Zhang et al.: Use of GNSS SNR data to retrieve soil moisture and vegetation variables over a wheat crop, Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-152, 2017.

RESPONSE TO REVIEWER #1

The authors thank anonymous reviewer 1 for his/her review of the manuscript and for the fruitful comments.

1.1 [The study deals about soil moisture, vegetation height and phenological stages estimation by GNSS for a site in southern France and validation to in situ measurements and model simulations. The approach is sound, the manuscript well-written and adequate for the audience of HESS. Because of its high quality, just few attempts need to be made to improve the presentation of the study. E.g., a brief discussion how much in situ (soil moisture) data is necessary to retrieve soil moisture from GNSS signal could clarify the need for adequate calibration.]

Response 1.1:

Retrieving absolute VSM values in m^3m^{-3} is possible after a calibration phase. The minimum VSM has to be derived from the *in situ* observations during the experimental time period in order to determine the VSM_{resid} term in Eq. (6). Moreover, a locally adjusted value of the *S* parameter is needed. The retrieval of the *S* parameter requires at least one or two months of VSM *in situ* observations because soil moisture conditions ranging from dry to wet need to be sampled. However, if a scaled soil wetness index is used instead of soil moisture (see Response 1.17), no *in situ* VSM observations are needed. This aspect will be clarified in the revised manuscript.

1.2 [During the investigation period little soil moisture variation has been recorded by in situ and GNSS sensors. The authors should discuss this low range and its relationship to the retrieval accuracy of 0.03 m^3m^{-3}.]

Response 1.2:

Yes, a short period of time is considered in this study. Vey et al. (2015) used the method from Chew et al. using field observations over a long period of time (2008-2014) for a site presenting a high percentage of bare soil. They obtained the following scores for GPS VSM retrievals: R^2 = 0.8, RMSE = 0.05 m^3m^{-3}. We successfully assessed this method for a wheat crop field. But the little soil moisture variation in the experiment time period limited the representativeness of the retrieval accuracy. Longer time periods should be investigated in further studies. We will clarify this in the revised manuscript.

1.3 [Similarly, longer time periods should be envisaged for further studies, this delivers the basis for further statistical methods such as Triple Collocation. This would better identify the different uncertainties between the data sets. Especially with the very good results of ISBA simulations, one could question the need for (additional) GNSS measurements.]

Response 1.3:

Yes. In situ VSM observations are not widespread in France and the ISBA simulations are key for water resource monitoring at the country scale. It must be noted that the ISBA model is forced by the SAFRAN atmospheric analysis and that SAFRAN is able to integrate thousands of in situ raingage observations over France. However, in situ VSM observations are needed to validate land surface models and/or satellite-derived products (e.g. Albergel et al., 2010). From this point of view, the spatial resolution of GNSS retrievals is an asset. The area sampled by GNSS retrievals is much larger than what can be achieved using individual soil moisture probes and much smaller than pixel size of satellite-derived products. Longer time periods of GNSS retrievals should be envisaged to serve as independent validation data sources in statistical methods such as Triple Collocation (Dorigo et al., 2010).

References:

Albergel, C., J.-C. Calvet, P. de Rosnay, G. Balsamo, W. Wagner, S. Hasenauer, V. Naemi, E. Martin, E. Bazile, F. Bouyssel, J.-F. Mahfouf, "Cross-evaluation of modelled and remotely sensed surface soil moisture with in situ data in southwestern France", Hydrol. Earth Syst. Sci., 14, 2177–2191, 2010b.

Dorigo, W. A., Scipal, K., Parinussa, R. M., Liu, Y. Y., Wagner, W., de Jeu, R. A. M., and Naeimi, V.: Error characterisation of global active and passive microwave soil moisture datasets, Hydrol. Earth Syst. Sci., 14, 2605–2616, doi:10.5194/hess-14-2605-2010, 2010.

1.4 [Soil moisture retrieval results could better be discussed by including recent literature and comparing to other GNSS soil moisture retrieval methods.]

Response 1.4:

The method from Chew et al. is the latest proposed method, as far as we know. We will further increase the accuracy of our GNSS VSM retrievals using a scaled soil wetness index in the revised manuscript (see Response 1.17).

1.5 [The authors ask the question if phenological stages can be inferred from GNSS. The outcome and visibility of the paper could be increased by giving more specific information about different stages or managements, e.g. in form of an index or threshold for wheat as an important representative for all cereals.]

Response 1.5:

We found in our case study, that the tillering date (12 March) obtained from a GDD model is close to the start date (10 March) of a multiple peak period (see Section 5.5), when the vegetation height is about 20 cm, close to one wavelength. Flowering and ripening occur towards the end of the growing period when the vegetation height is no longer increased compared with 15 days before but slightly declines due to wheat heads tipping down. In order to confirm these findings, it could be recommended to perform GNSS-R measurements further over wheat fields and other crops, together with phenological stages observations. We will clarify this in the revised manuscript.

1.6 [Specific comments: Abstract: More information about the retrieval method should be added.]

Response 1.6:

Soil moisture is retrieved from the multipath phase assuming the relative antenna height is constant, and the vegetation height is retrieved using the SNR's dominant period derived from a wavelet analysis. We will rephrase the abstract accordingly.

1.7 [P. 2, L. 10f: Refer also to the other L-band satellite SMAP.]

Response 1.7:

Yes, we will cite the Soil Moisture Active Passive (SMAP) mission (Chan et al., 2016), in addition to SMOS.

Reference:

Chan S. K., Bindlish, R., O'Neill, P. E., Njoku, E., Jackson, T., Colliander, A., Chen, F., Burgin, M., Dunbar, S., Piepmeier, J., Yueh, S., Entekhabi, D., Cosh, M. H., Caldwell, T., Walker, J., Wu, X., Berg, A., Rowlandson, T., Pacheco, A., McNairn, H., Thibeault, M., Martínez-Fernández, J., González-Zamora, A., Seyfried, M., Bosch, D., Starks, P., Goodrich, D., Prueger, J., Palecki, M., Small, E. E., Zreda, M., Calvet, J.-C., Crow, W., and Kerr, Y.: Assessment of the SMAP passive soil moisture product, IEEE Trans. Geosci. Remote Sens., 54 (8), 4994 - 5007, doi:10.1109/TGRS.2016.2561938, 2016.

1.8 [P. 3, L. 15: introduce L2C.]

Response 1.8:

The SNR of L2C signal is only transmitted by the recent Block IIR-M ("Replenishment Modernized") and IIF ("Follow-on") GPS satellites, which is with higher power and more precise than the signal L1 C/A. We will introduce L2C in the revised manuscript.

1.9 [P. 3, L. 26: What characterizes the dominant period?]

Response 1.9:

The definition of the dominant period is: the peak period of the average power spectrum from the valid SNR segment data at elevation angles ranging from 5 to 20 degrees. We will clarify this in the revised manuscript.

1.10 [P. 4, L. 10: Introduce PBO.]

Response 1.10:

PBO H_2O is an initiative to translate data from the Plate Boundary Observatory (PBO) sites of the GPS network in the western United States into environmental products (Larson, 2016).

1.11 [P. 5, L. 15: Start the section with explaining the aim of the calculations.]

Response 1.11:

Due to the motion of the GPS satellites, the path delay δ between the direct and reflected signals cause an interference pattern in the signal power of SNR data. The SNR frequency/period is directly affected by the perpendicular distance from the antenna to the dominant reflecting surface. Provided the reflecting surface is stable, the a priori antenna height can be used to estimate the SNR frequency. The SNR frequency is used to calculate the multipath SNR phase. Then, the SNR phase is used to estimate VSM. If the reflecting surface is changing in response to vegetation growth, vegetation height can be retrieved instead of VSM by directly estimating the dynamic SNR frequency/period with a wavelet analysis.

1.12 [P. 6, L.10: Again, explain in one or two sentences the general concept of soil moisture retrieval before starting the details of this section.]

Response 1.12:

As the SNR frequency is known (Eq. (3)), it is possible to estimate the SNR amplitude and phase. Larson et al. (2008) and Larson et al. (2010) showed that phase varies linearly with near-surface VSM (R^2 = 0.76 to 0.90). This result was used by Chew et al. (2014) to develop an algorithm to estimate surface soil moisture (top 5 cm) over bare ground.

1.13 [P. 7, L. 9: A discussion about the reasons and needs for omitting a soil moisture retrieval under vegetation is necessary. Why were alternative methods not used?]

Response 1.13:

In conditions of significant vegetation effects, Chew et al. proposed an algorithm able to correct the phase for vegetation effects. Firstly, $A_{LSPnorm}$ and ΔH_{eff} are derived by a Lomb-Scargle Periodogram (LSP) method. Then the observed SNR metrics (A_{norm}, $A_{LSPnorm}$ and ΔH_{eff}) are smoothed using a low-pass filter (Savitzky-Golay filter or moving average filter). A linear nearest neighbor search algorithm with A_{norm}, $A_{LSPnorm}$ and ΔH_{eff} is used to find the estimated phase (φ_{veg}) caused by vegetation in a modeled lookup table. The φ_{veg} values derived from the lookup table are then smoothed through time using the same filter. Then the expected phase changes (φ_{VSM}) due to soil moisture is equal to $\varphi_{VSM} = \Delta\varphi - \varphi_{veg}$, where $\Delta\varphi$ is the original observed phase change. This algorithm is based on the assumption that the total phase change is a linear combination of the phase change due to soil moisture and of the phase change due to vegetation. Another important difference for retrieving soil moisture with significant vegetation effects is that the slope (*S*) of the relationship between phase (φ_{VSM}) and soil moisture changes throughout the year. *S* is a function of time, which also needs to be searched for in the lookup table. Additionally, this algorithm is based on an unpublished lookup table for new L2C GPS signals. Since the receiver we used could not track L2C signals and since we could not access a relevant lookup table, we were not able to correct for vegetation effects and we retrieved surface soil moisture over a period with rather sparse vegetation, from 16 January to 5 March.

1.14 [P. 10, L. 3: how independent are the in situ data when some have been used for calibration? This needs to be clarified.]

Response 1.14:

With the a priori S = 0.0148 $m^3m^{-3}degree^{-1}$, only the minimum soil moisture observation during the time period is used as the VSM_{resid}. We also used the *in situ* soil moisture observations and phases from SNR data to fit the local slope: S = 0.0033 $m^3m^{-3}degree^{-1}$. In this situation, only ISBA simulations can be considered as independent from the GNSS retrievals. This aspect will be clarified in the revised manuscript.

1.15 [P. 10, L. 11ff: The reason for larger variability in GPS daily soil moisture estimates could be found in different locations observed. During satellite overpasses the observed location moves within the larger "footprint" of the GNSS system.]

Response 1.15:

Yes. Larger variability in GPS sub-daily VSM estimates might originate from the different locations observed. Many local environment factors such as vegetation effects, precipitation, changes in soil roughness and soil composition, can perturb the GPS VSM estimates. During satellite overpasses the observed location changes together with the size of the footprint (the First Fresnel Zone) of the GNSS system, in relation to the antenna height and elevation angle range. It might be another cause of the sub-daily variability of VSM estimates. Additionally, issues with the SNR data of the L1 C/A signal and the receiving antenna gain pattern may also affect the VSM estimates.

1.16 [P. 11, L. 12: What is the reason for using a curve smoothing procedure? What are the reasons for the leveling effect?]

Response 1.16:

The possible causes of the leveling effect are discussed in Section 5: (1) the occurrence of more than one dominant reflecting surface at different heights (Sect. 5.3) and (2) rapid phenological changes in the wheat canopy triggering a response of the H retrieval (Sect. 5.5). It must be noted that absolute daily changes in H (and h), of about 1.1 cm d^{-1} are fairly uniform throughout the growing period. Since h decreases when plants grow, relative changes in h tend to increase. According to Eq. 4, T behaves similarly. This means that the sensitivity of the retrieval method to changes in H is larger at the end of the growing period. This is probably why leveling is more pronounced between mid-March and mid-April than at the end of April (see Fig. 7). Leveling is less noticeable in May.

1.17 [P. 12, L. 22ff: The authors could show the retrieval of a soil wetness index and relate it to in situ soil moisture by multiplying it to porosity (from in situ measurements or soil maps).]

Response 1.17:

Yes. The phase time series can be normalized for each satellite track. Then the median value of the normalized phases from all available satellite tracks can be considered as the final soil wetness index (φ_{index}) for each day as shown in Fig. R1.1 (red line).

$$\varphi_{index} = \frac{\varphi - \varphi_{\min}}{\varphi_{\max} - \varphi_{\min}} \tag{R1.1}$$

This soil wetness index time series is linearly related with in situ observations ($R^2 = 0.74$) and ISBA simulations ($R^2 = 0.65$). Moreover, VSM can be estimated from φ_{index}

$$VSM = VSM_{obs\_\min} + \varphi_{index} \cdot (VSM_{obs\_\max} - VSM_{obs\_\min}) \tag{R1.2}$$

VSM_{obs_min} and VSM_{obs_max} are the minimum and maximum *in situ* VSM observations during the experimental time period, respectively. Figure R1.2 presents the estimated VSM from GPS soil wetness index (φ_{index}), together with *in situ* VSM observations and ISBA simulations. More related scores are shown in Table R1.1 and the scatter plot between GPS retrievals from φ_{index} and *in situ* observations are shown in Fig. R1.3. We will present these results in the revised manuscript.

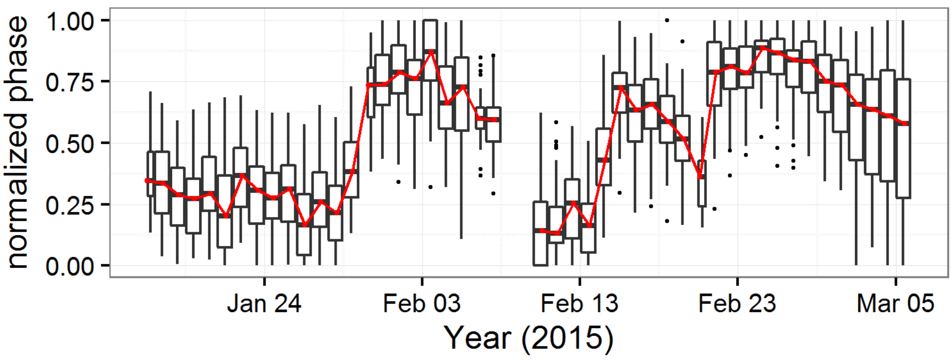

Fig. R1.1 - Median of the daily GPS normalized phases (soil wetness index, red line) and their daily statistical distribution (black box plots) for all available satellite tracks from 16 January to 5 March 2015.

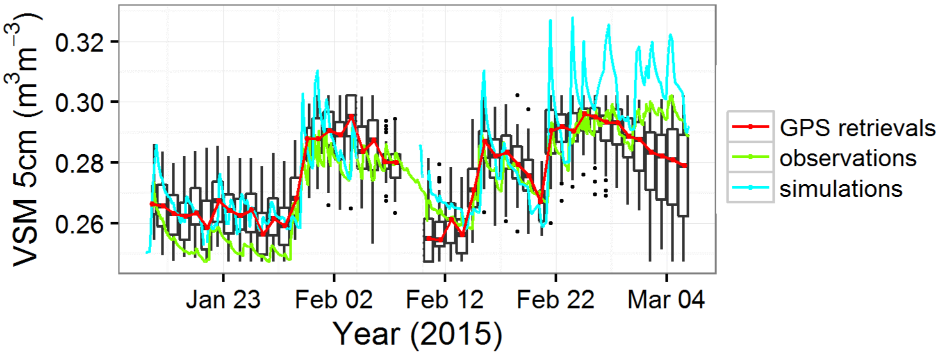

Fig. R1.2 - In situ daily mean surface volumetric soil moisture (VSM) observations at 5 cm depth (green line), ISBA daily mean simulations (blue line), median of the daily GPS retrievals with soil wetness index (red line) and their daily statistical distribution (black box plots) for all available satellite tracks from 16 January to 5 March 2015.

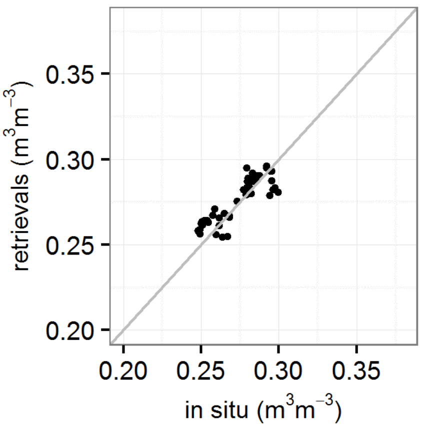

Fig. R1.3 - Scatter plot between GPS retrievals (Eq. (R1.1)) and *in situ* VSM observations (m^{3}m^{-3}) from 16 January to 5 March 2015.

Table R1.1 - Soil moisture scores from 16 January to 5 March 2015

	GPS vs. *in situ*	GPS vs. ISBA	GPS vs. *in situ*	GPS vs. ISBA	GPS (φ_{index}) vs. *in situ*	GPS (φ_{index}) vs. ISBA	ISBA vs. *in situ*
S ($m^3m^{-3}deg^{-1}$)	0.0148		0.0033		-	-	-
N	47	43	47	43	47	43	43
MAE (m^3m^{-3})	0.036	0.034	0.011	0.018	0.007	0.009	0.009
RMSE (m^3m^{-3})	0.046	0.041	0.014	0.022	0.009	0.012	0.010
SDD (m^3m^{-3})	0.036	0.037	0.009	0.012	0.008	0.011	0.006
Mean bias (m^3m^{-3})	0.029	0.019	-0.010	-0.018	0.003	-0.005	0.008
R^2	0.73	0.63	0.73	0.63	0.74	0.65	0.88