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Validation of GPS-IR Soil Moisture Retrievals: Comparison of Different Algorithms to Remove Vegetation Effects

Eric E. Small, Kristine M. Larson, Clara C. Chew, Jingnuo Dong, and Tyson E. Ochsner

***Abstract*—The GPS interferometric reflectometry (GPS-IR) technique can be used to estimate near-surface soil moisture from signal-to-noise ratio (SNR) data collected with standard geodetic instrumentation. However, the effects of vegetation on GPS-IR soil moisture retrievals must be considered in some environments. *In situ* soil moisture observations from 11 GPS sites are used to compare the performance of three different retrieval algorithms that represent vegetation effects with different degrees of complexity. A bare-soil retrieval algorithm does not perform well, even at sites where seasonal variations in vegetation water content (VWC) are less than $1\ \mathrm{kg\ m^{-2}}$. The range of volumetric soil moisture (VSM) is too large due to the effects of vegetation on phase of the SNR interferogram, yielding an RMSE between *in situ* and GPS-IR VSM of $0.055\ \mathrm{cm^3\ cm^{-3}}$. Errors are reduced by an algorithm that adjusts for vegetation effects using variations in the amplitude of the SNR interferogram. RMSE is $0.038\ \mathrm{cm^3\ cm^{-3}}$ using this algorithm, below the typical limit required for validation of satellite data. This simple vegetation algorithm performs poorly at sites where seasonal variations in VWC are $1\ \mathrm{kg\ m^{-2}}$ or greater. A more complex algorithm, that uses amplitude in conjunction with frequency analysis of the SNR interferogeram to predict vegetation effects, provides acceptable performance at these sites ($\mathrm{RMSE} = 0.039\ \mathrm{cm^3\ cm^{-3}}$). The additional complexity of this algorithm is only warranted at sites where the simple vegetation algorithm cannot adequately represent the effects of the vegetation fluctuations.**

***Index Terms*—Global positioning system, hydrologic measurements, remote sensing, soil measurements.**

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I. Introduction

THIS GNSS reflections measured by ground-based receivers can be used for monitoring near-surface soil moisture, an important hydrologic state variable [1]. Soil moisture estimated from GNSS reflections is particularly useful because the sensing footprint is orders of magnitude larger than that from typical soil moisture sensors [2]. One ground-based approach is to use an antenna–receiver system designed specifically to measure reflections from the land surface [3]–[5]. Alternatively, it is possible to use existing geodetic-grade instruments that are found in operational networks [6]. The latter approach is the focus of this paper.

Geodetic-grade instruments were not designed or installed to estimate soil moisture from GNSS reflections. However, there are thousands of these instruments operating worldwide, providing a cost-effective approach for monitoring hydrologic land surface conditions for applications such as satellite validation [7]. The basic observation is the interference pattern of the observed signal-to-noise ratio (SNR) that results from the interaction between the direct and ground-reflected signal [Fig. 1(a)]; thus, this method is referred to as GPS interferometric reflectometry (GPS-IR). The GPS-IR technique has been applied to data collected from both geodetic-grade (e.g., [6]) and specially designed systems (e.g., [3]). GPS-IR differs from GNSS-reflection methods that are based on changes in the autocorrelation of the received and replica carrier signals at longer delays (e.g., [8], [9]).

As for all remote sensing techniques, it is necessary to validate the GPS-IR technique to quantify its accuracy (e.g., [10]). In this paper, we evaluate the accuracy of GPS-IR soil moisture retrievals from operational geodetic-grade receivers at 11 sites in the western U.S. As vegetation growth has been shown to obscure and complicate the soil moisture signal [11], we consider the performance of three retrieval algorithms that represent the effects of vegetation with different degrees of complexity.

The basic GPS-IR procedure is to estimate a geophysical variable (e.g., soil moisture) from the pattern of an SNR interferogram. The general shape of the SNR interferogram is determined by the antenna gain pattern, the height of the reflecting surface relative to the antenna, as well as other factors including surface topography and roughness. A detailed description of SNR formulation is outside the scope of this paper. For more information, see [12] and [13]. Temporal variations in interferograms are caused by changes in the permittivity

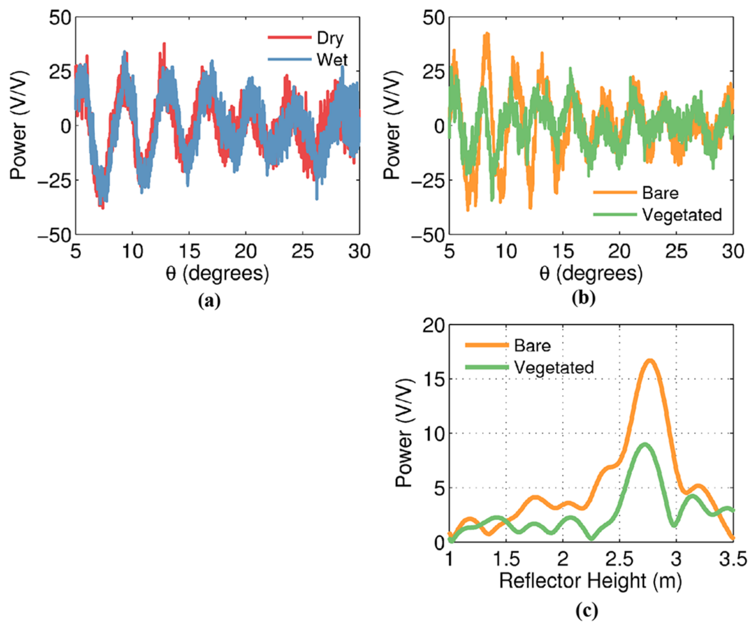

Fig. 1. (a) Example SNR data for wet and dry soil conditions. (b) Example SNR data for bare-soil and vegetated conditions (from site OKL2). (c) Lomb–Scargle Periodogram for bare-soil and vegetated conditions, from analysis of the SNR data shown in panel B. H_{eff} decreases by more than 0.1 m from the bare-soil to vegetated case.

of the ground surface (e.g., soil moisture) as well as vegetation [Fig. 1(b) and (c)]. Due to the noise present in SNR interferograms, the following equation is used to fit the data:

$$\mathrm{SNR} = \mathrm{A}\cos\left(\frac{4\pi H_0}{\lambda}\sin E + \phi\right) \tag{1}$$

where E is the elevation angle, λ is the GPS wavelength, and H_0 is the *a priori* reflector height (discussed below). Amplitude A and phase ϕ are referred to here as SNR metrics. Larson *et al.* [6], [12] showed that phase varied linearly with near-surface soil moisture, using observations from a site in Colorado. Zavorotny *et al.* [14] used a model of GPS reflections to demonstrate the physical basis leading to this relationship. The model was subsequently used by Chew *et al.* [15] to develop an algorithm to estimate soil moisture for bare-soil conditions. Vey *et al.* [10] used this algorithm to develop a multiyear soil moisture time series from a site in South Africa. They found the root-mean-square error (RMSE) between soil moisture estimated via GPS-IR and measured *in situ* was $0.05\,\mathrm{cm}^3\ \mathrm{cm}^{-3}$, an error too large for some applications.

The phase of the SNR interferogram is also affected by vegetation. Chew *et al.* [11] showed that variations in phase due to seasonal changes in vegetation are of the same magnitude as the variations in phase due to soil moisture fluctuations [Fig. 1(a)]. Therefore, effects of vegetation on phase must be considered in soil moisture estimation, at least at sites where seasonal vegetation changes are significant. It is possible to account for vegetation effects in soil moisture retrieval algorithms by considering aspects of the SNR interferogram other than phase. Amplitude decreases as vegetation grows [Fig. 1(b)] [16], [11]. The changes in amplitude resulting from vegetation growth are approximately an order of magnitude larger than those from soil moisture variations. In addition, amplitude varies nearly linearly with vegetation water content (VWC), at least up to $\sim 1.0\,\mathrm{kg\ m}^{-2}$ [16], [11]. Therefore, it is possible to use amplitude to estimate vegetation conditions at a site, and then adjust phase and soil moisture accordingly.

Additional information about vegetation conditions can be retrieved via frequency analysis of the SNR interferogram. The dominant frequency of the SNR interferogram can be converted to an effective reflector height, H_{eff}

$$\mathrm{H}_{eff} = \frac{1}{2} f_m \lambda \tag{2}$$

where f_m is the peak frequency found using a Lomb–Scargle periodogram (LSP). H_{eff} tends to decrease as vegetation grows [Fig. 1(c)]—the dominant reflecting surface moves closer to the antenna [11]. The amplitude of the peak frequency A_{LSP} also decreases [Fig. 1(c)]. This occurs because there are reflections from throughout the vegetation canopy, rather than only from the soil surface. The relationship between these two metrics and vegetation is not as simple as for amplitude [11], particularly when VWC exceeds $1\,\mathrm{kg\ m}^{-2}$. Chew *et al.* [17] described a method to estimate vegetation effects on soil moisture estimation by comparing observations of A, H_{eff}, and A_{LSP} with model simulations. The additional complexity and data requirements of this approach may not be warranted at many sites.

The goal of this paper is to evaluate the accuracy of near-surface soil moisture estimated from the GPS-IR technique, using data collected with standard geodetic instrumentation. Validation is based on comparisons to *in situ* observations of soil moisture collected from within the GPS-IR sensing footprint. To date, validation of GPS-IR soil moisture estimates has only been reported for two sites (e.g., [6], [10]). The results presented here extend this validation to 11 sites, several in locations with substantial seasonal variations in vegetation cover. Six of the validation sites were established as part of NSF's

Plate Boundary Observatory (PBO) network, which includes over 1000 sites with standard geodetic instrumentation. The remaining sites were installed specifically for development of the GPS-IR technique, including evaluation of the impact of vegetation on the retrieval algorithm. These sites have subsequently become part of the operational PBO H_2O network, a network of sites for which soil moisture, snow, and vegetation status are estimated via GPS-IR on a daily basis [7]. Thus, the analysis presented here provides the information necessary to gauge the accuracy, and therefore potential applications of the soil moisture data provided by PBO H_2O.

Our validation of GPS-IR soil moisture using *in situ* data is designed to compare the performance of three different retrieval algorithms, each representing the effects of vegetation with a different degree of complexity. Our intent is to identify the simplest algorithm that can be used for different vegetation conditions. This provides guidance for the development of operational soil moisture products in different environments. The simplest algorithm was developed for bare-soil conditions [14], and thus relies upon the assumption that the effects of vegetation are negligible. Chew *et al.* [14] and Vey *et al.* [10] used this algorithm in their comparisons with *in situ* soil moisture observations. The second algorithm adjusts soil moisture estimates for temporal fluctuations in vegetation cover. The vegetation effects are determined from variations in the amplitude of the SNR interferogram. The most complex approach relies upon all three SNR metrics other than phase to quantify the effects of vegetation on estimated soil moisture [17].

The plan of this paper is as follows. The field sites used for validation and the data collection and analysis are described in Section II. The three algorithms are described and compared in Section III. GPS-IR soil moisture is compared to *in situ* observations in Section IV. Recommendations for use of the different algorithms are provided in Section V.

II. Field Sites and Data

A. Field Sites

Data from 11 PBO H_2O sites are used for validation. Eight of these sites are in Colorado and New Mexico (Table I). These eight sites were chosen primarily based on their location: we were able to visit at least two sites per day on sampling trips starting and ending in Boulder, CO, USA. These eight sites are similar in several ways to the soil moisture sites throughout the PBO H_2O network. First, the climate is semiarid with annual precipitation of $\sim$500 mm. There is minimal or ephemeral snowcover during the winter. Second, the vegetation at each site is predominantly native grasses (Fig. 2). This is typical of the relatively low elevation areas of semiarid western U.S., where most PBO H_2O soil moisture sites are located. The exception is P123, which is located in a shrubland. The amount of vegetation varies seasonally at the validation sites. The highest VWC measured at each site during the validation surveys is $\sim$0.5 kg m^{-2} (Table I). The maxima in VWC are likely higher, as the survey dates do not necessarily correspond to peak vegetation growth. At peak growth, the vegetation height is typically less than 50 cm. Third, surface topography around the antenna is nearly planar, with surface slopes less than a few degrees.

Fig. 2. (Left) Site photo from OKL3, located in Marena Oklahoma. (Right) Site photo from P037, located in Fremont Colorado (Table I).

The three remaining sites are located at an intensively monitored research site in Oklahoma (Table I, Fig. 2). The three GPS installations at this site are separated by $\sim$500 m. The Oklahoma sites were included in this analysis for two reasons. First, annual precipitation is $\sim$1000 mm, so the seasonal peaks in vegetation are greater than for the Colorado and New Mexico sites. Maximum VWC is $1.0 - 1.5$ kg m^{-2} and height is $\sim$1 m. Again, maximum VWC is likely higher than shown in Table I, as VWC was only measured on the survey dates. Second, extensive *in situ* validation data were collected as part of a soil moisture sensor intercomparison effort. Although the three Oklahoma sites are close to each other, at least compared to the Colorado and New Mexico sites, they are not identical. Differences exist in topography around the antenna. In addition, the timing and amount of vegetation growth varies between sites due to differences in grazing management.

B. GPS Instrumentation, Data Stream and SNR Metrics

All sites have identical geodetic-grade Trimble NetRS GPS antennas and receivers. Choke-ring antennas are mounted $\sim$2 m above the ground surface, except at Oklahoma, where the antenna is 2.7 m. 1 Hz L2C SNR data were available and thus used at all our validation sites, but this sample rate is not required. Each rising (setting) satellite yields an SNR trace as the reflection point moves toward (away from) the antenna (e.g., [12]). The number of available ground tracks has increased as new GPS satellites have been launched. Not all of these tracks are used. At each site, usable ground tracks are selected based on the clarity of the reflected signal, as determined from visual inspection of SNR interferograms and lower limits on A_{LSP}. The number of usable tracks varies between the sites (Table I).

The soil moisture retrieval algorithms use daily averages of the SNR metrics across usable tracks at a site. SNR metrics are calculated for each SNR interferogram individually using (1) and (2). Then, the average value for each metric is calculated using data from all usable ground tracks. Details of the SNR

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TABLE I
VALIDATION SITE INFORMATION

Site	Lat/Long	Elevation (m)	Annual precipitation (mm)	Maximum measured VWC ($kg\ m^{-2}$)[a]	Number of validation surveys	Minimum normalized amplitude	Maximum number of tracks used
P036	36.42/–105.29	2530	525	0.65	6	0.78	16
P037	38.42/–105.10	1617	332	N.D.	5	0.81	23
P038	34.15/–103.41	1213	440	N.D.	3	0.83	20
P039	36.44/–103.15	1494	400	0.33	4	0.82	25
P040	38.07/–102.69	1103	388	0.47	5	0.81	16
P070	36.04/–104.70	1884	492	0.41	6	0.82	21
P123	36.63/–105.91	2411	337	0.24	3	0.76	10
MFLE	39.95/–105.19	1727	432	0.32	9	0.72	24
OKL2	36.06/–97.22	300	936	1.02	17	0.68	9
OKL3	36.06/–97.22	305	936	1.01	14	0.53	8
OKL4	36.07/–97.22	310	936	1.40	16	0.55	7

Mean annual precipitation (mm) is estimated from National Land Data Assimilation System (NLDAS) precipitation input field [24] at the location of the sites. VWC was not measured at P037 or P038.
[a]N.D. indicates no data available.

metric calculations can be found in Chew *et al.* [17]. For each track, A and A_{LSP} are normalized so that the highest values equal 1.0, in order to compensate for differences in power transmission between satellites, yielding A_{norm} and $A_{LSPnorm}$, respectively. The standard deviation of SNR phase between the tracks is used to calculate uncertainty.

C. Soil Moisture Validation Data

Validation of remotely sensed soil moisture is typically based on a comparison to one of two types of *in situ* volumetric soil moisture (VSM) data. First, VSM can be measured via the thermo-gravimetric method: a metal ring of known volume is inserted into the soil, the soil is weighed wet, then dried and reweighed (e.g., [18]). This method is problematic at sites where the soil contains appreciable gravel and coarser particles [19]. The coarse fraction of the soil makes it difficult to cleanly insert a gravimetric sampling ring, yielding voids along the inside the ring and errors in the resulting measurement of VSM. At more than half of the validation sites (and many PBO H_2O sites), the fraction of the soil volume that is gravel or larger is high enough (typically $\sim 10\%$) so that the thermo-gravimetric method does not yield reliable data.

The second approach to collect validation data is to use calibrated soil moisture probes, either deployed permanently (e.g., [6], [18], and [10]) or inserted into the soil for an instantaneous measurement (e.g., [20]). We used hand-held theta probes (Theta ML2, Delta-T Devices, Cambridge, U.K.) for collection of the *in situ* validation data, thus avoiding errors associated with using the thermo-gravimetric method in coarse soils. In cases when the narrow prongs of the theta probe impacted coarse grains, the probe was simply reinserted nearby. The theta probe has three 6-cm long prongs, providing a measurement of VSM in the top 6 cm of the soil when inserted perpendicular to the ground surface. At the Oklahoma sites, an empirical theta probe calibration curve was established via comparison to collocated therm-gravimetric samples. At the Colorado and New Mexico sites, we used the factory calibration curve to convert from voltage to VSM. The factory calibration and the Oklahoma-specific curves provide VSM values that are within $0.01\,\mathrm{cm}^3\ \mathrm{cm}^{-3}$ across the measurement range.

Our goal is to evaluate GPS-IR soil moisture estimates at the scale of the sensing footprint. The effective sampling area for each ground track is an ellipse that is roughly 30 m long by several m wide, radiating out from the antenna [12]. The sampling area is $\sim 1000\ \mathrm{m}^2$ after the usable ground tracks at a site are combined. For each validation site visit, we collected ~ 30 theta probe measurements randomly distributed within 30 m of the antenna. No attempt was made to limit the sampling locations to the azimuths with usable ground tracks.

Validation data were collected on a series of visits to each site. The New Mexico and Colorado validation sites were visited between 5 and 7 times during 2013 and 2014 (Table I). The timing of each visit was determined by the availability of field technicians, although we did attempt to collect data from both dry and wet conditions. The Oklahoma sites were visited approximately 15 times during 2011 and 2012. Site MFLE near Boulder, CO, USA, was visited 10 times during 2014. All site visits did not yield data that could be compared with GPS-IR estimates. There were GPS data gaps at the time of multiple site visits, including several visits for P123 and P038 (Table I).

The theta probe VSM data from a single validation visit was averaged and compared to the daily GPS-IR estimate from the corresponding day (UTC). Depending on the exact time of day of field sampling, the validation data were collected at a different time than data from some of the individual satellite tracks, by up to 18 h in the most extreme cases. On most days, this would introduce only small errors in the validation comparison, as near-surface VSM only changes by $\sim 0.02\,\mathrm{cm}^3\ \mathrm{cm}^{-3}$ per day (e.g., [21]). However, larger errors can occur on days with precipitation, particularly when the *in situ* sampling was completed prior to the rainfall event but some of the SNR data were collected afterward. Therefore, we excluded validation data collected on days when rainfall exceeded 5 mm. A similar

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exclusion of data from rainy days has been applied in validation studies of satellite-based soil moisture (e.g., [18]).

III. Algorithms for Estimating Soil Moisture from SNR Data

In this section, we describe the three soil moisture algorithms, from simplest to most complex. We do not try to provide a complete description of the first and third algorithms, as detailed information is provided by Chew *et al.* [15], [17]. The second algorithm has not been described in a prior publication.

A. Bare Soil Algorithm

The bare-soil algorithm was described by Chew *et al.* [15], and used in the validation study of Vey *et al.* [10]. A forward model of GPS reflections [14] was used to predict how phase varies with soil moisture for bare-soil conditions. Central to this model is the relationship between permittivity and soil moisture [22], as it is the permittivity contrast at the air–soil interface that causes the modeled phase shift. Model results showed that phase varies nearly linearly with soil moisture. The slope S of the relationship between phase and VSM is 1.48 ($\mathrm{cm}^3\ \mathrm{cm}^{-3}\ \mathrm{deg}^{-1}$). Although soil texture changes the relationship between permittivity and VSM (e.g., [22]), the magnitude of the slope varies by only 1% between different soil textures. Phase only provides information about relative soil moisture variations. Therefore, variations in phase must be referenced to a known soil moisture value. First, residual VSM VSM_r is determined from mapped soil texture, e.g, using the STATSGO dataset [23]. Second, the median of the lowest 10% of phase values (ϕ_r) is selected to equal residual soil moisture. The lowest phase value is not used because a single outlier would affect all other estimates of VSM. Then, VSM is calculated using the observed phase and value for S

$$\mathrm{VSM}(t) = S\left(\phi\left(t\right) - \phi_r\right) + \mathit{VSM}_{\mathrm{r}}. \tag{3}$$

The bare-soil algorithm may not provide accurate estimates of soil moisture in many environments because it is based on several simplifying assumptions. First, the value for S was based on simulations using a uniform soil moisture profile, even though vertical soil moisture variations do affect the relationship between phase and soil moisture [15]. Second, the ground surface is assumed to be flat. Third, the ground surface is assumed to be free from vegetation, which is not a reasonable assumption at many GPS sites. Vey *et al.* [10] reported a RMSE of $0.05\,\mathrm{cm}^3\ \mathrm{cm}^{-3}$ between GPS-IR and *in situ* observations at a semiarid site in South Africa. Although the site had limited vegetation (see Fig. 1 [10]), some portion of this error may be due to effects of the vegetation canopy on soil moisture retrieval.

B. Veg-Simple: Amplitude-Based Adjustment For Vegetation Effects

We refer to the second algorithm as the "veg-simple" algorithm. Like the bare-soil algorithm, the veg-simple algorithm is also based on (3), but phase is first adjusted for the effects of vegetation prior to estimation of soil moisture. This adjustment includes four steps. First, the normalized, site-averaged amplitude (A_{norm}) time series is smoothed using a low pass filter. Filtering is necessary to remove the high frequency variations (timescales of days to weeks) in A_{norm} that result from soil moisture fluctuations. Modeling studies have shown that soil moisture-induced variations in amplitude are small compared to those from vegetation alone, but they are not negligible [11], [15]. In reality, the scattering from the soil surface cannot be fully decoupled from the scattering of the combined soil and vegetation canopy, though the results here will show that the low pass filter is sufficient for soil moisture retrieval.

TABLE II
Parameter Values of (4) and (5)

	a_1	a_2	a_3	a_4	a_5
Equations (4)	10.6	–34.9	41.8	–22.6	5.24
Equations (5)	–5.65	43.9	–101	20.4	–2.37

Veg-simple parameter values are used in (4) and (5).

Second, the smoothed amplitude time series is used to estimate VWC

$$\begin{aligned}\mathit{VWC}(t) = a_1 A_{norm}^4 + a_2 A_{norm}^3 + a_3 A_{norm}^2 \\ + a_4 A_{norm} + a_5.\end{aligned} \tag{4}$$

Third, the estimated VWC is used to predict the phase shift ($\Delta\phi$) resulting from the vegetation canopy

$$\Delta\phi_{veg}(t) = a_1 \mathit{VWC}^4 + a_2 \mathit{VWC}^3 + a_3 \mathit{VWC}^2 + a_4 \mathit{VWC} + a_5. \tag{5}$$

Equations (4) and (5) are based on model simulations of GPS reflections through a uniform vegetation canopy [11]. Although canopy heterogeneities would affect the propagation of GPS signals, the simple uniform canopy was shown to be sufficient to quantify canopy effects on the SNR interferogram [11]. Each equation is the best-fit fourth-order polynomial that relates the SNR metric (A_{norm} or ϕ_{veg}) to VWC. A fourth-order polynomial was chosen because it provides a good fit at both low- ($<0.3\,\mathrm{kg\ m}^{-2}$) and high-VWC ($>1\,\mathrm{kg\ m}^{-2}$). The polynomial coefficients are listed in Table II. The vegetation parameters used in the simulations (e.g., canopy height) were constrained by field measurements at five sites [16], [11]. Different parameters would yield different coefficients in (4) and (5). Collocated SNR and vegetation data were used to quantify the uncertainty in the polynomial relationships. Equations (4) and (5) are accurate to within 20%, for canopies with VWC less than $1.5\,\mathrm{kg\ m}^{-2}$. Although there is uncertainty in the predicted value of $\Delta\phi_{veg}$, this approach does account for the first-order effects of vegetation on SNR phase. Fourth, phase is adjusted for the predicted effects of vegetation

$$\phi\prime\,(t) = \phi(t) - \Delta\phi_{\mathrm{veg}}(\mathrm{t}). \tag{6}$$

The adjusted phase values $\phi\prime\,(t)$ are then used to estimate soil moisture using (3), with $S = 1.48$. Zeroing is required to link variations in phase to absolute soil moisture. The median of the bottom 10% of adjusted phase values ($\phi\prime$) is linked to residual

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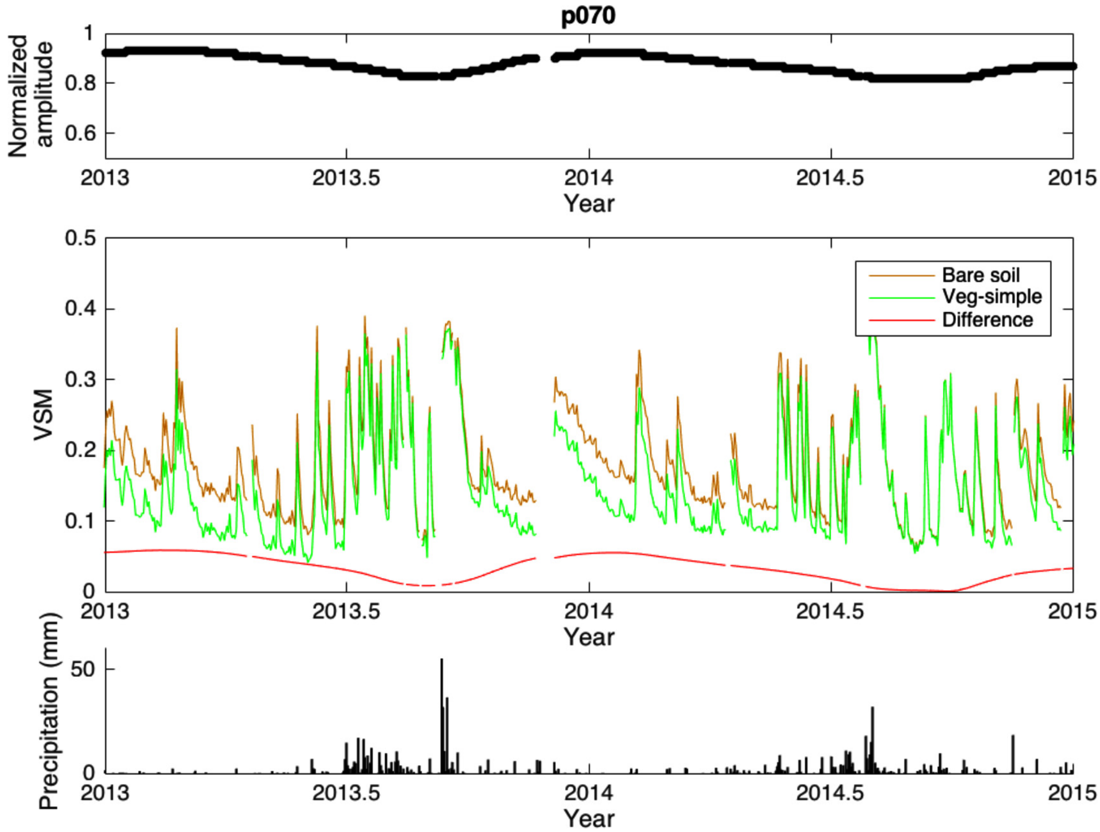

Fig. 3. Top: Smoothed normalized amplitude from site P070. Middle: VSM in $\mathrm{cm}^3\ \mathrm{cm}^{-3}$ time series from site P070 using the bare-soil and veg-simple algorithms. The difference between them (bare-soil minus veg-simple) is shown by the red line. Bottom: Daily precipitation in mm from NLDAS for the grid cell containing site P070.

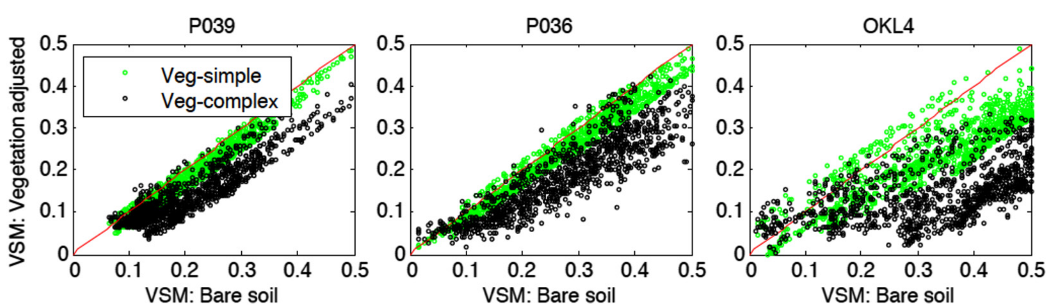

Fig. 4. Scatter plots of VSM determined using the bare-soil algorithm (x-axis) versus VSM adjusted for vegetation (y-axis): green points show VSM from the veg-simple algorithm and black points show VSM from the veg-complex algorithm. The one-to-one line is shown in red. Three sites are shown (P039, P036, and OKL3) in order of increasing vegetation amount.

soil moisture. If the measured phase values were used, as in the bare-soil algorithm, VSM would reach the residual value at the time of peak vegetation growth, instead of when the soil is driest.

For typical values of A_{norm}, (4)–(6) yield soil moisture estimates that differ considerably from those calculated using the bare-soil algorithm. For example, if A_{norm} is 0.85, (4) yields VWC of $0.33\,\mathrm{kg\ m}^{-2}$ and (5) yields $\Delta\phi_{veg}$ of $-5.2°$, equivalent to a change in VSM of $0.076\,\mathrm{cm}^3\ \mathrm{cm}^{-3}$. This difference is significant when compared to the full range of possible soil moisture values ($\sim 0.4\,\mathrm{cm}^3\ \mathrm{cm}^{-3}$) and the target accuracy for satellite validation ($0.04\,\mathrm{cm}^3\ \mathrm{cm}^{-3}$). The vegetation adjustment compresses the range of phase values input to (3) because $\Delta\phi_{veg}$ is nearly always negative. $\Delta\phi_{veg}$ is negative because the permittivity and canopy height changes caused by vegetation growth move the effective reflector closer to the antenna. This results in a negative shift when phase is estimated from the SNR interferogram.

There are thus two differences in VSM between the bare-soil and veg-simple algorithms. First, the range of VSM using the veg-simple algorithm is less (Figs. 3 and 4). Second, the average VSM from the veg-simple algorithm is lower, given that the minimum in both cases is set to residual soil moisture. The average difference at the validation sites is $\sim 0.05\,\mathrm{cm}^3\ \mathrm{cm}^{-3}$.

The magnitude of the difference varies throughout the year, from ~ 0 to 0.1 VSM (Fig. 3). Differences in VSM are greatest at the time of year when amplitude is closest to 1.0, when vegetation is at its seasonal minimum. VSM differences are smallest at the time of year when amplitude is lowest, typically in late spring or early summer, when vegetation reaches it maximum extent. This is counterintuitive because the vegetation correction is greatest when amplitude is lowest. However, phase minima typically occur in mid-summer, which is when both time series are referenced to residual moisture content.

C. Veg-Complex: Multimetric Adjustment for Vegetation Effects

The third algorithm (veg-complex) is described in Chew *et al.* [17], so only a brief explanation is provided here. As for the veg-simple algorithm, the effects of vegetation on the SNR interferogram are based on the model of GPS reflections through a uniform vegetation canopy [11]. The veg-complex algorithm was developed for two reasons: 1) when VWC exceeds 1 kg m^{-2}, amplitude alone is not a good predictor of the phase shift caused by the vegetation canopy; and 2) the veg-simple algorithm is based on a single relationship between VWC, canopy height and other vegetation parameters. In reality, many possible combinations of these vegetation parameters exist.

The veg-complex algorithm uses a lookup table that was constructed using an ensemble of 16 000 model simulations, in which vegetation parameters were varied over the range expected at PBO H_2O sites: VWC less than 3 kg m^{-2}, canopy height less than 1 m, and vegetation gravimetric moisture between 20 and 90 percent. The lookup table, unlike the veg-simple algorithm, consists of the modeled effect of vegetation on all SNR metrics ($\Delta\phi_{veg}$, A_{norm}, $A_{LSPnorm}$, and ΔH_{eff}). The observed SNR metrics are smoothed using a low-pass filter, and then the lookup table is used to identify the model simulation that most closely replicates the three observed SNR metrics. The $\Delta\phi_{veg}$ from that model simulation is used in (6). For any observed A_{norm}, there is a range of possible $\Delta\phi_{veg}$, which is then constrained by the values of the other two metrics ($A_{LSPnorm}$ and ΔH_{eff}) (Fig. 5). This range exists because different types of vegetation canopies (e.g., short, dense vegetation versus tall, sparse vegetation) affect the SNR interferogram in different ways. In contrast, the veg-simple algorithm yields a single value of $\Delta\phi_{veg}$ for each value of A_{norm}. Including $A_{LSPnorm}$ along with A_{norm} provides additional information about $\Delta\phi_{veg}$ because these two amplitude metrics do not simply covary (Fig. 5). For example, $A_{LSPnorm}$ varies from nearly 1.0 to less than 0.7 for $A_{norm} = 0.75$.

There is a second important difference between the veg-complex and veg-simple algorithms. The veg-complex algorithm accounts for changes in S that occur due to the vegetation canopy. Each simulation that was used to create the lookup table was repeated varying the soil moisture beneath the vegetation canopy, yielding a value of S for each combination of vegetation parameters in the ensemble. Once the model simulation that best matches A_{norm}, $A_{LSPnorm}$, and H_{eff} is identified, S for these vegetation conditions is used in (3). The magnitude of S is close to 1.48 when VWC is <1.0 kg m^{-2} and canopy heights are less than ~20 cm, but decreases significantly for both taller canopies with those with greater water contents, perhaps due to the fact that at this point the path through the canopy is on the order of one wavelength.

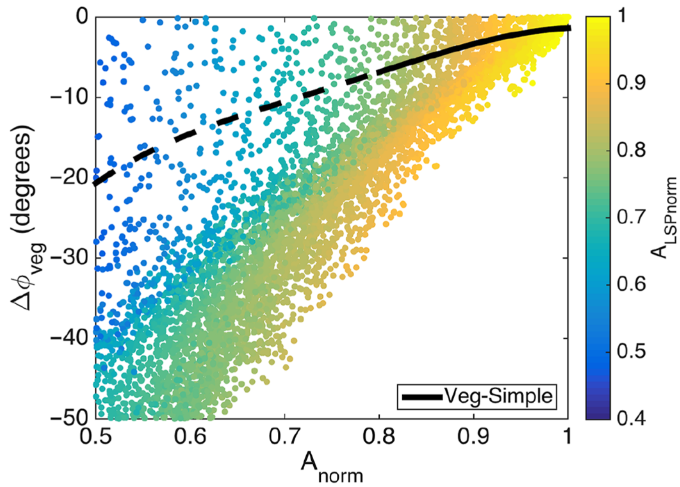

Fig. 5. Black line shows $\Delta\phi_{veg}$ from the veg-simple algorithm, which is calculated only from A_{norm}. The veg-simple algorithm was not originally designed for sites where A_{norm} drops below ~0.8. $\Delta\phi_{veg}$ from the veg-complex algorithm is shown by the points, color-coded based on $A_{LSPnorm}$. Variations in effective reflector height are also considered in the veg-complex algorithm (not shown).

As in the first two algorithms, the veg-complex algorithm requires that the phase time series is zeroed for calculation of absolute soil moisture. First, the median of the bottom 10% of observed phase values is set to zero for comparison to the lookup table. Then, the lookup table is used to estimate $\Delta\phi_{veg}$ and S for each day, yielding the adjusted phase time series, $\phi\prime(t)$. The final VSM time series is then adjusted so that the lowest retrieved soil moisture values correspond to residual soil moisture.

The range of soil moisture is smaller, and the average VSM is lower when the veg-complex algorithm is used, compared to the unadjusted (bare soil) soil moisture time series (Figs. 4 and 6). Thus, the veg-complex algorithm has the same general effect on the soil moisture time series as the veg-simple algorithm. At all sites, soil moisture from the veg-complex algorithm is lower than for the veg-simple algorithm. This is due to a combination of both the $\Delta\phi_{veg}$ and lower S calculated in the veg-complex case. This difference is greatest at the Oklahoma sites, where seasonal peaks in VWC are 1 kg m^{-2} or higher, and the amplitude-only adjustment cannot fully account for the effects of vegetation on the SNR interferogram. The differences between the adjustment from the veg-simple and veg-complex algorithms are discussed more completely below.

IV. Results

We now compare GPS-IR soil moisture estimates to the *in situ* validation data. For this comparison, we split the sites into two groups. First, we evaluate performance of the GPS-IR soil moisture at the eight sites in Colorado and New Mexico. The peak VWC is lower than 1 kg m^{-2} at these sites (Table I), so the veg-simple algorithm is anticipated to be sufficient to adequately represent the effects of the vegetation canopy. At these sites, the operational PBO H_2O soil moisture data are produced using this algorithm. Performance is compared to the bare-soil algorithm, to quantify the importance of accounting for vegetation effects. Second, we evaluate the performance

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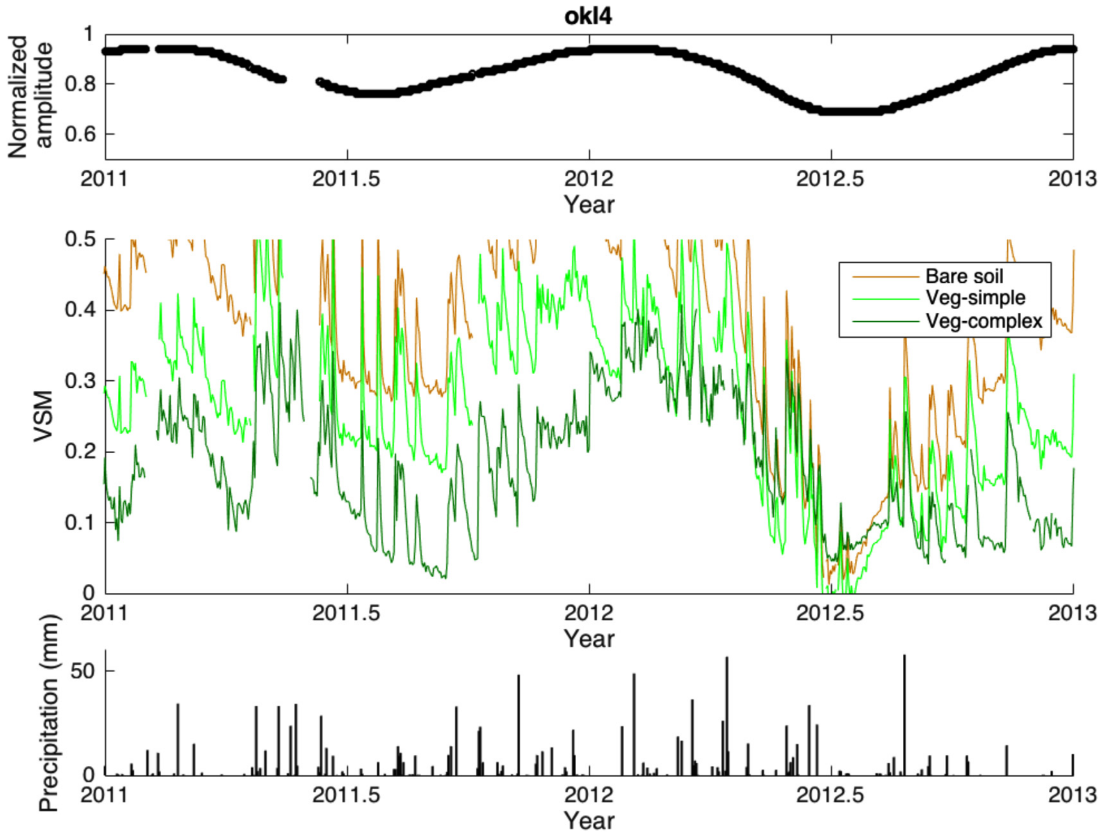

Fig. 6. Top: Smoothed normalized amplitude for site OKL4. Middle: VSM in cm^3 cm^{-3} for site OKL4 using all three algorithms. Bottom: Daily precipitation in mm from NLDAS for the grid cell containing site OKL4.

of the three soil moisture algorithms at the Oklahoma sites. We also include data from P036 (in New Mexico) in the comparison, as it is the only non-Oklahoma site where VWC approaches $1\,kg\ m^{-2}$.

A. Evaluation of Bare-Soil and Veg-Simple VSM at Sparsely Vegetated Sites

We first evaluate the performance of the seven Colorado and New Mexico sites grouped together, and subsequently examine results from individual sites. The veg-simple algorithm provides an accurate measure of 0–6 cm soil moisture (Fig. 7 and Table III). The RMSE between the veg-simple and *in situ* VSM is $0.038\,cm^3\ cm^{-3}$, below the $0.04\,cm^3\ cm^{-3}$ limit required for validation of satellite soil moisture data [20]. There is no bias (Table III), partly due to errors from several sites which tend to cancel one another out: veg-simple VSM tends to be higher than *in situ* at P036 and lower than *in situ* at MFLE. These site-level errors result in scatter around the 1:1 line ($r^2 = 0.83$). A linear regression between veg-simple and *in situ* VSM does not indicate that the veg-simple algorithm results in systematic errors: the slope of the best fit line is 1.02 ± 0.15 with an intercept of 0.01 ± 0.02.

The bare-soil algorithm does not perform as well (Fig. 7 and Table III). RMSE between the base soil and *in situ* VSM is $0.055\,cm^3\ cm^{-3}$, above the $0.04\,cm^3\ cm^{-3}$ limit. This is nearly identical to the RMSE reported by Vey *et al.* [10] also using the bare-soil algorithm. There is a positive bias of $0.04\,cm^3\ cm^{-3}$. Even when this bias is removed, the bare-soil performance is inferior to that from veg-simple: r^2 is slightly lower ($r^2 = 0.78$) and the unbiased RMSE is $0.042\,cm^3\ cm^{-3}$. The differences in performance between the veg-simple and bare-soil algorithms are consistent with the vegetation adjustment described in Section III-B. When the bare-soil algorithm is used, the entire range of observed phase variations is attributed to soil moisture variations. The result is that the range of soil moisture is too high. Once the phase time series is zeroed and linked to residual soil moisture, the average soil moisture is also too high. This is consistent with the positive bias found via comparison to the *in situ* data. This problem is apparent even without comparison to validation data. Bare-soil VSM exceeds the expected saturated water content during some intervals of the year at many sites. This problem cannot be remedied by simply removing a constant bias of $0.03\,cm^3\ cm^{-3}$ (or similar) because the magnitude of the vegetation effects varies seasonally.

Examination of performance on a site-by-site basis is imperfect because most of the sites have six or fewer validation surveys. Even with the limited data, several results are apparent. First, bare-soil VSM is higher than *in situ* VSM at six of the seven sites (MFLE is the exception). This positive bias is largely removed, or at least significantly reduced (P036), by using the vegetation adjustment in the simple-veg algorithm. This result is consistent with the differences between the two algorithms. Second, the r^2 value between GPS-IR and *in situ* VSM is very high: 0.94 or greater at all sites for which there are five or more surveys (Table III). The r^2 value is nearly identical for VSM estimated using the bare-soil and veg-simple algorithms. This shows that the relationship between GPS-IR

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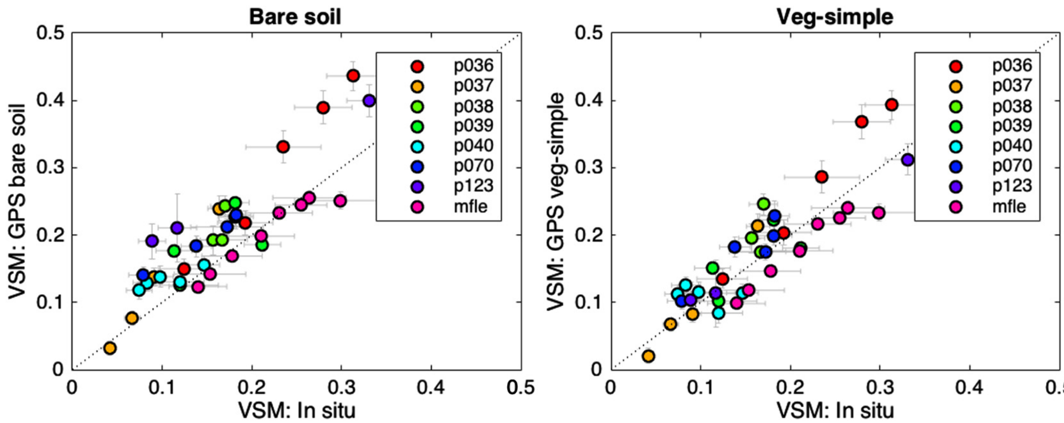

Fig. 7. Scatter plots of GPS-IR versus *in situ* VSM (both in $cm^3\ cm^{-3}$), using the bare-soil algorithm (left) and the veg-simple algorithm (right). The black dashed line is the one-to-one line. Colors indicate site. Horizontal error bars represent one standard deviation for each *in situ* VSM survey. Vertical error bars represent one standard deviation of GPS-IR VSM on the survey date, calculated using phase from individual ground tracks and converted to VSM using S (3).

TABLE III
VEG-SIMPLE AND BARE-SOIL STATISTICS: SITES WITH VEGETATION <1 KG M^{-2}

Site	RMSE		r^2		Slope		Bias	
	Veg_{simple}	Bare	Veg_{simple}	Bare	Veg_{simple}	Bare	Veg_{simple}	Bare
All CO/NM	**0.038**	0.055	0.83	0.78	1.02	0.98	0.00	0.03
P036	0.059	0.087	0.98	0.98	1.45	1.59	0.04	0.08
P037	**0.027**	0.053	0.98	0.98	1.35	1.54	0.01	0.04
P038							0.04	0.04
P039							0.01	0.03
P040							0.02	0.04
P070	**0.030**	0.045	0.95	0.99	0.81	0.74	0.02	0.04
P123							0.00	0.09
MFLE	**0.035**	**0.019**	0.94	0.94	0.91	0.85	−0.03	−0.01

Bold in root-mean-standard error (RMSE) column indicates values are below the $0.04\,cm^3\ cm^{-3}$ standard described in Jackson *et al.* [20]. "Slope" is the slope of the best-fit line between the *in situ* and GPS-IR VSM. Blank cells indicate insufficient data for calculation of site-specific statistics (fewer than 5 validation surveys).

phase and VSM is effectively linear, confirming prior empirical and modeling results [8], [15]. Third, the slope values from linear regression between GPS-IR and *in situ* data (Table III) are close to 1.0, more so from the veg-simple algorithm. This shows that the slope (S) used in (3) provides a reasonable approximation for the scaling between phase and soil moisture variations, especially when the veg-simple adjustment is applied. The exception is at P036, where the slope via regression is nearly 1.5 for veg-simple and even higher when using the bare-soil algorithm. Of the eight Colorado and New Mexico sites, P036 has the greatest seasonal fluctuations in vegetation. Even though the veg-simple algorithm improves upon the bare-soil results, it may not be sufficient to fully represent vegetation effects, at least with the parameter values currently used (Table II). This is evaluated in Section IV-B.

B. Evaluation of Veg-Complex and Veg-Simple Algorithms at Moderately Vegetated Sites

We now compare GPS-IR and *in situ* VSM at the four sites with the greatest seasonal fluctuations in vegetation: the three Oklahoma sites and P036. We compare performance of the veg-simple and veg-complex algorithms. Results from the bare-soil algorithm are not considered, as we showed above this approach is not adequate at the sites with even less vegetation.

The RMSE between veg-complex and *in situ* VSM is $0.039\,cm^3\ cm^{-3}$ when all four high vegetation sites are grouped together, and $0.04\,cm^3\ cm^{-3}$ for the group of three Oklahoma sites (Fig. 8, Table IV). P036 was the only site outside of Oklahoma where the veg-simple algorithm did not achieve the $0.04\,cm^3\ cm^{-3}$ standard (Table III, Section IV-A). Performance at P036 is greatly improved when the veg-complex algorithm is used. For the individual Oklahoma sites, veg-complex is below $0.04\,cm^3\ cm^{-3}$, except at OKL4.

In comparison, performance of the veg-simple algorithm is not nearly as good at the four sites with significant vegetation variations: RMSE is approximately $0.10\,cm^3\ cm^{-3}$, for individual sites or when the sites are grouped together. The failure of the veg-simple algorithm is the product of two factors. First, the veg-simple VSM has a positive bias of $\sim 0.10\,cm^3\ cm^{-3}$. Second, even if the positive bias is removed, the performance of the veg-simple algorithm is not sufficient. The unbiased RMSE is still considerably higher than $0.04\,cm^3\ cm^{-3}$. The veg simple algorithm does not represent all the variations in VSM shown by the data (Fig. 8): r^2 is only 0.5, compared to 0.8 when the veg-complex algorithm is used.

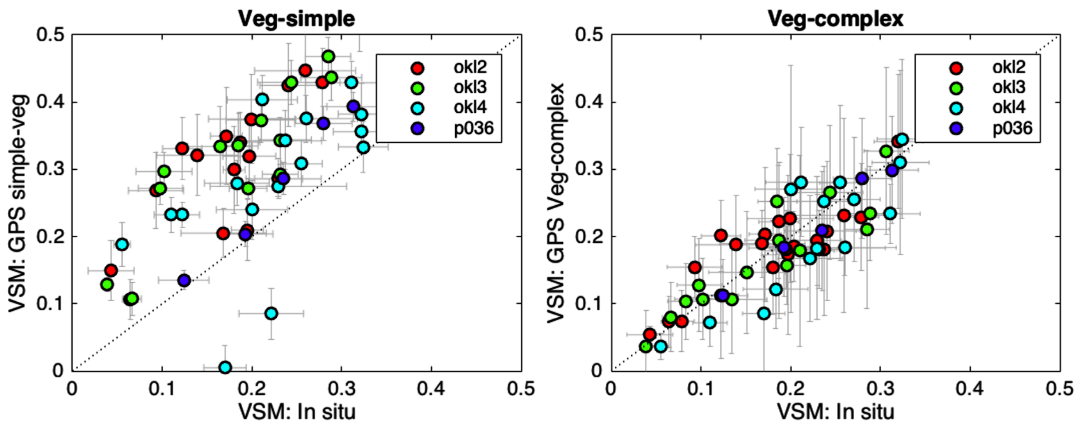

Fig. 8. Scatter plots of GPS-IR versus *in situ* VSM (both in cm^3 cm^{-3}) using the veg-simple algorithm (left) and the veg-complex algorithm (right). The black dashed line is the one-to-one line. Colors indicate site. Horizontal error bars represent one standard deviation for each *in situ* VSM survey. Vertical error bars represent one standard deviation of GPS-IR VSM on the survey date, calculated using phase from individual ground tracks and converted to VSM using S (3).

TABLE IV
VEG-COMPLEX AND VEG-SIMPLE STATISTICS: SITES WITH VEGETATION OF $\sim$1 kg m $^{-2}$

Site	RMSE		r^2		Slope		Bias	
	Veg$_{complex}$	Veg$_{simple}$	Veg$_{complex}$	Veg$_{simple}$	Veg$_{complex}$	Veg$_{simple}$	Veg$_{complex}$	Veg$_{simple}$
All	**0.039**	0.13	0.76	0.49	0.95	1.01	0.00	0.11
OKL ALL	**0.040**	0.14	0.74	0.49	0.95	1.00	–0.01	0.11
OKL2	**0.038**	0.15	0.74	0.58	0.98	1.23	0.00	0.14
OKL3	**0.036**	0.15	0.80	0.81	0.92	1.29	0.00	0.14
OKL4	0.051	0.11	0.72	0.35	0.93	0.84	–0.02	0.06
P036	**0.015**	0.059	0.98	0.98	0.96	1.45	–0.01	0.05

Bold in root-mean-standard error (RMSE) column indicates values are below the 0.04 cm^3 cm^{-3} standard described in Jackson *et al.* [20]. "Slope" is the slope of the best-fit line between the *in situ* and GPS-IR VSM.

The results shown in Fig. 8 indicate that the veg-simple algorithm does not adequately account for vegetation effects at the four sites with the greatest variations in vegetation amount. When the veg-simple algorithm is used, some of the phase variations from vegetation are attributed to changes in soil moisture. As a result, the estimated soil moisture is too high once the time series is zeroed. The two outliers from OKL4 are extreme examples of this problem (Fig. 8). These two data points are from summer of 2012 when normalized amplitude was the lowest for all validation points. The veg-simple VSM is too low because the phase adjustment for vegetation (6) was not large enough. Below, we discuss if different parameters in (4) and (5) could be used to increase the sensitivity of the veg-simple algorithm.

V. DISCUSSION

We now use the results described above to develop recommendations for selecting which of the three soil moisture algorithms should be used, given conditions at a site and objectives of the monitoring.

The bare-soil algorithm described by Chew *et al.* [15], and tested by Chew *et al.* [15] and Vey *et al.* [10], provides estimates of VSM that may be acceptable for some applications. However, the effects of vegetation on phase are ignored. As a result, the bare-soil VSM time series have a larger range than collocated *in situ* measurements, and a positive bias once the phase time series are linked to residual soil moisture. Even if the bias was removed, significant errors remain due to seasonal fluctuations in vegetation and its effect on phase. Even the unbiased errors exceed the limit set for satellite validation [20]. The Colorado and New Mexico validation sites used here are not heavily vegetated. At these sites, the vegetation is typical for temperate climates with $\sim 300-600$ mm y^{-1} of precipitation. Even with this limited vegetation, the effects on phase are considerable and the bare-soil algorithm is not optimal. The bare-soil algorithm may be sufficient for arid sites or other locations free of vegetation (e.g., [10]), but data from these types of sites were not considered here.

The veg-simple algorithm provides acceptable performance at typical sites in the PBO H_2O network (RMSE $<$ 0.04 cm^3 cm^{-3}). The vegetation adjustment algorithm is simple to implement, requiring only that a smoothed time series of SNR amplitude is used in conjunction with phase. The veg-simple algorithm can also be used at bare-soil sites and sites with very limited vegetation. At these sites, the phase adjustment will be minimal (or zero), and the soil moisture time series from the veg-simple and bare-soil algorithms will be identical. Therefore, we recommend use of the veg-simple algorithm at sites where VWC fluctuates by less than 1 kg m^{-2}. This limit should be considered an approximate guideline.

The parameter values used in the veg-simple algorithm (Table II) are based on model simulations, designed to replicate collocated GPS and vegetation data from only five sites [11]. The parameter values used here are likely not optimal for all PBO H_2O sites, or sites in other networks. Using these values, the phase adjustment from the veg-simple algorithm is similar to that from the veg-complex algorithm for normalized amplitudes between 0.85 and 1.0 (Fig. 5). However, the phase adjustment calculated in the veg-simple algorithm is considerably less for amplitudes below 0.85. Different parameters values could improve the agreement between the phase adjustment from the veg-simple and veg-complex algorithms for amplitudes <0.85. This would improve performance of the veg-simple algorithm at sites where VWC is close $1\,\mathrm{kg\ m^{-2}}$, e.g., P036. This could also extend the range of the veg-simple algorithm to environments with VWC greater than $1\,\mathrm{kg\ m^{-2}}$, where the veg-simple algorithm yields VSM values that are too high. Even if this bias is removed, the veg-simple algorithm cannot represent the range of $\Delta\phi_{veg}$ that exists at any normalized amplitude value, resulting from differences in geometry, height, and water content of the vegetation canopy. The other metrics ($A_{LSPnorm}$ and ΔH_{eff}) are needed to more accurately estimate $\Delta\phi_{veg}$. In addition, the veg-simple algorithm does not allow for changes in S caused by the vegetation canopy.

The veg-complex algorithm yields the best performance at sites where fluctuations in VWC are $\sim 1\,\mathrm{kg\ m^{-2}}$. This algorithm also performs well at sites with less vegetation, yielding error statistics very similar to those from the veg-simple algorithms. Use of the veg-complex algorithm is warranted at sites where fluctuations in VWC are $\sim 1\,\mathrm{kg\ m^{-2}}$ or greater. However, preliminary data from agricultural sites with VWC greater than $4\,\mathrm{kg\ m^{-2}}$ indicate that the lookup table may not be sufficient for these environments. Therefore, while the veg-complex algorithm does extend the sensing capability of GPS-IR, it still may not be possible to estimate soil moisture via GPS-IR at sites with the greatest fluctuations in VWC. Given the additional SNR metrics and data processing required by the veg-complex algorithm, we recommend that the veg-simple algorithm should be considered the default to use at all sites, since in many cases the two algorithms perform equally well. If, after implementing the veg-simple algorithm, there is still a seasonal vegetation effect observable in the data or if A_{norm} drops below ~ 0.75, then the veg-complex algorithm could be implemented.

Finally, we note that adjusting for vegetation effects is not the only challenge faced when estimating soil moisture via GPS-IR. There are multiyear trends or shifts in SNR metrics that are unrelated to vegetation. If not accounted for, these changes will impact the VSM time series, regardless of the vegetation algorithm used. Although rare, we have found instances where a satellite was maneuvered by the U.S. Department of Defense (DoD) in a way that introduced a small bias in phase. This change was irrelevant for sites with little terrain variation, as is the case for almost all PBO H_2O sites. Since we can easily determine when the satellites are maneuvered, this effect can be removed. The addition of new satellites (and their associated ground tracks) through time can cause shifts in all SNR metrics. In our experience, the first thirty days of data for any new GPS satellite should be discarded for GPS-IR, as this is when the DoD is most likely to be implementing small changes in its orbit. One approach to mitigate the errors resulting from these changes is to zero the VSM time series annually, rather than just once for an entire time series.

VI. Conclusion

1. The bare-soil algorithm yields VSM time series with errors that exceed $0.04\,\mathrm{cm^3\ cm^{-3}}$, even at sites where VWC varies by only $0.5\,\mathrm{kg\ m^{-2}}$ throughout the year. Even vegetation fluctuations of this magnitude affect the phase time series enough to yield considerable soil moisture errors.
2. The veg-simple algorithm provides improved performance (RMSE $< 0.04\,\mathrm{cm^3\ cm^{-3}}$) at sites where VWC varies by less than $\sim 1.0\,\mathrm{kg\ m^{-2}}$, typical of sites in the PBO H_2O network. The vegetation adjustment is based only on a smoothed time series of SNR amplitude, and thus is simple to implement across an operational network.
3. The veg-complex algorithm extends the range of GPS-IR soil moisture sensing to sites with greater variations in VWC. This algorithm should be used at sites where the veg-simple algorithm fails to provide reasonable soil moisture time series.

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