A methodology to eliminate snow- and ice-contaminated solutions from GPS coordinate time series

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[1] Positions derived from continuously operating GPS sites are used throughout the world for geophysical research. These positions are estimated assuming that the GPS signals have not been obstructed by either snow or ice on the GPS antenna. Unfortunately, in many regions of the world, this assumption is not correct. Snow and ice attenuate and scatter the GPS signal in a way that leads to significant positioning errors. These positioning outliers are typically removed by assuming geophysical models of displacement. In this study an algorithm is developed that uses signal strength data to determine when the GPS signal has been impacted by snow or ice. This information is then used to remove outliers in GPS coordinate time series. The signal strength-based algorithm was tested on 6 years of data from the EarthScope Plate Boundary Observatory network. The algorithm improves the precision of ~10% of these coordinate time series, with most of the improvement found for sites operating in Alaska.

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1. Introduction

[2] The GPS constellation has revolutionized our ability to measure how the Earth deforms. Over the past 25 years, the software and hardware required for geophysical applications of GPS have become well established. Tens of thousands of GPS receivers have been deployed around the world and are being used to measure global plate motion, volcanic inflation, subsidence, etc. We have come to expect that daily positions can easily be measured with precisions of a few millimeters. However, these precisions can only be achieved if the GPS carrier phase observations can be properly modeled.

[3] Relatively early in the development of continuously operating GPS networks, it was reported that snow accumulation on a GPS antenna produces significant positioning biases [*Webb et al*., 1995; *Jahldehag et al*., 1996]. This was expected because snow and ice are conducting media and affect the properties of the antenna. Thus, their presence will attenuate and scatter the transmitted GPS signal in a way that contaminates the carrier phase data. This leads in turn to a positioning bias. Later, even larger positioning biases were reported for sites where not only snow, but also ice accumulation, was found on GPS antennas [*Lisowski et al*., 2008; *Willis*, 2008].

[4] Removing the position estimates contaminated by snow and ice effects is complicated. If the formal errors produced by the least squares code used to determine position showed some effect, it would be straightforward. Unfortunately, in many cases, the carrier phase data are well fit and there is no indication of a snow and ice bias. Most geodesists that maintain GPS instruments in snowy regions of the world have simply come to expect that the GPS data collected in winter cannot be trusted.

[5] Other efforts to remove outliers caused by snow and ice have focused on the position time series themselves. In these cases, geodesists assume that the ground should behave a certain way (e.g., a linear rate or an exponential decay). Any points that deviate from these assumptions (within some limit) are removed. This is certainly an effective way to produce "clean" time series, but it does suffer from the restriction that you have to know a priori how the Earth should deform [*Tian*, 2011]. Other efforts have focused on the statistical properties of geodetic time series [*Khodabandeh et al*., 2012].

[6] As more and more GPS instruments are deployed in harsh climates, and real-time applications with societal implications are developed for these instruments, it is important that the presence of biases in coordinate time series that are the result of snow and ice be detected. In this study a method to identify outliers related to snow and ice effects on GPS antennas is described. The methodology has no dependence on geophysical models and thus requires no assumptions about how the Earth should deform. It is evaluated using 6 years of data at 280 GPS sites in the western United States. Success of the algorithm is tested by comparing coordinate time series with and without these outliers removed.

2. Description of the GPS Data Set

[7] This outlier detection algorithm is tested on GPS data from the EarthScope Plate Boundary Observatory (http://pbo.unavco.org). This network is operated by the University

Additional supporting information may be found in the online version of this article.

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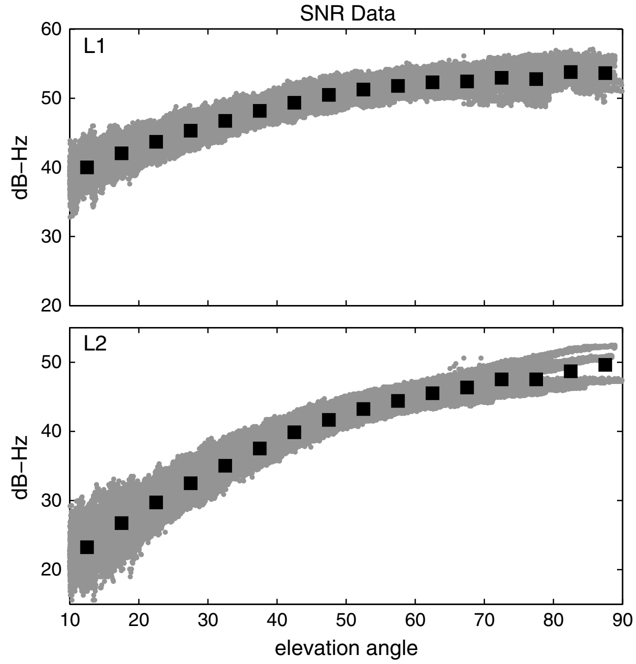

Figure 1. L2 SNR data (gray) for all satellites plotted with respect to elevation angle for PBO site P101 on 1 July 2012. The average SNR values computed for 5° elevation angle bins are shown as black squares. The average L2 SNR values between 55° and 60° are used in this study.

NAVSTAR Consortium (UNAVCO) (http://www.unavco.org). Consisting of ~1100 sites, this network is almost entirely located in the western United States. Nearly half the receivers were installed in California to measure motions of the San Andreas and related fault systems. Little or no snowfall impacts these sites. However, sites in western Washington and Oregon, the Rocky Mountains, Alaska, and the Sierra Nevada Mountains do see significant snowfall. It is these latter sites that will be used to test the algorithm.

[8] All Plate Boundary Observatory (PBO) sites initially operated a Trimble NetRS dual-frequency GPS receiver with 12 channels and a choke ring antenna. Starting in late 2012, several dozen receivers were replaced with newer model receivers; these new data are not incorporated into this study. Raw GPS observations are provided in the receiver-independent exchange (RINEX) format [*Gurtner*, 1994]. A Trimble NetRS receiver tracks L1 using the C/A code; it uses non-code-based tracking for L2. The standard PBO sampling rate records a measurement every 15 s. Each day, the translation, editing, and quality control (TEQC) program is run, and its log is posted online for public access [*Estey and Meertens*, 1999]. TEQC calculates statistics related to observation completeness, pseudorange multipath, cycle slips, and signal-to-noise ratio (SNR) data. In this study only the SNR statistics from the TEQC logs are used.

[9] PBO used drill-braced monuments. Most of the PBO sites are ~2 m above the ground, but some are 1–1.5 m. For sites without direct power, solar panels and batteries are used to power the GPS system. Receivers are located in nearby equipment boxes. The latter is minimally insulated. The choke ring antenna is covered by an acrylic radome. Optimally, antenna lengths between the antenna and receiver are kept to less than 30 m. Changes to the antenna, receiver, radome, and receiver firmware used at a PBO site are logged by UNAVCO. These equipment and firmware changes are documented in TEQC logs, RINEX files, and via the International Global Navigation Satellite Systems Service format site logs. In this study the equivalent metadata records consolidated by a java program provided by UNAVCO were used to access this information (http://pbo.unavco.org).

[10] In addition to RINEX files and metadata, official position estimates are produced for each PBO site; these are available online (ftp://data-out.unavco.org/pub/products/position). The PBO north, east, and up coordinate values (and their uncertainties) are based on 24 h averages for position. They are defined in a North American fixed frame. Offsets caused by equipment changes are not removed in PBO positioning products.

3. GPS SNR Data

[11] Geodesists using GPS focus on the L1 and L2 carrier phase data. However, SNR data are also commonly reported by geodetic quality GPS receivers and can be output to RINEX files. These SNR data measure signal power relative to a receiver-calculated noise floor. Although there are small variations in transmit power as a satellite rises and sets (Figure 1), most of the observed low-order SNR variations are due to the antenna gain pattern; in other words, data from high elevation angles have much larger SNR values than data from low elevation angles. Signal strength monotonically increases as elevation angle increases. This slow change represents the "direct signal." Not shown in this representation are the oscillations commonly observed in SNR data at low elevation angles; these are caused by ground reflections. The oscillation frequencies of these SNR data can be used to measure environmental parameters such as soil moisture and snow depth [*Larson et al*., 2008; *Larson et al*., 2009]. To avoid misinterpreting reflected GPS signals as the presence of ice or snow, only the higher elevation angle data will be used in this study. Figure 1 also shows SNR data that have binned and averaged in 5° elevation angle increments. The binned data—for both L1 and L2 frequencies—are calculated each day and provided by the PBO station operators. In this study the average SNR data from the elevation angle bin for 55–60° are used.

[12] Before defining the parameters used in the algorithm, it is useful to demonstrate the typical behavior of a SNR time series that is not impacted by snow and ice. In Figure 2a, three general features of SNR data are present. First, there appears to be a strong annual signal. This is driven by temperature and will be discussed in the next paragraph. Second, there is a marked offset of ~1 dB-Hz in 2010 that correlates with a reported change in receiver firmware. This bias can be removed by fitting a few days of data before and after the firmware change. Finally, there are a handful of large positive outliers in September 2010. These anomalous points correspond to a Department of Defense test of flex power transmissions on L2C-transmitting satellites. These points will be removed from all subsequent discussions. Significant offsets are also observed when receivers and antennas are changed (Figures 2b and 2c). For example,

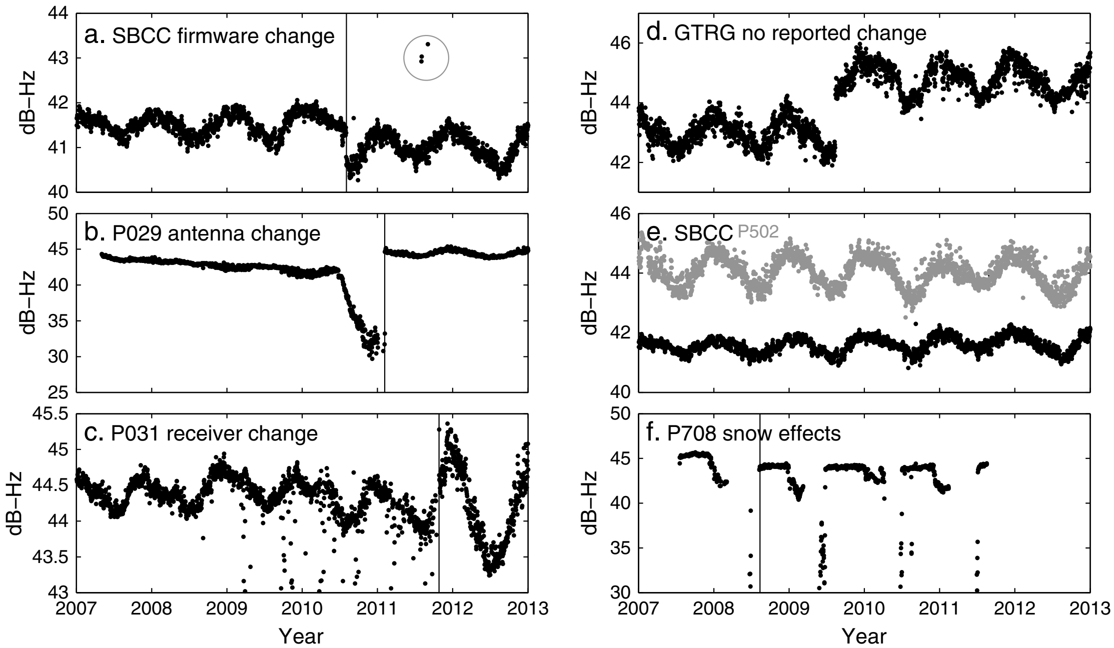

Figure 2. (a) Station SBCC, vertical line showing time of firmware update. Days when the U.S. Department of Defense conducted flex power tests are circled. (b) Station P029, vertical line showing time of antenna change. (c) Station P031, vertical line showing time of receiver change. (d) Station GTRG. There was no reported receiver or antenna change for this site, but maintenance logs indicate a cable was changed. (e) Stations P502 and SBCC, with firmware offsets removed. (f) Station P708, vertical line showing time of antenna change.

the antenna change at P029 was preceded by a large decrease in SNR values before the new antenna was installed. The receiver change example at P031 shows that the equipment change resulted in larger annual amplitude in SNR. Singleton outliers are also quite prominent at P031. This is likely related to incomplete data records (i.e., the daily file has less than 24 h of data in it, and thus, the average would be inconsistent when compared with those days that do not have gaps). Figure 2d (station GTRG) shows a significant offset in 2009, but the publicly available metadata do not indicate that anything changed at the site. A query to the station operators revealed that a new antenna cable had been installed on the date in question (K. Feaux, personal communication, 2012). It is likely that this cable change is the cause of the 2009 SNR offset at station GTRG.

[13] In Figure 2e, two SNR time series (GPS stations P502 and SBCC) with firmware biases and flex power test days removed are shown. The sites have different mean values as well as significantly different annual amplitudes. The SNR data also have consistently lower values in the summer and higher values in the winter. Why is this? SNR is explicitly defined by the receiver's noise floor. A cold receiver/antenna has lower noise levels, and thus, its SNR values will be higher. In hot temperatures, the converse is true (see, e.g., the noise analysis in *Misra and Enge* [2006, section 8.3]). The temperature dependence of GPS components (receiver electronics, antenna, cables) is generally of little interest in geodesy because the temperature dependence affects all satellites in view in the same way. In practical terms, this means that temperature effects are absorbed by receiver clock terms and not into position estimates.

[14] Figure 3 shows both L1 and L2 SNR data compared to average daily temperature data. Both sites show a strongly linear relationship with temperature with a negative slope. Why are the mean values and slopes different? Although the PBO equipment at each site is similar, it is not identical. Temperature dependence and SNR levels will be related to small differences in the antennas (especially amplifiers), receivers, connectors, length and quality of the cables (and whether they are shielded from the elements), as well as how insulated the receiver is in its equipment box. Note in

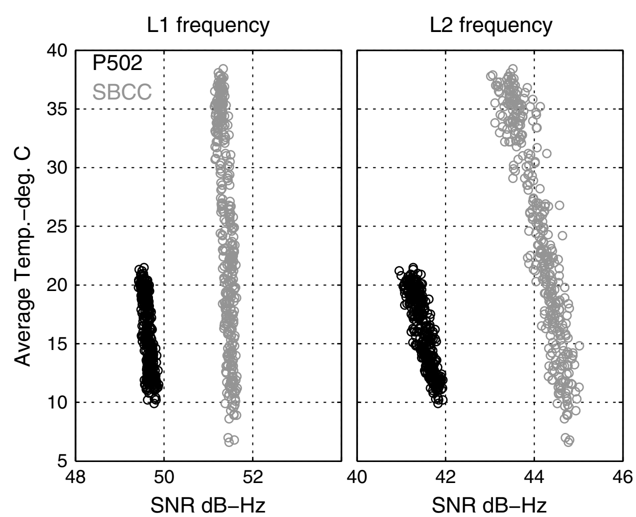

Figure 3. Comparison of L1 and L2 SNR records for PBO stations SBCC and P502 and average daily temperature records.

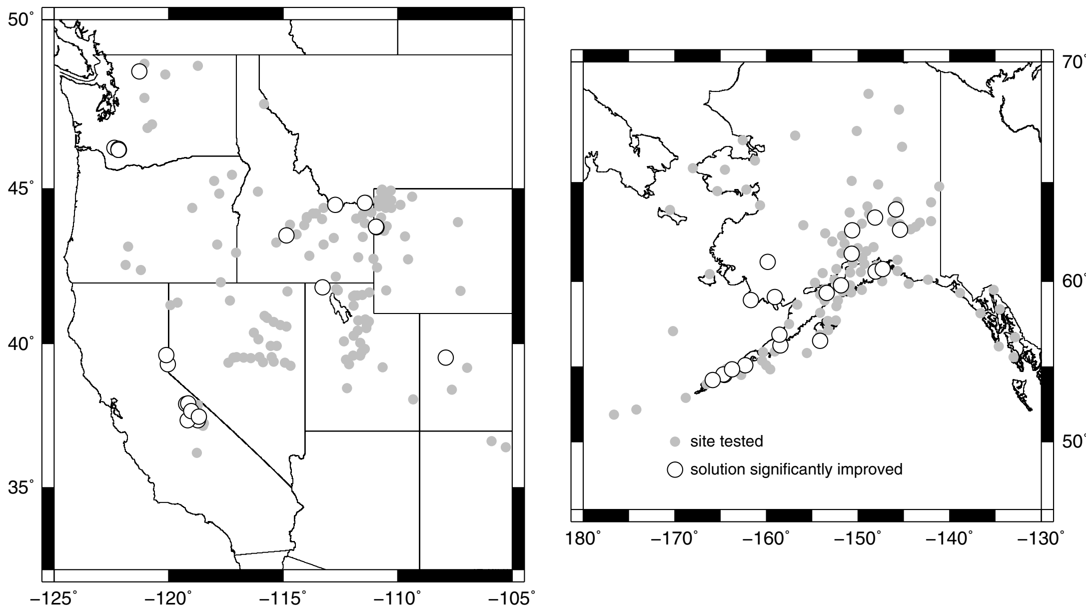

Figure 4. Locations of PBO sites assessed in this study are show in gray; larger white circles indicate sites that are significantly improved by the algorithm.

particular that the L1 SNR data are much less sensitive to temperature than the L2 SNR data. For this reason, this study utilizes only the L2 data.

[15] The SNR data from GPS station P708 highlight the focus of this study (Figure 2f). Unlike the other sites, where values were above 40 dB-Hz, biases were well correlated with equipment changes, and annual variations were ~1 dB-Hz, this site shows SNR values varying by 15 dB-Hz each winter. These signal strength losses are consistent with published results for interference from snow and ice at GPS frequencies [*Tranquilla and Al-Rizzo*, 1994; *O'Keefe et al.*, 1999; *Gergnot*, 2007].

[16] In summary, at most, SNR data show fairly consistent behavior from day to day. Based on an evaluation of more than 1000 PBO sites, healthy behavior for the Trimble NetRS GPS system usually shows SNR values above 40 dB-Hz. The primary time dependence in SNR data is an annual signal linked to temperature; the bias and linear dependence between SNR and temperature is site specific. SNR data collected in the summer (when it is hot in North America) have lower values than in the winter (when the GPS system will be cold). Offsets in SNR data are caused by changing receivers, antennas, or firmware. In order to accommodate these offsets, accurate metadata is extremely important. This study suggests that changes to antenna cables should be also be logged in metadata files. A failing receiver or antenna can also introduce significant time-varying behavior. In these cases, the signal strength levels always decrease. Finally, on rare occasions, the Department of Defense can change the transmit power levels. In this study period covering the years 2007–2012, this happened on only one occasion.

4. Algorithm

[17] The SNR-based outlier detection algorithm has the following steps:

[18] 1. Timing of receiver firmware changes must be identified and biases removed.

[19] 2. Timing of equipment changes must be identified. Subsequently, the SNR data should be analyzed in segments defined by the dates of these equipment changes.

[20] 3. Gross outliers are removed. First, SNR data with values below 40 dB-Hz are removed. Subsequently, the remaining SNR data are required to have values within 4 standard deviations of the mean.

[21] 4. An annual minimum SNR value for each segment is defined for the summer months. Any SNR data below this minimum value are discarded.

[22] 5. A model consisting of a seasonal term and a second-order polynomial is fit to the SNR segments. SNR data that are outside a user-defined outlier threshold are moved. Sites in Alaska were required to fit the model within 2.5 standard deviations; a 3 standard deviation threshold was used at other sites.

[23] A subset of PBO sites was tested for snow and ice effects for the time period 2007–2012 (Figure 4). The sites fall into two categories: PBO stations located in Alaska and PBO stations where climatology models predict annual snow water equivalent totals of 50 mm or more [*Armstrong et al.*, 2007].

[24] A total of 311 PBO sites meet one of these criteria. Of these, 31 sites were discarded because either the metadata was incomplete (e.g., GTRG in Figure 2d) or a receiver or antenna failed during this 6 year time period (e.g., P029 in Figure 2b). A total of 280 stations were assessed.

[25] SNR data from station P013 (latitude 41.42873°, longitude −117.32997°, Figure 5) will be used to demonstrate how the algorithm works in the absence of snow or ice. There is a strong seasonal signal and a slight positive drift in the data. There are no SNR data below 40 dB-Hz and no reported receiver or antenna changes. The effect of a firmware bias was removed in 2010; there are no apparent undocumented offsets in the SNR data. No gross outliers

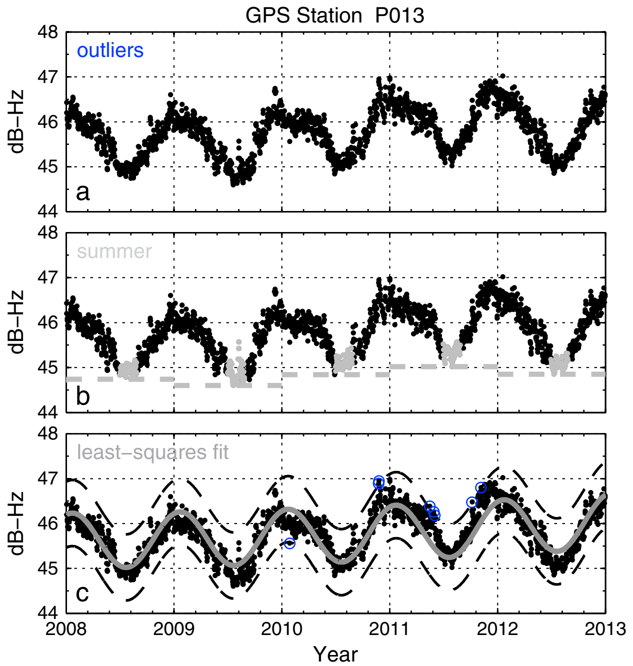

Figure 5. (a) L2 SNR data for GPS station P013. (b) SNR data in black, with data from the summer months in gray. The dashed lines are the minimum allowed SNR values for each year. (c) SNR data (black) and least squares fit in gray, with 3 standard deviation values as dashed lines. Detected outliers are in blue.

(4 standard deviations) are removed from the time series (Figure 5a) nor were any data removed because they violated the "summer months" minima. Figure 5b shows a close-up view of the data after these initial outlier detection steps. The final test is a least squares estimation of a model consisting of a second-order polynomial and annual term. If the equipment had no aging components or new satellite launches, the polynomial term would not be needed. SNR residuals with respect to this model were computed and a standard deviation computed. The dashed lines indicate 3 standard deviations (Figure 5c). SNR data outside these boundaries are then removed. Of the 2078 points in the SNR time series for P013, 8 were flagged by the algorithm as outliers.

[26] Figure 6a shows SNR data that are representative of an antenna that has been buried in snow (P150, latitude 39.29238°, longitude −120.03385°). Very low SNR values occurred in February–April of 2011 along with a few other singleton outliers. Twenty-two points are removed because they are 4 standard deviations from the mean value. Using the summer minimum values eliminates an additional 22 points. However, the simple algorithm used a conservative definition for the minimum summer value (Figure 6c). In this example, the minimum summer value for 2010 is defined by an outlier. Even so, the remaining SNR data are well modeled by an annual term and a slight linear trend (Figure 6c). This step removes an additional seven outliers.

[27] Figure 7a shows SNR data that are representative of an Alaskan coastal site (AV29, latitude 54.472354°, longitude −164.58615°). Unlike P150, where only 1 year appears to have significant snow or ice issues, low SNR values occur at AV29 each winter. Two equipment changes were made, one in 2009 and another in 2010, so the SNR data are analyzed in three independent segments. More than 100 points are less than 40 dB-Hz and immediately discarded. Defining outlier points is also hampered by the limited data from the summer of 2008. The final model fit is shown in Figure 7c.

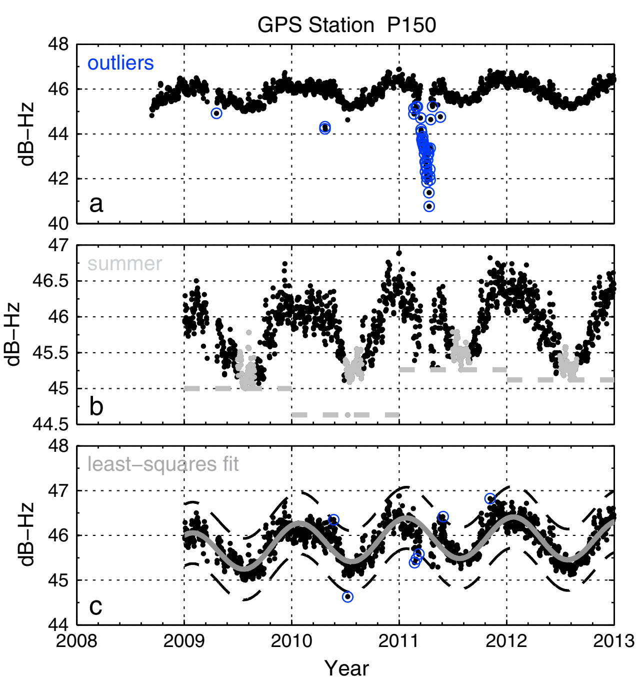

Figure 6. (a) L2 SNR data for GPS station P150. (b, c) Same as Figures 5b and 5c, respectively.

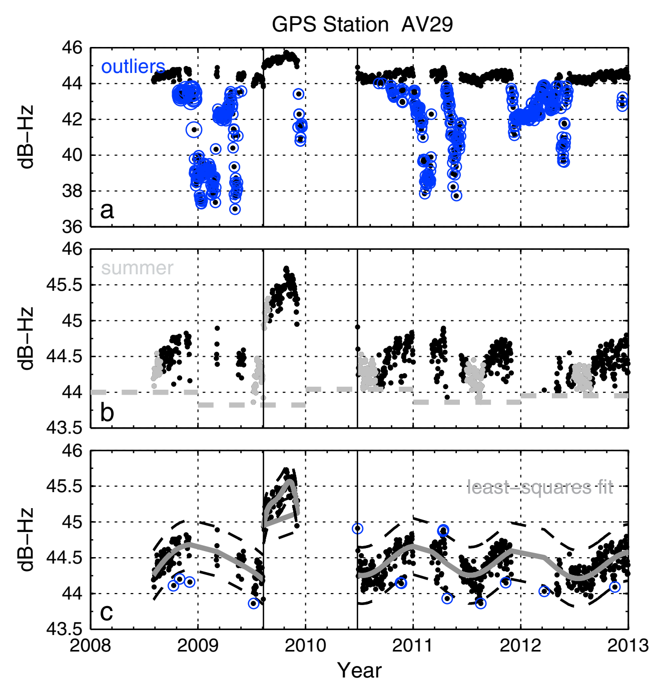

Figure 7. (a) L2 SNR data for GPS station AV29. (b, c) Same as Figures 5b and 5c, respectively.

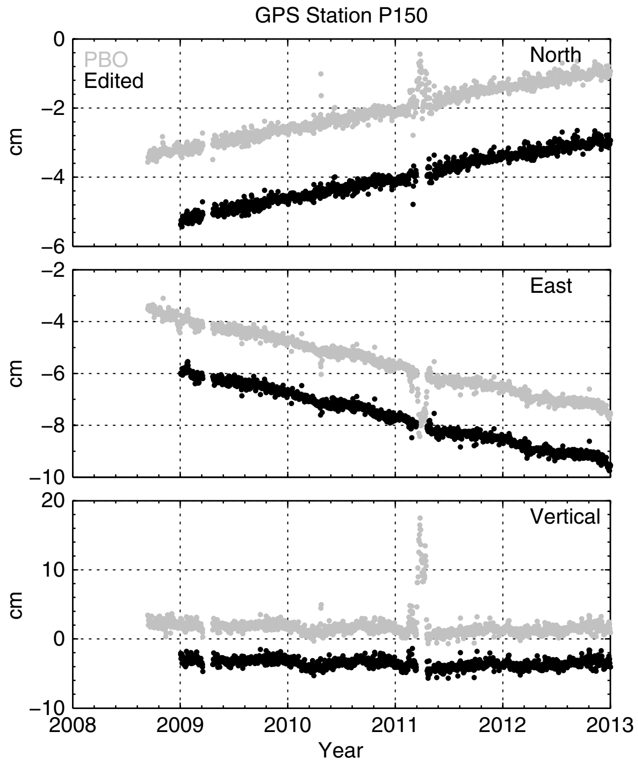

Figure 8. Coordinate time series for GPS station P150 with and without SNR algorithm corrections applied. For clarity, time series are offset vertically and error bars are not shown.

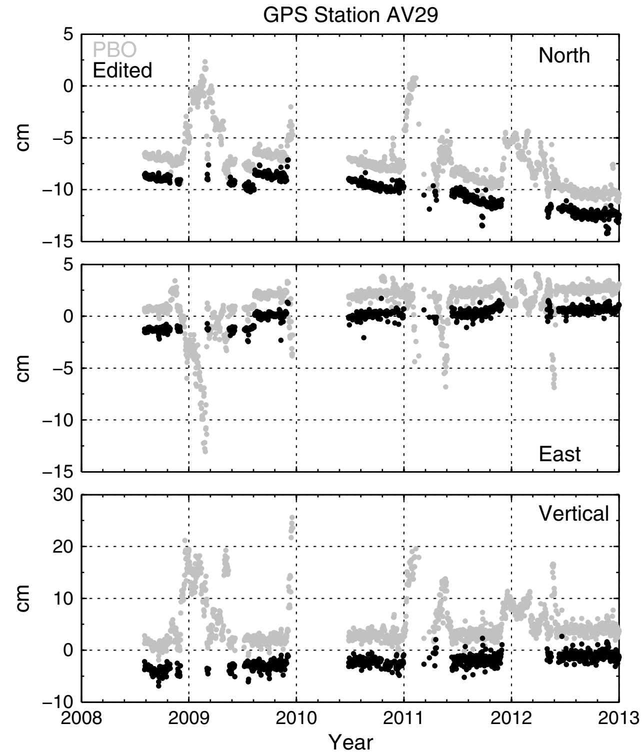

Figure 9. Coordinate time series for GPS station AV29 with and without SNR algorithm corrections applied. For clarity, time series are offset vertically and error bars are not shown

[28] The rejected SNR data can now be used to flag outliers in position time series. First, the official coordinate time series provided by PBO for site P150 are examined (Figure 8). P150 mostly shows deformation rates that are consistent with plate boundary deformation. P150 also exhibits abrupt, large displacements in winter 2011, reaching 15 cm above the linear trend in the vertical direction. There are also smaller outliers in winter 2010. The edited coordinate time series correctly removes both the small outliers in 2010 and larger outliers in 2011. The RMS about the best fit straight line improves from 0.29, 0.16, and 1.67 cm before the SNR edits to 0.12, 0.11, and 0.44 cm (east, north, and vertical components, respectively).

[29] Next, the coordinate time series for AV29 is considered (Figure 9). Large nonlinear motions are present in each direction. Most of these excursions correlate well with the points rejected based on the SNR data (Figure 7). The edited coordinate time series for AV29 shows nearly a factor of 4 improvement in residual RMS, assuming that the site moved linearly.

[30] How well did the algorithm work for the entire data set? This is difficult to assess because PBO coordinate time series include not only linear tectonic motions but also episodic slip, volcanic inflation episodes, hydrologic effects, and coseismic steps. Even so, most of the vertical motion at these sites can be successfully modeled with a single linear term. The metric used here is the standard deviation of the edited, detrended vertical time series, divided by the standard deviation of the original detrended vertical time series. Statistics for the years 2009–2012 are presented in Figure 10. This figure emphasizes that the SNR outlier detection algorithm is not needed for the vast majority of sites. If it had been tested for all 1100 PBO sites, the percentage of improved site coordinates would be even smaller. Positively, the algorithm does not degrade precision at many sites. Of those few, all were sites that had low initial standard

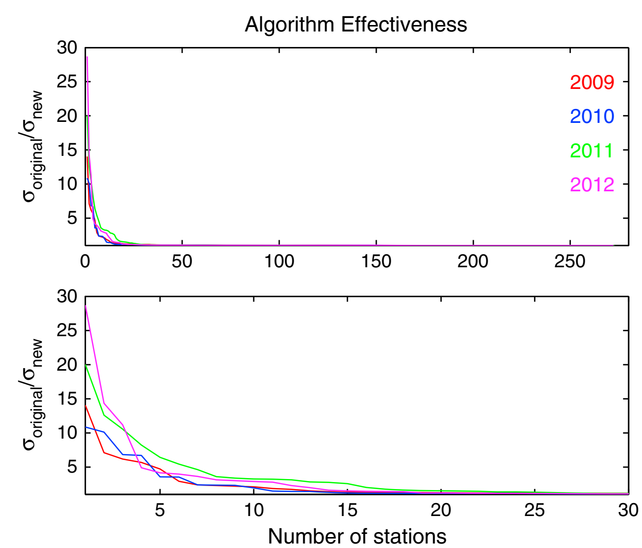

Figure 10. Algorithm effectiveness (standard deviation of original vertical coordinate time series divided by the standard deviation of the edited vertical coordinate time series) is plotted for the 280 stations used in this study for the years 2009–2012. The bottom panel shows a close-up view.

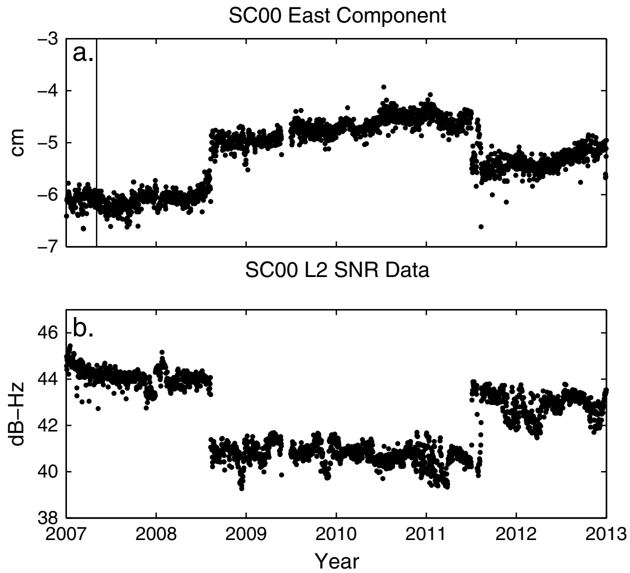

Figure 11. (a) PBO east component estimates for PBO station SC00. The vertical line indicates a receiver change. (b) L2 SNR data for station SC00.

deviations before applying the SNR edits.

[31] Approximately 30 sites report standard deviations that improved by greater than 10%. Overall, half of the sites that improved are located in Alaska; data from 2011 show improvement at most sites. This is consistent with the very high snow levels reported in 2011 throughout the western United States. While the coastal Alaskan sites were most likely impacted by buildup of ice or snow on the antenna, some of the 2011 outliers in the western United States were most likely caused by the antennas being buried in high levels of snowpack. An additional 10 time series are provided in the supporting information.

5. Discussion

[32] The advantage of the algorithm described here is that no assumption about the true geophysical behavior of the Earth was needed. The algorithm works identically on sites located in plate interiors, on volcanoes, near plate boundaries, and moving ice sheets. Unlike outlier detection that assumes seasonal behavior related to loading or deformation, the algorithm only assumes a seasonal dependence with temperature.

[33] The discussion thus far has focused on position outliers caused by ice and snow. Clearly, this algorithm could be modified to also sense a failing receiver or antenna (recall the SNR data shown for site P029 in Figure 2b). Given that many organizations are operating hundreds if not thousands of GPS receivers, having an algorithm that could flag such failures—or alert the user to unusual instrument behavior—would be extremely valuable. One such example is given in Figure 11. Here SNR data are plotted for a site (SC00, latitude 46.950925°, longitude −120.72460°) in central Washington. There are clear breaks in the east component time series in 2007, 2008, and 2011. However, the logs for this site only show an equipment change for the first break, a receiver change. There is a very clear correspondence between the SNR data and the east component time series. In this example, the coordinate time series does not represent ground motion. At least two offsets must be estimated for this coordinate time series to be of any geophysical value. The SNR data provide independent information that a geodesist could use to determine the validity of the estimated coordinates.

[34] However, the SNR-based outlier detection algorithm described has limitations. As noted in the three examples shown in Figures 5–7, it deletes points that may be accurate. It is impossible to determine how often the SNR method reports a "false positive," but for the ~250 sites not improved by the algorithm, 10–30 points are typically deleted over the 6 year time period, leaving ~99% of the data intact. Second, the algorithm relies on accurate record keeping about receiver, antenna, and firmware changes. If these data are not available, the algorithm fails. Finally, results for the algorithm are not reported for eight sites because the SNR data do not follow the proposed model. Two examples of these SNR data (stations FRED and SEDR) are shown in Figure 12. At these GPS sites, SNR data have lower values in the winter and higher values in the summer. This is opposite to what was seen in Figures 5–7. FRED has a nearly 3 dB-Hz variation each season, whereas the other data examined for this analysis generally varied by less than 1 dB-Hz per season. Although the receiver and antenna models at these eight sites are the same as used at the other PBO sites, the cables were installed by the previous network operators. They were not upgraded or changed when the new PBO receiver and antenna were installed. It is likely that these cables are responsible for the differences observed in the SNR data at these eight sites. While the algorithm worked well at the 280 sites summarized in Figure 10, further study would be needed to demonstrate whether it works for other

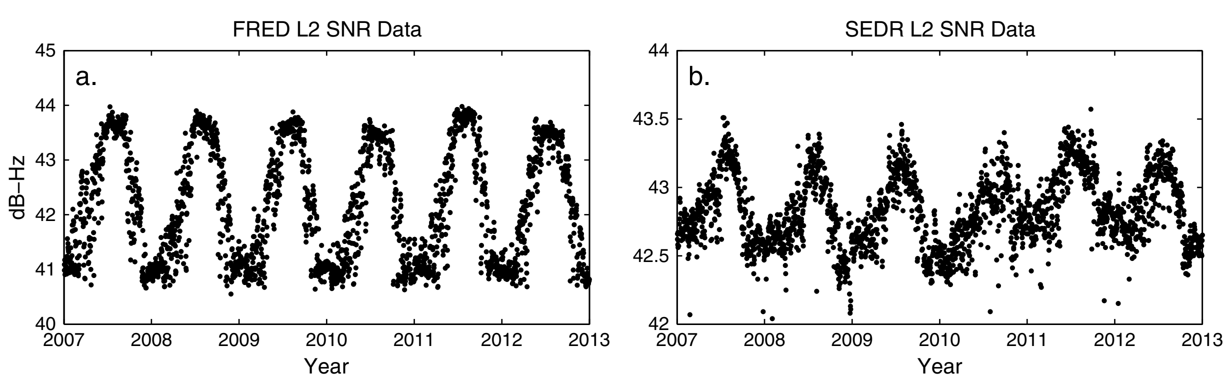

Figure 12. (a) L2 SNR data for GPS station FRED. (b) L2 SNR data for GPS station SEDR.

receiver models and antennas. Ideally, the SNR edits would be used with other quality control information such as carrier phase residuals and file size.

[35] As a final discussion point, there are very good reasons that geodesists maintain extensive metadata for all GPS instruments. This information is critical for determining if offsets in time series are coincident with equipment changes. However, the tendency has always been to maintain the metadata separately from the time series estimated from the data. It would be useful—particularly for nonexperts—if data distribution centers could collate this information in a way that makes it easier for nonexperts to correctly use GPS time series. For example, simple flags could indicate receiver, antenna, and firmware changes in the same row that the east, north, and vertical positions are provided. While a geodesist might want to know the serial number of the new antenna (as fully documented in the metadata), most users would simply want to know that an important piece of equipment had been changed. Similarly, the quality flags estimated by the algorithm described here could be attached to coordinate time series. It would then be left to the geophysicist to use them or not.

6. Conclusions

[36] An algorithm has been developed that uses GPS SNR data to detect coordinate outliers that are caused by ice and snow on the antenna. To test this algorithm, 280 coordinate time series provided by the EarthScope Plate Boundary Observatory were assessed. This algorithm significantly improved positioning estimates at ~10% of the sites. It was particularly successful at improving position estimates for Alaskan sites. Although not implemented here, SNR data are also potentially valuable for determining when a GPS receiver or antenna has begun to fail.

[37] **Acknowledgments.** K.L. acknowledges useful discussions with Penina Axelrad, Staffan Backan, Felipe Nievinski, Karl Feaux, Fran Boler, Lou Estey, and Lee Snett. This research was supported by EAR 0948957, EAR 1144221, and NNX12AK21G. Some of this material is based on data, equipment, and engineering services provided by the Plate Boundary Observatory operated by UNAVCO for EarthScope and supported by NSF. All PBO data and information used in this study are freely available from the UNAVCO archive. This manuscript benefited greatly from two careful reviews.

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