  
120 of the Earth. Each GPS satellite orbits the Earth with a ~12 hour orbital period, meaning that the  
121 ground tracks repeat at a nearly sidereal (23h:56m) period [41]. The satellites are separated into 6  
122 orbital planes spaced at 60-degree intervals and inclined at an angle of 55 degrees with respect to  
123 the equator. As a result, GPS receivers in the continental U.S. can track anywhere from 6-12  
124 GPS satellite signals at any given time. All GPS satellites transmit Right-Handed Circularly-  
125 Polarized (RHCP) signals at L-band. The primary GPS transmission frequencies ( $f_1$  for the  $L_1$

126 band and  $f_2$  for the  $L_2$  band) are 1.57542 and 1.22760 GHz; the equivalent  $L_1$  and  $L_2$  carrier  
127 wavelengths  $\lambda_1$  and  $\lambda_2$  are approximately 0.19 and 0.244 m.

128 The geometry of these GPS satellite tracks strongly depends on the receiver's latitude. Figure 1  
129 displays the azimuth and elevation angle of all visible GPS satellites for a site located in southern  
130 Montana (Elevation is the angle of the satellite with respect to the local horizon). No  
131 observations are shown below 10 degrees for reasons that will be discussed in Section 3. While  
132 individual satellite tracks vary, the satellite highlighted in Figure 1A takes approximately 4 hours  
133 to rise and set, reaching a maximum elevation angle of  $\sim 45$  degrees (Figure 1B). Longer satellite  
134 tracks – that reach higher elevation angles – generally correspond to  $\sim 6$  hours in the western  
135 United States.

136 In North America there is a distinctive hole in GPS observations to the north, which is due to the  
137 inclination of the GPS orbit; there is an equivalent measurement hole in the south for GPS users  
138 in the southern hemisphere. Depending on which satellites are in which orbital planes and the  
139 user's location, a stationary GPS receiver will track a given GPS satellite once or twice per day.  
140 The location of GPS satellites within their orbital planes has varied somewhat over the past six  
141 years, but not in a way that significantly impacts the footprint of the GPS reflections.

142

## 143 **2.2 Ground Networks**

144 Starting in the mid-1980s, geodesists and geophysicists demonstrated that dual-frequency  
145 carrier-phase GPS instruments could be used to measure fault motions [42]. However, the cost of  
146 such receivers was prohibitive for permanent installations. As the price of GPS instrumentation  
147 decreased in the 1990s, geophysicists began deploying continuously-operating GPS instruments.

148 Data from these networks are typically downloaded once per day and made immediately  
149 available via the internet.

150

151 More than 3000 geodetic-quality GPS sites are currently operating in the United States. Many of  
152 these are operated by individual city, county, and state agencies. These GPS sites primarily  
153 support precise surveying activities; others are operated by the U.S. Geological Survey to  
154 support hazard studies for earthquakes and volcanoes. Universities have augmented these  
155 networks to study specific faults. In this study we use GPS data from the NSF EarthScope Plate  
156 Boundary Observatory (PBO) (Figure 2A). The locations of the PBO sites were chosen to  
157 facilitate scientific investigations of tectonic signals. Thus, there are a very large number of sites  
158 that follow the general outline of the San Andreas Fault in California. Likewise there are  
159 receivers across the Basin and Range that trend east to west because the fault zones in this area  
160 are oriented north-south. Clusters of instruments can also be seen at Yellowstone, Mt. St. Helens,  
161 and Mammoth Volcanoes. Although a large number of sites are located in urban areas,  
162 particularly near Los Angeles, over 90% are situated in natural environments. There are a total of  
163 1100 GPS sites in the PBO network (See <http://pbo.unavco.org> for a current listing).

164

165 The GPS instrumentation at each PBO site is nearly identical (Figure 2B). The GPS receivers  
166 (the Trimble NetRS model) can track up to 12 GPS satellites at a time. The antenna is covered by  
167 an acrylic dome; the latter provides protection from the snow, leaves, dirt, etc. This “choke-  
168 ring” antenna is designed to preferentially receive RHCP signals from above the horizon, i.e.  
169 elevation angles greater than zero [43]. Most of the antennas deployed by PBO were mounted on  
170 a 2-meter tall tripod that was drilled into bedrock. Standard data retrievals are every 15 seconds.

171 While consistent receiver/antenna units were used at each site, the terrain at each site does vary  
172 significantly. The digital elevation map for a representative GPS site (P048) is provided in  
173 Figure 2C.

174

175 The PBO network was built between 2005-2008. Those initial years were valuable for  
176 identifying problems with the GPS hardware, telemetry, and receiver firmware. By late 2006,  
177 most of these issues had been resolved. The database described in this study begins on January  
178 1, 2007 and extends through the end of 2013.

179

### 180 **3. GPS Multipath - Theory**

181 In order to estimate position, GPS units measure biased distances (ranges) from multiple  
182 satellites to the receiving antenna, measurements called pseudoranges and carrier phases. As a  
183 GPS antenna must be able to track multiple satellites from different directions in the sky, an  
184 “omni-directional” antenna is used. It is difficult to design an antenna that rejects all energy from  
185 reflected signals (i.e. those arriving from negative elevation angles) without negatively impacting  
186 the direct signals that arrive from positive elevation angles. The antenna used by geodesists is a  
187 compromise. The gain pattern is fairly homogeneous, which is important to geodesists because  
188 they want each antenna to have the same geometric phase center location. The antenna gain  
189 pattern was designed to strongly prefer RHCP over LHCP measurements so that direct signals  
190 (RHCP) would dominate over reflected signals (LHCP). For elevation angles above ~25 degrees  
191 and natural surfaces such as soil and snow, this antenna design is adequate. However, its  
192 efficiency breaks down at lower elevation angles for two reasons:

- 193 (1) The antenna RHCP gains are nearly equal for positive and negative elevation angles.  
194 (2) Reflections from most natural land surfaces retain the polarization of the incident  
195 vector electric field in the limit of grazing incidence.

196 For example, the Brewster angle is 10-25 degrees for bare soil, depending on whether it is wet or  
197 dry. This is far different than what would be observed, for example, if the GPS antenna were  
198 deployed over a large metal surface such as copper. In this case, the reflected energy at low  
199 elevation angles would be LHCP and would be rejected by the antenna.

200 In addition to issues related to the antenna, reflected GPS signals are defined by their geometry  
201 (Figure 3). The GPS antenna receives both direct and reflected energy and the receiver measures  
202 the interference between them. To characterize the behavior of this “GPS interferometer,” we  
203 need to know the wavelength of the carrier signal and how well the two signals are synchronized  
204 (i.e. its phase).

205 To determine the phase of the interference pattern, we first calculate the excess path delay  $D$   
206 generated by the reflection. Figure 3 shows the geometric representations of both the direct and  
207 the reflected signals. For a horizontal planar reflector, it can be shown that  $D$  is:

208 (1)

$$D = 2H \sin e$$

209

210 where  $H$  is the height of the antenna above the reflecting surface and  $e$  is the elevation angle of  
211 the satellite with respect to the horizon [44]. The phase  $\varphi_1$  of the interference for a GPS carrier  
212 wavelength  $\lambda_1$  is then:

213

214

215 (2)

$$\varphi_1 = \frac{2\pi}{\lambda_1} D = \frac{4\pi H}{\lambda_1} \sin e$$

216

217 The frequency of the interference (also known as its modulation) is the time derivative of the

218 phase:

219

220 (3)

$$\frac{d\varphi_1}{dt} = \frac{d}{dt} \left( \frac{4\pi H}{\lambda_1} \sin e \right) = \frac{2\pi}{\lambda_1} 2H \cos e \frac{de}{dt}$$

221

222

223 Equation 3 shows that the interferometric frequency will be greater for large H than small H, and

224 will change as the satellite rises (or sets).

225

226 A full derivation of multipath effects on GPS signals is beyond the scope of this paper. A short

227 summary is provided in Appendix 1. Pseudorange multipath error on the L1 frequency

228 ( $M_1$ ) depends directly on excess path length D and is defined:

229

230 (4)

$$M_1 = \frac{\alpha D \cos \varphi_1}{1 + \alpha \cos \varphi_1}$$

231

232 where  $\alpha$  is a damping factor defined as the ratio between the reflected (multipath) amplitude  
233 ( $A_m$ ) and the direct signal amplitude ( $A_d$ ).

234

235 Both  $A_m$  and  $A_d$  depend strongly on elevation angle. The direct signal term  $A_d$  is mostly  
236 controlled by the antenna gain. It has several key characteristics in a geodetic GPS instrument:

237

- 238 1. The antenna gain for RHCP is many orders of magnitude stronger than for LHCP.
- 239 2. The antenna trades off tracking higher elevation satellites at the expense of lower  
240 elevation satellites; therefore  $A_d$  is smaller at low elevations than high elevations.
- 241 3.  $A_d$  depends on transmission power levels. However, this effect is much smaller than the  
242 antenna gain effect.

243

244 The reflection characteristics of the surface are encompassed in  $A_m$ . This is the parameter that is  
245 sensitive to vegetation water content: higher vegetation water content leads to lower  $A_m$ . For the  
246 choke ring antenna used by the PBO network (and using equation 4), one can predict the general  
247 characteristics of pseudorange multipath errors. Figure 4 shows multipath predictions for  
248 antennas at 3 different heights above a horizontal planar reflector. We can see that the dominant  
249 frequency in multipath errors depends directly on the height of the antenna above the reflecting  
250 surface ( $H$ ), i.e. “far” reflectors have high frequencies and vice versa. Secondly, the amplitude of  
251 multipath also depends strongly on  $H$ , so that far reflectors have much larger amplitudes than  
252 near reflectors.

253

254 These multipath predictions shown in Figure 4 are very simplified in the sense that the model

255 uses a generic representation of  $\alpha$  and because only a simple planar reflecting surface was used.  
256 To fully model GPS multipath errors, the actual reflection coefficients of the surface must be  
257 known (e.g. bare soil, surface roughness, soil type and wetness, characterization of the  
258 vegetation), the gain of the antenna for both RHCP and LHCP must be defined, and the terrain  
259 surrounding the antenna must be modeled. A simulator to make these types of model predictions  
260 is under development, with initial efforts focusing on simple geometries and bare soil [50,51,52].  
261 At the current time, we use the simple principles outlined in sections 3 to help us define a GPS  
262 multipath metric (NMRI) that is sensitive to vegetation water content. In the next section we  
263 define how GPS pseudorange multipath can be observed.

## 264 **4. GPS Multipath - Observations**

### 265 **4.1 Observable Equations**

266 There are two kinds of GPS observables: pseudoranges and carrier phases (carrier phase is *not*  
267 the same as the interferometric phase discussed in the previous section). We first define the  $L_1$   
268 ranging observable  $P_1$ (pseudorange). For a given receiver and satellite and time,  $P_1$  is defined as:

269 (6)

$$270 \quad P_1 = \rho + c\delta_r - c\delta_s + I/f_1^2 + T + M_1 + \varepsilon_1$$

271 The terms that depend on the transmit frequency have subscripts of 1 for the  $L_1$  frequency. The  
272 geometric range term  $\rho$  represents the path traveled by the signal from the satellite to the receiver  
273 in a vacuum (i.e. the straight-line path). For a GPS receiver on the Earth this term varies from  
274 ~22,000-25,000 km.  $\delta$  represents clock errors for either the receiver or satellite; it is scaled by the

275 speed of light,  $c$ . Clock errors can easily produce error terms greater than 100 km (Note:  
 276 relativistic effects have been subsumed into the satellite clock term). The ionospheric delay term  
 277 ( $I$ ) depends on how many electrons are along the path between the satellite and receiver and is  
 278 scaled by the inverse square of the transmit frequency. The tropospheric delay  $T$  (gases and  
 279 precipitable water vapor) also depends on the path between the receiver and the satellite,  
 280 however, it is not frequency-dependent at GPS frequencies. For convenience, the frequency-  
 281 scaled ionospheric and tropospheric error terms are shown as having units of meters. The  
 282 measurement error term is shown as  $\varepsilon_1$ .  $M_1$  is the pseudorange multipath term described in  
 283 section 3 and the parameter of interest in this study. We must remove as many terms as possible  
 284 from equation 6 in order to isolate  $M_1$ . Although not used in this paper, we note that there is a  
 285 pseudorange observable on the  $L_2$  frequency.

286 The codes (used to define the pseudoranges) are transmitted on carrier signals. The phases of  
 287 these carrier signals can be converted into very precise, biased ranges. The carrier phase  
 288 observables ( $\phi_1$  and  $\phi_2$ ) are very similar to  $P_1$ :

289 (7)

$$\lambda_1 \phi_1 = \rho + c\delta_r - c\delta_s - I/f_1^2 + T + m_1 + N_1 \lambda_1 + \varepsilon_\phi$$

290 (8)

$$\lambda_2 \phi_2 = \rho + c\delta_r - c\delta_s - I/f_2^2 + T + m_2 + N_2 \lambda_2 + \varepsilon_\phi$$

291  $N_1$  and  $N_2$  are known as carrier phase ambiguities. These must be estimated for positioning  
 292 applications. The terms can change due to “cycle slips” or “loss of lock,” meaning new values  
 293 must be estimated. To mitigate their impact, only data above elevation angles above 10 degrees

294 are used in this study. The measurement error term for carrier phase ( $\varepsilon_\phi$ ) is several mm and  
 295 much smaller than that of pseudorange ( $\varepsilon_1 \sim 25\text{-}30$  cm). Note that the ionospheric error for  
 296 carrier phase data has the opposite sign as for pseudorange. Carrier phase multipath errors ( $m_1$   
 297 and  $m_2$ ) are bounded to be one quarter of the carrier phase wavelength,  $\sim 5$  cm. The geometric  
 298 range, clock errors, and tropospheric errors are identical for carrier phase and pseudorange data.

299 The reader will note that simply subtracting  $\lambda_1 \phi_1$  from  $P_1$  would isolate pseudorange  
 300 multipath, but at the expense of doubling the ionospheric error. If however  $P_1$  and both carrier  
 301 phase observables are used, one can isolate pseudorange multipath and remove the ionospheric  
 302 error. This observable -  $MP_1$  - is frequently used in the geodetic community because it has no  
 303 dependence on orbits, clocks, or atmospheric delays:

304

305 (9)

$$MP_1 = P_1 - \frac{f_1^2 + f_2^2}{f_1^2 - f_2^2} \lambda_1 \phi_1 + \frac{2f_2^2}{f_1^2 - f_2^2} \lambda_2 \phi_2 = M_1 + C + \varepsilon_1$$

306  $C$  is a scaled linear combination of the carrier phase biases. As long as there are no cycle slips,  $C$   
 307 is a constant bias and of no intrinsic interest. In future discussion, it will be assumed that a mean  
 308 value has been removed from computed values of  $MP_1$ . Note also that  $\varepsilon_\phi$  and the carrier phase  
 309 multipath terms have been dropped. This is because they are 1-2 orders of magnitude smaller than the  
 310 equivalent pseudorange terms.

## 311 **4.2 Example of $MP_1$ for one satellite track**

312 Equations (6)-(8) are defined at the time a GPS signal is received on the Earth. For any given  
313 GPS receiver that records measurements every 15 seconds, there are thousands of  $MP_1$   
314 measurements per day per satellite. We use the satellite track highlighted in Figure 1 to  
315 demonstrate some of the features of  $MP_1$  data (Figure 5). The satellite rises in the northwest and  
316 sets in the southwest several hours later; we split it into a northwest track and a southwest track  
317 (Figures 5A and B). For elevation angles greater than 20 degrees, the  $MP_1$  time series for this  
318 satellite track is dominated by a white noise process, with a somewhat larger RMS in the  
319 northwest than in the southwest portion. There is no obvious evidence of the multipath effects  
320 that were shown in section 4. However, at low elevation angles (Figure 5C), the northwest track  
321 is dominated by high-frequency, high-amplitude oscillations. These observations are consistent  
322 with multipath predictions for a reflector height of  $\sim 40\text{m}$  (Figure 4, bottom panel). In contrast, at  
323 best there is only a weak multipath signal as the satellite sets in the southwest (Figure 5D). Since  
324 the same satellite transmitted the signal (satellite 1) and the same receiver (P048) recorded the  
325 data, the source of the difference must be related to the terrain at the site. Recall, that it is  
326 geometry (i.e. reflector heights) that controls pseudorange multipath frequencies, not vegetation.  
327 The latter only impacts pseudorange multipath amplitudes.

328 The digital elevation map (Figure 2C) for P048 provides insight as to the source of the  
329 differences. P048 site is located on a hill. To the northwest, there is a flattening in the terrain  
330  $\sim 100\text{m}$  from the antenna. This region is locally planar and  $\sim 40\text{m}$  below the antenna. In contrast,  
331 reflections from satellites rising/setting in the northeast, at the same elevation angles (10-15  
332 degrees) and at the elevation difference, are not observed. This is because the hill blocks the  
333 antenna from receiving the far reflections from the northeast.

334 In contrast, the terrain to the southwest has a fairly gentle slope. Forward models using the DEM  
335 for this site indicates that the terrain southwest of the antenna is consistent with a nominal  
336 reflector height of  $\sim 2$  m [51]. We can also see in Figure 5C that the amplitude of the  $MP_1$   
337 oscillations is significantly smaller in the late spring than was observed in early spring. Since we  
338 know that GPS has a repeating ground track (section 2), this decrease in  $MP_1$  amplitude between  
339 early and late spring must be caused by a decrease in the multipath reflection coefficient  $\alpha$ . This  
340 change is consistent with an increase in vegetation water content between the two dates. The  
341 southwest satellite track shows no obvious variation in  $\alpha$  between early and late spring because  
342 the multipath error is small compared to the measurement error  $\epsilon_1$ .

### 343 **4.3 Defining A Multipath Reflection Metric**

344 We seek a precise GPS reflection metric based on  $MP_1$  that is (1) sensitive to the reflectivity (and  
345 thus vegetation cover) of the ground and (2) representative of the vegetation surrounding each  
346 site. Since  $MP_1$  time series vary to first order as  $\alpha D$  (recall that  $D$  is the excess path length), the  
347 RMS of an individual  $MP_1$  time series will also depend on  $\alpha D$  (accomplishing goal 1). Recalling  
348 the expansive azimuthal coverage of the GPS constellation (Figure 1A), an average of the all the  
349 satellite  $MP_1$  RMS data fulfills goal 2. A database of daily mean  $MP_1$  RMS statistics for each site  
350 is routinely compiled by the operators of PBO [53]; hereafter we will call this statistic  $MP_{1,rms}$ ,  
351 as in [39]. The  $MP_{1,rms}$  is a weighted mean, i.e. it is weighted by the number of observations for  
352 each satellite.

353

354 For a L-band bi-static radar, we expect that  $MP_{1,rms}$  in western Montana (the location of P048)  
355 will be largest in early spring (when vegetation has low water content) and smaller in early

356 summer (when vegetation water content peaks). This hypothesis is supported by the  $MP_{1rms}$   
357 observations (Figure 6A). The individual satellite  $MP_{1rms}$  data also show the effects of terrain.  
358 Satellites 30, 10, 4, 5, and 29 all have very large  $MP_{1rms}$  values. These satellites also have the  
359 largest percentage of satellite observations from the northwest azimuths (i.e. Figure 5A).

360 Even though it is difficult to see any kind of multipath effect in the individual  $MP_{1rms}$  time  
361 series at flatter sites, we have still found it possible to detect seasonal signals by averaging over  
362 the entire constellation. PBO site P041, located south of Boulder, Colorado, is a “flat” site. The  
363 antenna is 2 m above the ground, and there is less than 20 cm of terrain relief over the nominal  
364 GPS footprint. In Figure 6B we plot individual satellite  $MP_{1rms}$  values for two days, one in early  
365 and the other late spring. The seasonal variations are not nearly as striking as they were for  
366 P048. For a few satellites, the ground is more reflective in late spring than early spring (e.g.  
367 satellite 24). But overall, there are many more that follow the expected behavior of vegetation  
368 water content, high  $MP_{1rms}$  in early spring and low  $MP_{1rms}$  in late spring. We have found that  
369 by using averages of the individual satellite  $MP_{1rms}$  time series, vegetation signals are detectable  
370 at more than 300 PBO sites. Before these  $MP_{1rms}$  data can be used for phenological studies, we  
371 must first address the issue of outliers caused by snow and rain.

#### 372 **4.4 Outlier detection**

373 A typical time series of daily  $MP_{1rms}$  values is shown in Figure 7A. The six-year  $MP_{1rms}$  time  
374 series shows similar behavior as 16-day NDVI data (Figure 7D). However, there is significant  
375 scatter in the winter and late fall that appears to be more episodic in nature. Many – but not all –  
376 of these outliers are coincident with near-zero NDVI values, i.e. they are consistent with snow  
377 cover.

378 Because GPS is a L-band system, GPS reflections will be sensitive to water within and on the  
379 surface of vegetation, as well as water in soil and snow. It is this very sensitivity that is being  
380 used by other terrestrial hydrology investigators [26,27,36,37,38,53,54,55]. To isolate the  
381 vegetation signal,  $MP_{1rms}$  data impacted by snow and very wet soil must be removed. We used  
382 the [56] dataset of climatological monthly snow water equivalent to identify times when snow  
383 was likely; data from those months were removed (Figure 7B). This is an overly conservative  
384 data editor; an improved snow filter is being developed that uses measured snow-extent  
385 observations from MODIS. The remaining outliers in the  $MP_{1rms}$  data are mostly related to early  
386 or late snowstorms or rainfall. Modeled temperature and precipitation data from the North  
387 American Land Data Assimilation System (NLDAS) were used to identify these early/late  
388 snowfall events and rainfall [57]. Snow events were defined based on the minimum NLDAS  
389 temperature and the daily precipitation value being greater than 2 mm. For small rain events (5-  
390 10 mm), that day was removed. For larger rain events ( $> 10mm$ ), both the day it rained and the  
391 following day were removed. Finally, a two-week running mean was used to identify and remove  
392 three-standard deviation outliers. The resulting  $MP_{1rms}$  data are shown in Figure 7C.

#### 393 **4.5 Normalization**

394 The  $MP_{1rms}$  results for site P048 shown in Figure 7C are consistent with those presented by  
395 [39], although the time series is now six years long instead of three years. Outliers present in that  
396 initial study are now much less frequent. Changes in NDVI strongly correlate ( $\sim 0.8$ ) with  
397 changes in  $MP_{1rms}$  at P048 (Figure 7D). This is the case at many other PBO sites, although  
398  $MP_{1rms}$  changes in the P048 eco-region typically lag those observed in NDVI by 1-3 weeks.  
399 Since the  $MP_{1rms}$  values are influenced by the excess path length term  $D$  in equation (4),

400  $MP_{1rms}$  time series from different GPS sites cannot be directly compared with each other. For  
401 example, at a flat site (P041), the largest  $MP_{1rms}$  values are  $\sim 0.28$  m; at the hilly site, P048, the  
402 largest values are  $\sim 0.37$  m. This does not mean that P048 has vegetation water content that is  
403 32% (the ratio of  $0.37/0.28$ ) larger than for P041. In order to remove the first-order terrain effect  
404 caused by the excess path delay, we use a normalization (Normalized Microwave Reflection  
405 Index, NMRI) that scales  $MP_{1rms}$  by its maximum value. The latter represents the best estimate  
406 of when the signal is being reflected by the land surface with the minimum amount of vegetation  
407 water content. In Figure 7C, the maximum  $MP_{1rms}$  (shown by the dashed line) is based on the  
408 average of the largest 5% daily  $MP_{1rms}$  values. A negative ratio is used so that NMRI follows  
409 the vegetation growth cycle, i.e. NMRI increases as vegetation water content increases and vice  
410 versa.

411 (9)

$$NMRI = \frac{-(MP_{1rms} - \max(MP_{1rms}))}{\max(MP_{1rms})}$$

412 In paper II, we show that this normalization yields a consistent relationship between NMRI and  
413 *in situ* measured vegetation water content across four GPS sites in Montana.

#### 414 **4.6 Footprint**

415 Ordinarily the footprint of a remote sensing technique would be described before showing results  
416 using the technique. Here we have first developed simple theoretical descriptions of the method  
417 and showed representative results so that the footprint would be seen in that context. If all GPS  
418 sites were located in flat terrain, it would be straightforward to define the NMRI footprint (see,

419 e.g., the appendix of [58]). The Fresnel zone for a single rising or setting satellite track (for a  
420 typical antenna height) is an ellipse, ~22 m in length (starting close to the antenna), but quite  
421 narrow (~4m from side to side). By using the entire constellation, the flat-terrain footprint  
422 basically mimics the first satellite coverage plot we showed (see Figure 8). The pie-shaped  
423 region removed from the footprint represents the lack of satellites transmitting from the azimuth  
424 angles -30 to 30 degrees. The radius of this site footprint (~22m) depends directly on the antenna  
425 height  $H$ ,  $\sim 2H/\tan(e)$ , where  $e$  is the minimum elevation angle of 10 degrees and  $H$  is here  
426 assumed to be 2m. The area of the flat-terrain footprint is  $\sim 1000 \text{ m}^2$ . If the GPS antenna were  
427 deployed on a 10 m tower over flat terrain, the site footprint would have a radius of ~115 m and  
428 a correspondingly larger footprint area. However, there are no such tower-mounted sites in the  
429 PBO network (Figure 2).

430

431 What about a site like P048, where we know there are reflections coming a vertical distance  
432 greater than 2m? We have used a modified version of [51] to calculate the footprint of reflections  
433 for P048 using the digital elevation map (Figure 2C). In addition to the central footprint already  
434 discussed, this simulation shows a large circular footprint ~150 meters away from the antenna.  
435 The area of this “hotspot” is in fact larger than the central footprint. The NMRI measurement  
436 thus includes the effects of both reflection areas, but is dominated by the far reflections. This  
437 means that each NMRI site will have its own footprint. For example, at some GPS sites there  
438 will be hotspots to the east of the GPS antenna and at other GPS sites they will be to the south.  
439 Some GPS sites will have more than one hotspot. The location and size of the hotspot(s) depends  
440 on the vertical height of the planar surface with respect to the antenna. It will also depend on  
441 whether these local planar surfaces produce reflections that can be observed at the antenna.

442 These hotspots are most easily mapped out with an electromagnetic simulation software. Such an  
443 analysis requires a DEM. Because of the way a GPS receiver's tracking loop has been  
444 programmed, no reflected signals can be observed that are delayed more than 300 m. Therefore,  
445 the maximum distance of reflections contributing to NMRI is 300 m from the antenna. Thus  
446 unlike a satellite remote sensing system, NMRI does not have one pixel size. It has a variable  
447 footprint that will yield useful phenological metrics if the footprint is representative of the  
448 ecosystem surrounding the antenna. An initial study of 305 NMRI time series found significant  
449 correlations with vegetation optical depth estimates at 90% of the sites, suggesting that the PBO  
450 network does have sensing zones that are representative of the regional ecosystems [58].

## 451 **5. Discussion**

452 Reflected signals measured by GPS ground receivers sense variations that are consistent with  
453 vegetation growth. These GPS reflection measurements are calculated on a daily basis and are  
454 unaffected by atmospheric effects such as clouds. The spatial footprint of the method depends on  
455 the terrain at the site, with a minimum footprint of 1,000 m<sup>2</sup>. Methods have been developed to  
456 remove errors caused by snow and rain. A preliminary NMRI database has been compiled and  
457 consists of ~330 time series spanning the years 2007-2013 (<http://xenon.colorado.edu/portal>). A  
458 landcover classification is provided for each site. The bulk of the sites are grasslands, shrublands,  
459 and savannas (146, 74, and 70 sites, respectively). Since the purpose of the GPS network was to  
460 precisely measure the position of the ground, very few of the NMRI sites are located in heavily  
461 forested regions, as trees degrade positioning accuracy. It is expected that PBO will be  
462 maintained by NSF until at least 2020, providing an opportunity to measure the vegetation  
463 response to climate variability in the western United States over ~15 years. We plan to add

464 NMRI data for ~50 more sites to the data portal, with most of the new sites coming from desert  
465 ecosystems and Alaska. Surface soil moisture content and snow depth are provided for ~150  
466 GPS sites using similar GPS reflection methods [54,55].

467 Here we have not linked the observed fluctuations in NMRI to changes in any particular  
468 biophysical parameters. In paper II, we show that NMRI correlates with vegetation water content  
469 measured *in situ* at four sites and correlates strongly with NDVI at 12 sites. All these comparison  
470 sites are located in Montana grasslands.

471 We make five final observations about NMRI:

- 472 1. NMRI is based on average  $MP_{1rms}$  records for each GPS satellite. Other normalizations,  
473 such as azimuthally binned  $MP_{1rms}$  data, should also be examined.
- 474 2. The algorithm to remove snow-contaminated values is conservative, which results in  
475 significant data removal during the winter. The definition of maximum  $MP_{1rms}$  can be  
476 improved by using satellite products to determine snow cover instead of climatology  
477 models.
- 478 3. NMRI is sensitive to variations of  $\alpha$  from the multipath equation (4). It is not expected  
479 that  $\alpha$  will directly relate to vegetation water content exactly the same way for different  
480 vegetation types. Models for electromagnetic scattering for different vegetation structures  
481 should be examined to aid in future normalizations [59].
- 482 4. All pseudorange data recorded by geodetic GPS receivers are impacted by multipath  
483 reflections. That being said, studies should be undertaken to compare pseudorange  
484 multipath recorded by different receiver manufacturers in order evaluate the possibility of  
485 receiver-dependent biases.

486 5. GPS reflections are impacted by both soil moisture and vegetation growth. We are able  
487 to reliably remove the effects of soil moisture in this study because it has a smaller effect  
488 on the pseudorange observables than vegetation growth.

## 489 **6. Conclusions**

490 The EarthScope Plate Boundary Observatory was designed and deployed to measure  
491 deformation caused by tectonic forces. Here we have shown that these same GPS instruments are  
492 sensitive to changes in vegetation state. There are over 10,000 GPS receivers around the world  
493 providing data to public archives. Although some of these GPS sites are located in urban areas,  
494 many could provide invaluable data for phenological research at very low cost. However, the  
495 locations of these sites will always be determined by the primary operator of the network. In the  
496 example used in this paper, the site selection was directed by geophysicists. The GPS technology  
497 used in this study is commercially available and can be installed by investigators at individual  
498 ecosystem study areas, but it would be more useful for phenology if the GPS antennas were  
499 deployed on towers. This would provide a large, homogeneous footprint for phenology studies  
500 and would complement satellite methods. Since many scientists use differential GPS to locate  
501 field sites, such a tower-mounted GPS site could also serve as a base station.

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510 <http://xenon.colorado.edu/portal>.

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676

## 677 **Appendix I.**

678 Excellent summaries and discussions about the GPS pseudorange observable and multipath  
679 effects can be found in [45,46,47]. Here we follow the descriptions provided by [48,49]. The  
680 pseudorange multipath error ( $M$ ) is directly related to the code tracking loop behavior and its  
681 discriminator equation. In brief, a GPS receiver "tracks" by driving the difference between the  
682 early and late discriminator spacing ( $2T_{E/L}$ ) to zero. When no multipath is present (direct only,  
683 Figure A1):

684

$$A1. [R(T_{E/L}) - R(-T_{E/L})] = 0$$

685

686 where  $R$  represents the autocorrelation function of the code. However, multipath distorts the  
 687 correlation function as the receiver must now track the composite signal (combined, Figure A1)  
 688 while retaining correlator spacing  $2T_{E/L}$ . This results in shifted correlator values due to the  
 689 multipath delay, and a new discriminator equation

690

$$A2. [R(M + T_{E/L}) - R(M - T_{E/L})] + \alpha \cos \varphi [R(M + T_{E/L} - D) - R(M - T_{E/L} - D)] = 0$$

691 where  $\alpha$  is the ratio of the of the amplitudes of the reflected and direct signals and  $\varphi$  is the phase  
 692 shift of the reflected relative to the direct signal and  $D$  is the path delay. If we assume that the  
 693 autocorrelation function has an ideal triangular shape for multipath delays shorter than the chip  
 694 length  $T$

$$A3. R(\tau) = 1 - \frac{|\tau|}{T} \text{ for } |\tau| < T$$

695 we can reduce equation A2 to:

$$A4. \frac{-2M}{T} + \alpha \cos \varphi \left( -2 \frac{(M - D)}{T} \right) = 0$$

697 and subsequently:

$$A5. M = \frac{\alpha D \cos \varphi}{1 + \alpha \cos \varphi}$$

698

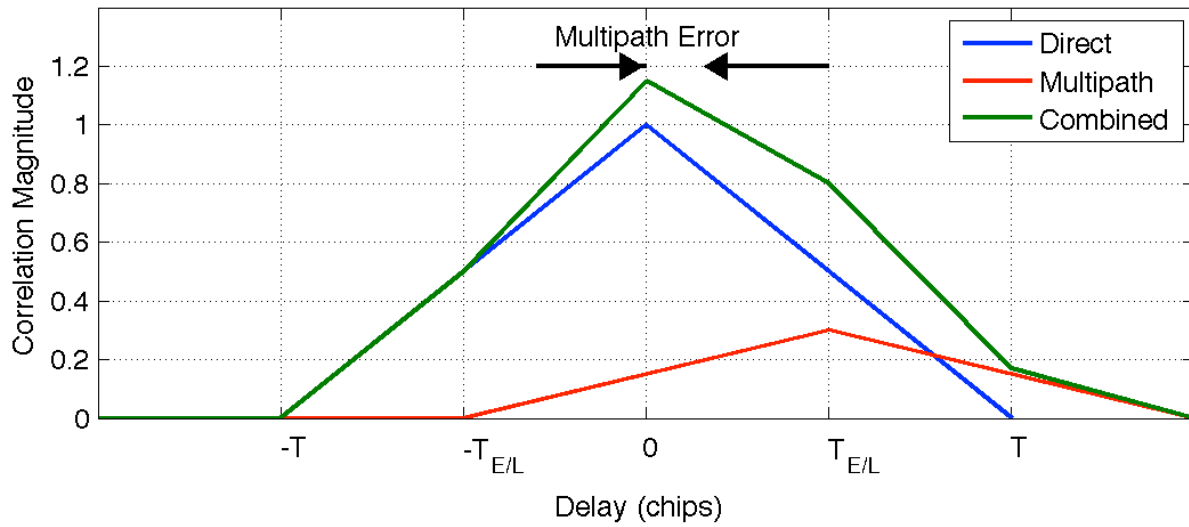
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706 Figure A1. A cartoon depiction of how multipath impacts the observed pseudorange  
707 measurement. The x-axis is measured in chips. The direct signal has no multipath. A single  
708 multipath reflection (0.5 chip delay and a relative amplitude of 0.3) is shown in red. The receiver  
709 tracks the combined signal (green). The y-axis is the normalized correlation function.

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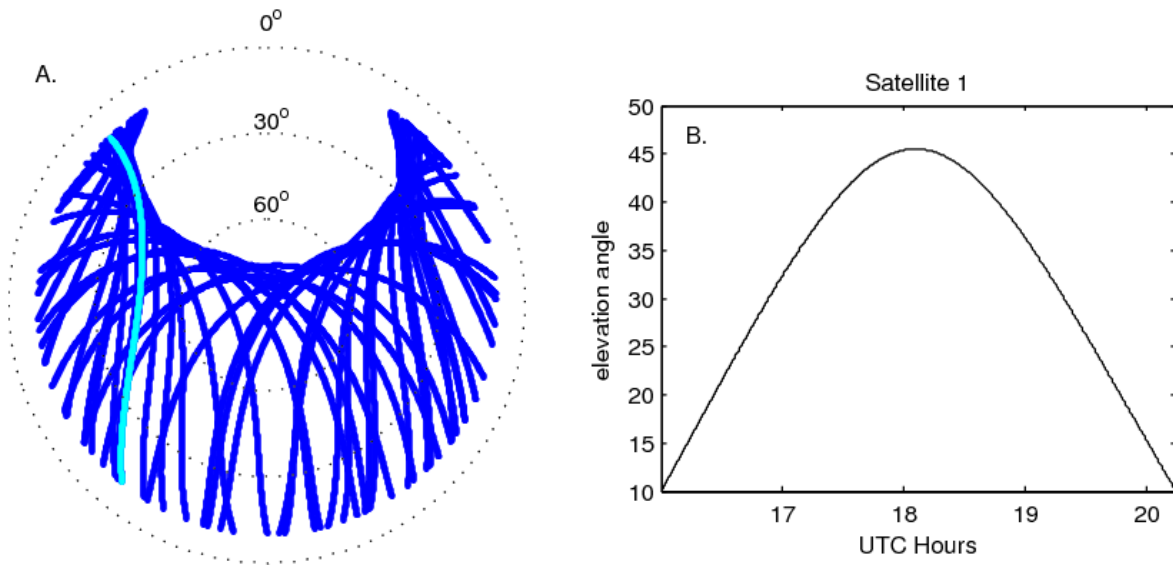
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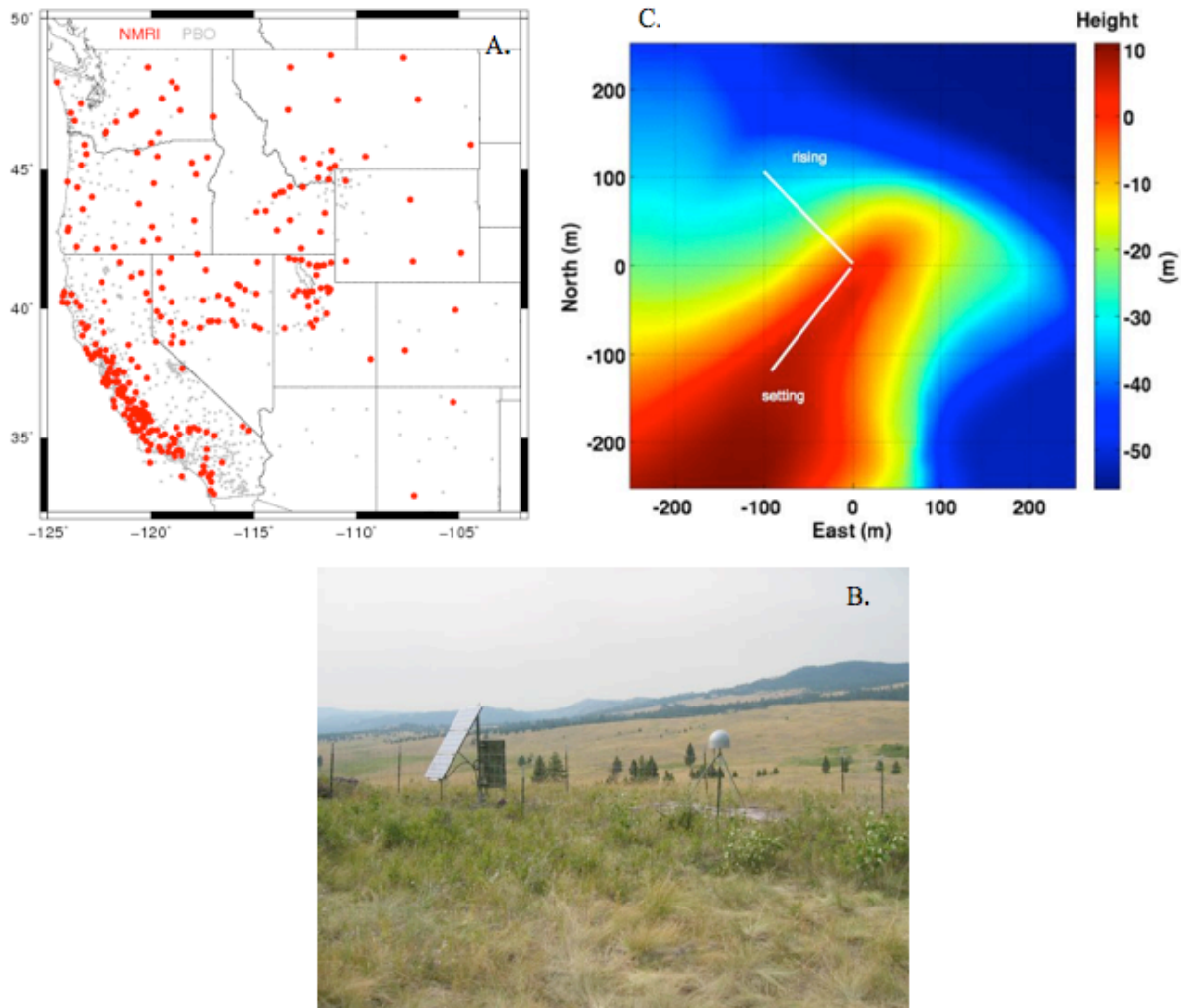


717

718 Figure 1. A. Polar plot representation of satellite azimuth and elevation angles for PBO site  
719 P048, located in southern Montana. Concentric circles represent satellite elevation angles (the  
720 angle with respect to the horizon). North is the top of the plot, east is to the right, etc. Note that  
721 there are no GPS satellite tracks to the north. The track for satellite 1 is highlighted in cyan; B.  
722 Time vs. elevation angle for satellite 1.

723

724



725

726 Figure 2A. Locations of GPS sites in the Plate Boundary Observatory (PBO) are shown in gray.

727 The sites with currently available NMRI time series are highlighted in red. An additional 150

728 PBO sites are in Alaska (30 NMRI sites); B. Typical setup at a continuously-operating PBO GPS

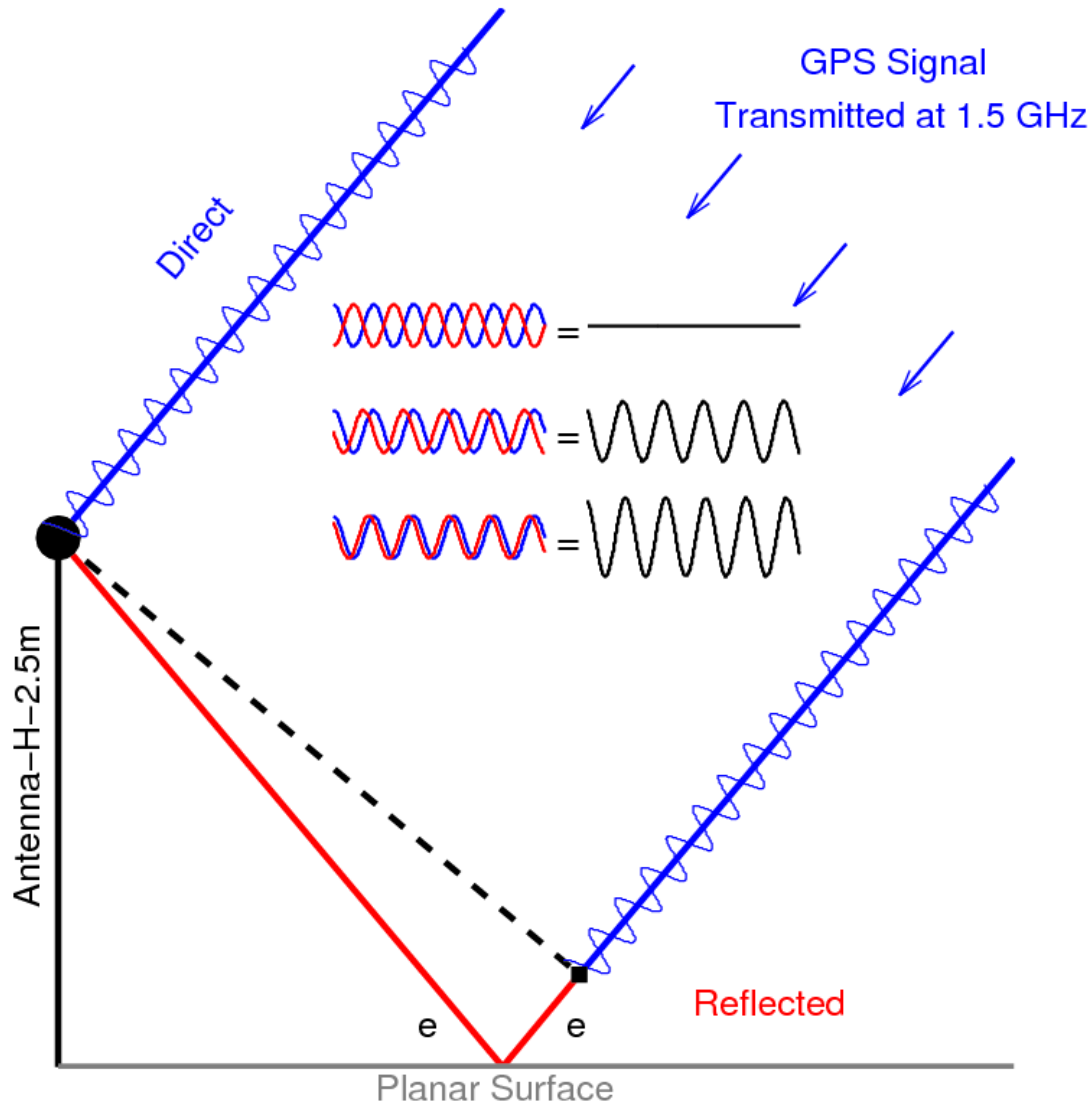
729 site in western Montana. The antenna (covered by an acrylic dome) is set atop a tripod

730 monument that has been drilled into the ground. A solar panel (and a bank of batteries) is used to

731 provide power for the system; C: Digital Elevation Map (DEM) for site P048. The ground track

732 for satellite 1 is shown in white.

733



734

735

736 Figure 3. Each GPS satellite transmits a signal that arrives at an individual receiver on the Earth  
 737 as a plane wave. A planar reflector is shown in gray. The antenna is 2.5m above the reflecting  
 738 surface and represented by the black circle. The direct signal (blue) travels a shorter distance  
 739 than the reflected signal (blue plus red). The elevation angle of the satellite with respect to the  
 740 horizon is  $e$ . The GPS carrier signal (wavelength  $\sim 19$  cm) is shown superposed on the direct  
 741 signal. Depending on the extra path travelled by the reflection (shown in red), the direct and

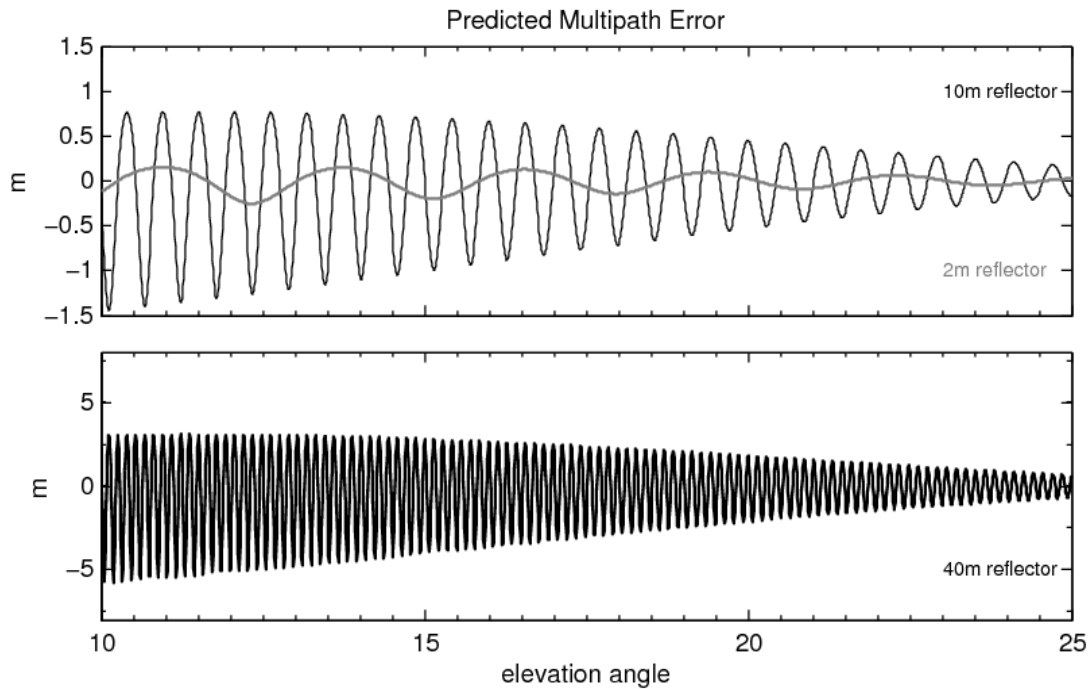
742 reflected signals will interfere (shown for three examples in the center of the figure). This

743 interference (shown in black) is what is measured by the GPS unit.

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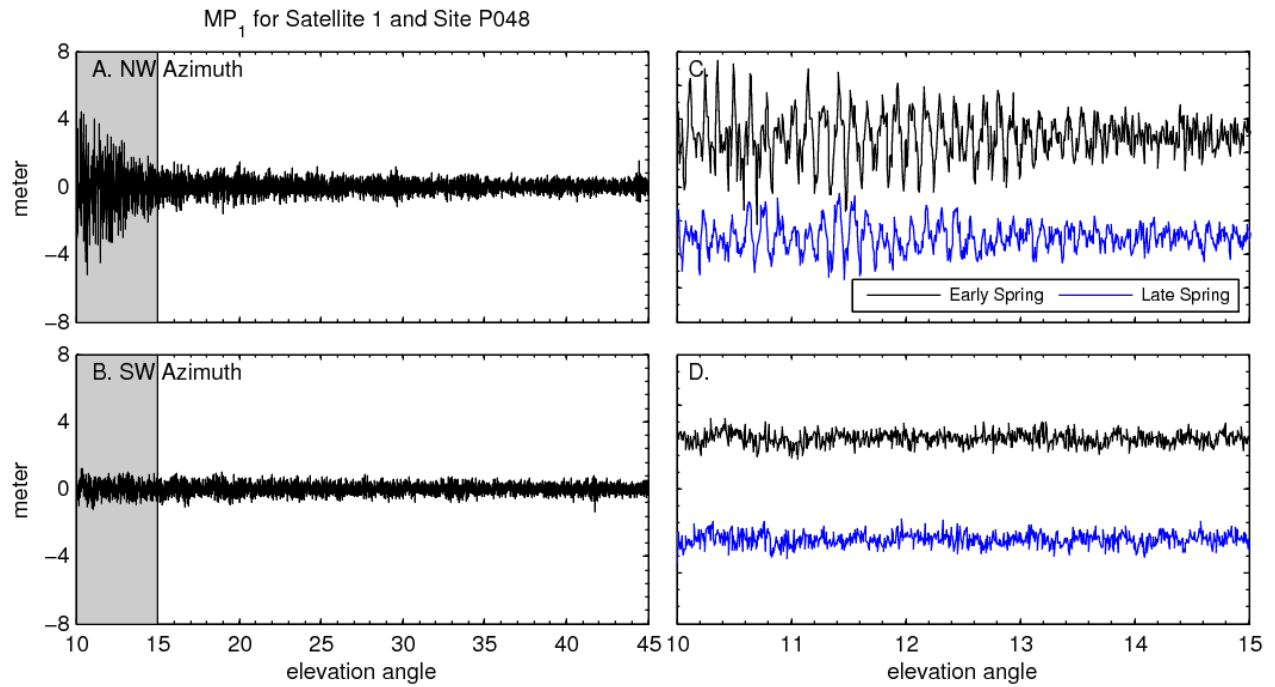
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749 Figure 4. Predicted multipath errors for planar, horizontal reflectors at three vertical distances: 2,  
750 10, and 40 m. Note the change in vertical scale. The  $\alpha$  profile used for the predictions was  
751 chosen to be consistent with GPS observations using PBO instrumentation, i.e. it exponentially  
752 decays as elevation angle increases.

753

754



755

756 Figure 5.  $MP_1$  data for site P048 and satellite 1; A. Rising arc (northwest azimuths); B. setting

757 arc (southwest azimuths); C. Lowest elevation angle data from panel A (shown in gray); D.

758 Lowest elevation angle data from panel B. Data in C and D are vertically offset to show data

759 from both late (blue) and early (black) spring.

760

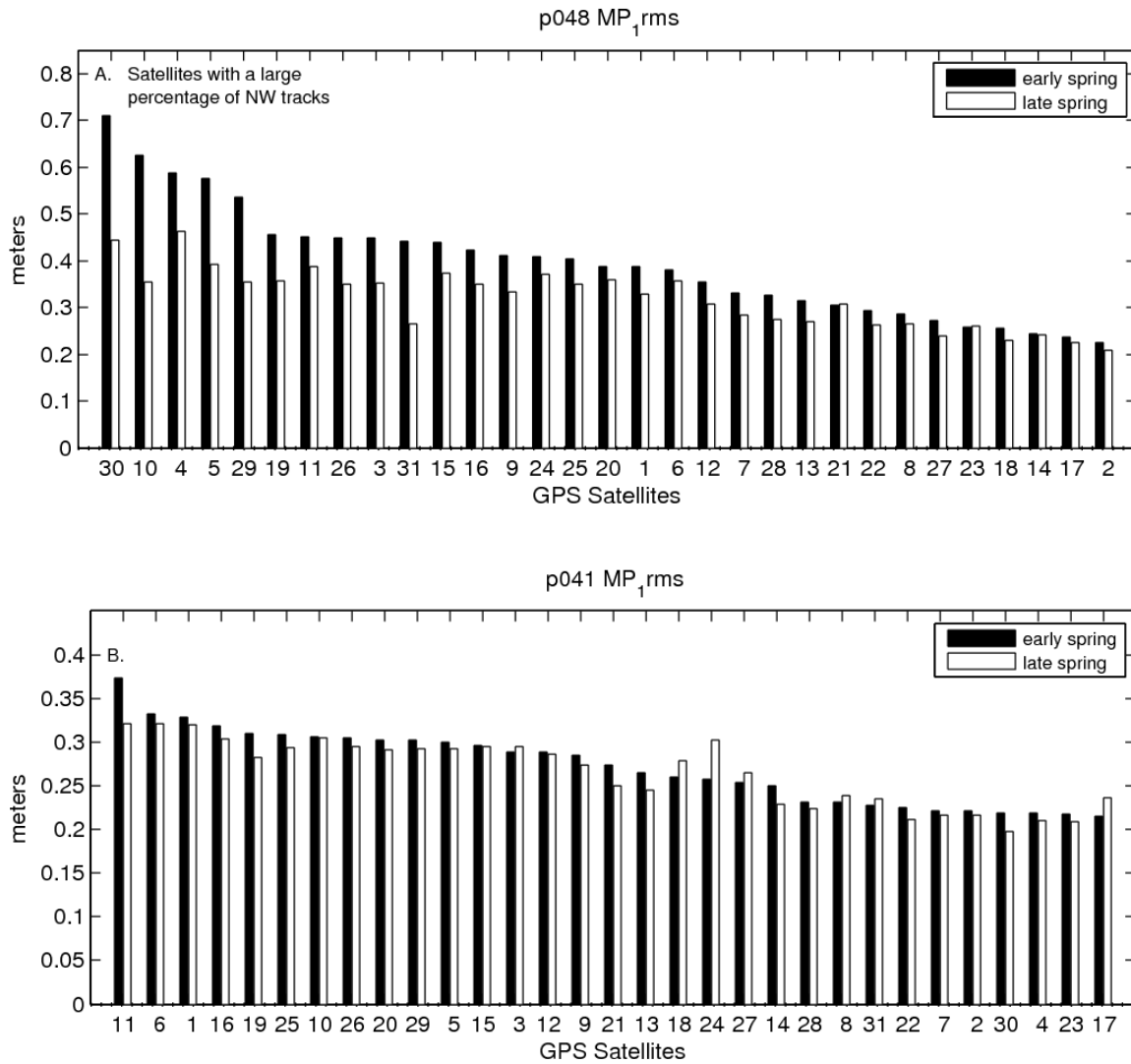
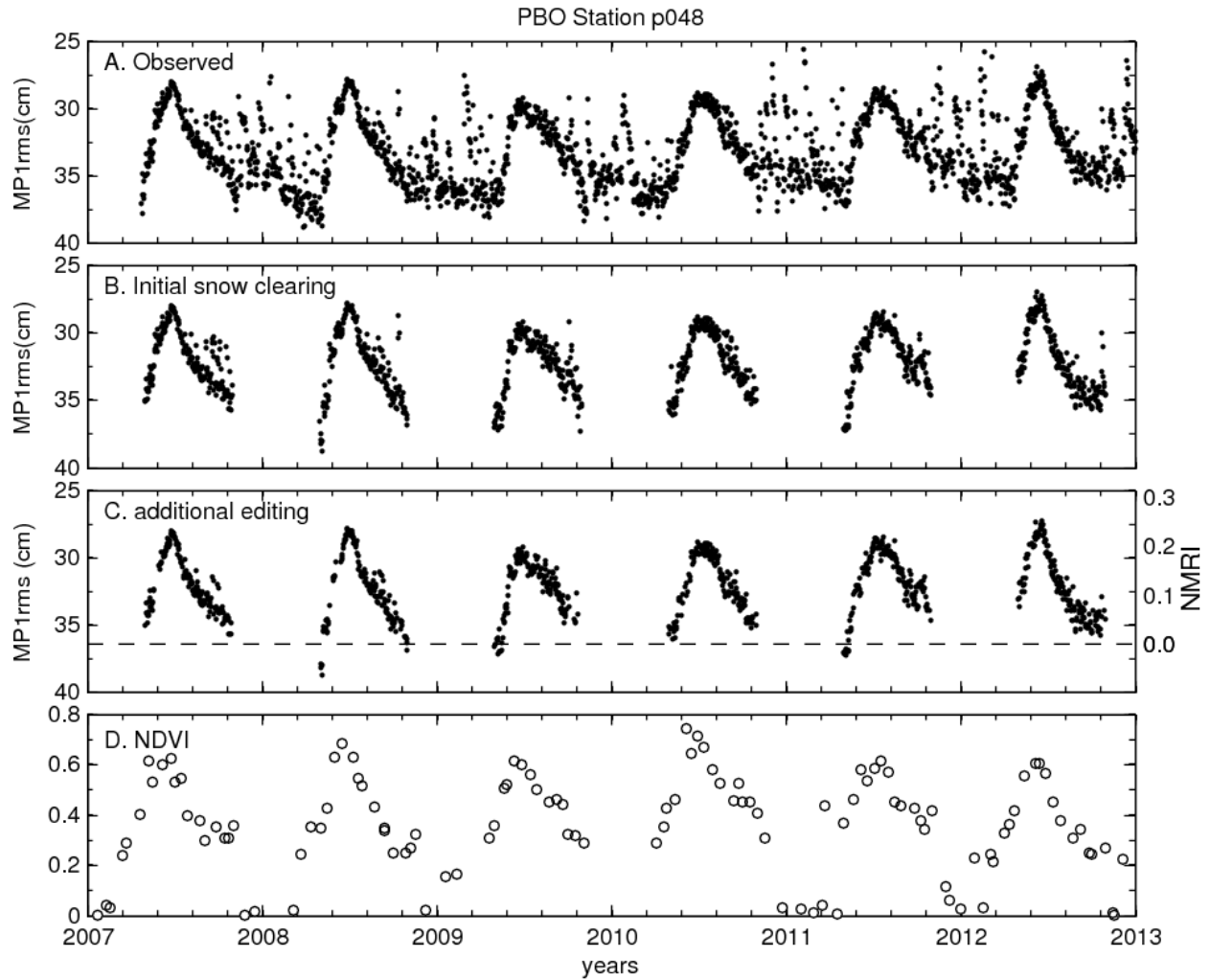


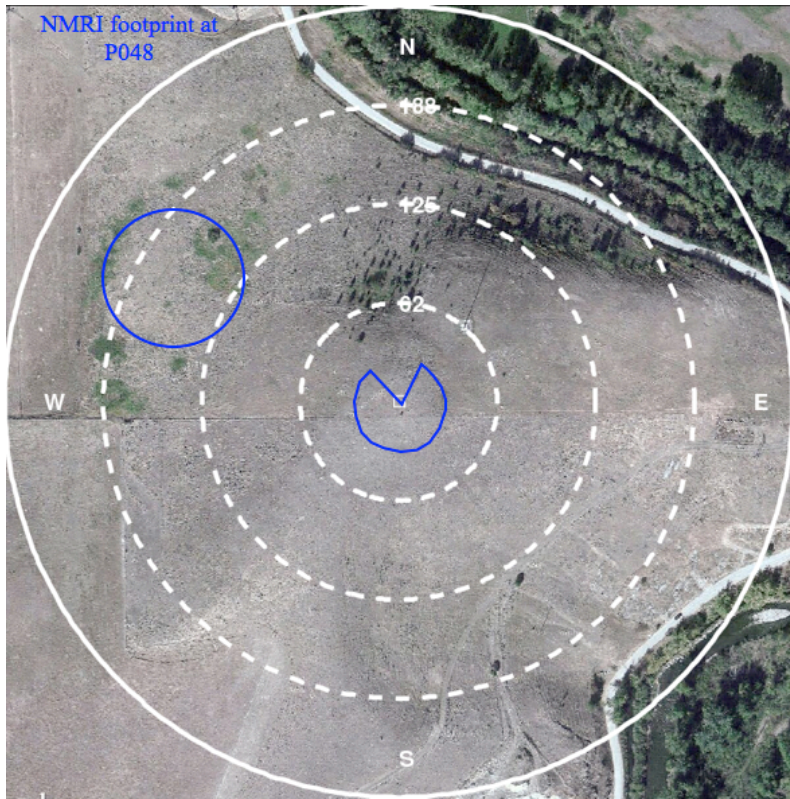
Figure 6. A. Station P048 MP<sub>1</sub>rms (ordered by magnitude) for individual GPS satellites for days in early and late spring; B. the same quantities for station P041, near Boulder, Colorado. GPS satellites are numbered from 1-31.



764

765 Figure 7. A.  $MP_{1rms}$  values for station P048 taken from the UNAVCO database (Estey and  
 766 Meertens, 1999); B.  $MP_{1rms}$  data after snow clearing using climatology model; C. final edited  
 767  $MP_{1rms}$  time series, with NMRI values shown on the right y-axis; D. 16-day MODIS NDVI  
 768 product.

769



770

771 Figure 8. Footprint of the NMRI metric at GPS site P048. This site's footprint includes both  
772 near- reflections (central circle with pie shape removed) based on the ~2-meter antenna height  
773 and a large secondary footprint (hotspot) to the northwest caused by terrain differences. Image  
774 taken from Google Earth. Radial distances given in meters (62, 125, 168, 250) for the white  
775 circles.