July 15th, 2016

Dear Prof. Franssen,

We thank the editor and 3 reviewers for their insightful comments and constructive criticism. In the uploaded files you will find a clean revised manuscript, a marked up manuscript and a detailed response to reviewer's comment. We look forward to publication of this manuscript in HESS.

Sincerely,

Trenton E. Franz

Editor Decision: Reconsider after major revisions (22 Jun 2016) by Prof. Harrie-Jan Hendricks Franssen
Comments to the Author:

Dear Dr Avery,

Your manuscript "Incorporation of globally available datasets into the cosmic-ray neutron probe method for estimating field scale soil water content" has been subjected now to review by three reviewers. Two of them recommended major revision and one of them minor revision. I think the paper can be reconsidered after major revision.

The main points to be handled are:
1. The advantage of using globally available soil datasets should be demonstrated more convincingly.

The third reviewer suggested changing the title to indicate that this paper is most appropriately used for rover applications. The new title is "Incorporation of globally available datasets into the roving cosmic-ray neutron probe method for estimating field scale soil water content". Standard best practices of local calibrations should still be used for fixed probes. This point was made several times throughout the manuscript (L22-24, L558-562).

2. Some variables which also influence neutron intensity (e.g. below-ground biomass) should be considered as well.

We have added text and citations for the need to incorporate below ground biomass. Details are provided in the response to reviewer 1 (see L255-260 for specific language).

3. The relation between neutron intensity and soil moisture content should be modelled according the model by Köhli et al. (2015).

We have added text describing this weighting procedure (L266-268). Unfortunately, only the nominal locations of sampled points were recorded during data collection and understanding of *probe response at the time. Therefore, we decided to use the simpler averaging technique instead of the more rigorous Köhli et al. (2015) sampling design. We also indicate that this is a first step towards incorporating global and regional datasets and expect future efforts to using higher spatial resolution products like SSURGO and Polaris (Chaney et al., 2016). The following text was added:*

L555-558: "We note that this analysis is a first step in the incorporation of existing soil databases that will no doubt continue to increase in spatial resolution and accuracy. Given the increasing use of the roving CRNP technology, we anticipate similar analyses and procedures will be undertaken on regional and local scales from existing and new databases as they become available."

In your answer to the main points and detailed comments, please indicate how comments have been handled exactly, indicating also whether text has been deleted and what the position of newly included text blocks is. I am looking forward to the new version of the paper.

The remainder of this document highlights the changes made and new location in the marked up manuscript that is provided in addition to the clean manuscript.

Best regards,

Harrie-Jan Hendricks Franssen - editor -

H. Bogena (Referee)
h.bogena@fz-juelich.de
Received and published: 22 March 2016

The mobile monitoring of cosmic-ray neutrons using cosmic rovers is a promising way to non-invasively measure soil moisture at larger scales. However, for the processing of cosmic rover data ancillary information is needed (e.g. soil and vegetation properties). This paper describes and tests methods to provide this information using commonly available data sets. The manuscript is well written, however it contains some unclear or incomplete scientific reasoning that need to be amended (see comments below).

General comments:
This study investigates relationships between vegetation indices from optical remote sensing and above ground biomass. However, there is already a vast amount of literature on this topic, see e.g. Kumar et al. (2015) and Duncan et al. (2016) for recent reviews on this topic. Thus, the findings of this study should be discussed also in the light of results from existing literature. For instance, already established relationships could be compared with those from this study or could be used to extend the presented method to other vegetation types.

We thank the reviewer for the updated literature and have investigated the suggested literature. The field of remote sensing and available indices on vegetation characteristics is growing at an

enormous rate given the interest in precision agriculture, food and water security, by both public and private industry.
We have added the following text:
L370-374:" We note that a variety of vegetation indices exist in the literature (c.f. Kumar et al. 2015 and Duncan et al. 2016) and that this analysis is a first step for use with maize and soybean. We anticipate that other vegetation indices may be more appropriate with use in other crops or vegetation types and more research is needed in this area.".

The usefulness of the derived soil properties from the GSDE data for CNRP rover applications needs to be better documented. At the moment, I am not fully convinced that the GSDE data is actually useful for CNRP rover applications.

We anticipate this is a first guess for a study or useful for rover applications in novel or austere environments. For example, the US government is interested in the rover technology and has supported research for assessing things like battlefield condition, which include information on soil strength and stability. The ability to make realtime soil moisture maps in hostile environments is of practical application to governments. In addition the monitoring of long transects, say a rover mounted on a train or commercial vehicle would be labor intensive for detailed sampling efforts.
In order to highlight this as a first step we have changed the title and added the following text to the discussion:
L558-562: "We note that this analysis is a first step in the incorporation of existing soil databases that will no doubt continue to increase in spatial resolution and accuracy. Given the increasing use of the roving CRNP technology, we anticipate similar analyses and procedures will be undertaken on regional and local scales from existing and new databases as they become available.".

First, it is recommended to determine these parameters from in-situ soil samples anyway (L503-505).

Yes, for the highest quality datasets it would still be advisable to collect local samples. I am not sure that will ever change for use of available soil datasets. We are excited about the possibility of using CONUS datasets like Polaris, which is a new 30 m product generated for high-resolution land surface modeling (Chaney et al., 2016, Geoderma). This same procedure can be used for incorporating the Polaris dataset in future roving CRNP work.

For instance, Franz et al. (2015) simply used the average values of these parameters derived from in-situ soil samples to successfully determine soil moisture for an area of 12 *12 km using the CNRP rover. A 12 *12 km area already seems to be the maximum area achievable by CNRP rover applications due to the speed limitation dictated by the CNRP sensitivity.

This scale and driving speed was selected in order to provide a soil moisture map at the critical agricultural 0.8 km resolution. For coarser spatial resolutions higher driving speeds and larger sampling areas would be appropriate. For example, this summer the UNL and USACE rovers have been used in tandem in the SMAPVEX16 Iowa campaign. The dual rovers cover 36x36 km for validation against SMAP. We have found the pixel can be driven in 6 hours to collect a 1 km *product. Direct soil and vegetation sampling of a 36x36 km grid very labor intensive requiring a team of 25+ individuals. We note that the Chrisman and Zreda 2013 paper also covered a large pixel.*

Secondly, given the very low spatial resolution of the GSDE soil data, it will most likely not provide any useful spatial information for such a small area.

Agreed, we are currently using SSURGO for Nebraska based work. For other countries, particularly in the developing there may be very poor national scale soil data bases. We would only recommend the GSDE for long transects, larger watershed sampling campaigns, or use in austere environments where SSURGO type data is not available. We are also excited about the new Polaris 30 m resolution dataset (Chaney et al. 2016). We know other regional databases exist and will be better for use in rovering. We emphasize that this is a first step and a similar methodology can be used with higher resolution and regional databases (L558-562).

Thirdly, the substantial uncertainties of relationships between the GSDE data and CNRP calibration parameters may lead to very uncertain calibration results (see also my specific comment L329). Thus, regional soil data bases like SSURGO in the USA or the soil information system FISBo in Germany would be more promising for CNRP rover applications.

Note that the GSDE data is derived from SSURGO following Shangguan et al. (2014). For hi-resolution surveys we would also suggest use of SSURGO and Polaris. We imagine other regional datasets exist as well, such as FISBo in Germany. The LSM community has generated a variety of products to support their increasing grid resolutions.

The error propagation method is useful to derive first guess estimates of the uncertainties involved in the proposed method. However, a stronger test would be the application of the method using data from existing CRNP rover applications (e.g. Christman et al. (2013), Dong et al. (2014), Franz et al. (2015).

Yes, this is a first approximation as suggested. Not totally sure what the reviewer is suggesting. In fact, the lattice water and soil bulk densities used in Chrisman, Dong and Franz are part of the dataset presented here. Seems having new independent samples to compare against would be most useful and avoid some circularity. We have suggested best practices for future rover surveys in 4.3, which include local soil sampling and independent SWC comparisons. Given the interest in the rover technology we anticipate other research groups will provide new datasets and strategies to generate the most accurate SWC information.

This study excludes below ground biomass, which can be a significant hydrogen pool depending on vegetation type (e.g. Bogena et al., 2013, Franz et al., 2013). Thus, the presented method should be extended by this factor. For instance, the plant specific root-shoot ratio could be used to calculate below ground biomass from above ground biomass (see e.g. Peichl et al., 2012).

Correct. However, we note that the above ground biomass estimates used to compute N0 slope and intercept corrections implicitly include below ground biomass in the N0 estimate. This means the method depends on the repeatability of below ground biomass development with

above ground biomass that is measured. This is essentially what the reviewer is suggesting by using a plant specific root-shoot ratio. We note this as an alternative procedure to encourage future directions and independent validations of the N0 biomass correction factors for above and below ground biomass.
We have added the following text: L256-260:" We also refer the reader to Coopersmith et al. (2014) and Baatz et al. (2015) for further discussion of CRNP use in forest canopies and Bogena et al. (2013) for a discussion of below-ground biomass and litter layers. In addition, plant specific root-shoot ratios (Peichl et al., 2012) or allometric relationships (Jenkins et al., 2003) may be used to derive a better understanding of the impact of time-varying below-ground biomass on N_0. This is an open and challenging research area and beyond the scope of the current work.".

Specific comments:
L60-61: This is not entirely true. In fact in-situ measurements of soil moisture have certain correlation lengths that can be used to infer larger scale information (e.g. Korres et al., 2015).

Thank you for the suggested paper, we have modified the text.
L65-67:"However, these sparse networks are difficult to place in the context of the surrounding landscape given the multifractal behavior that soil moisture fields exhibit (Korres et al. 2015)."

L70: A more recent review on non-invasive sensing of soil moisture dynamics from field to catchment scale is given by Bogena et al. (2015).

Thank you for the suggested paper, we have updated the citation.

L78: According to Köhli et al. (2015) the footprint diameter ranges between 160 and 210 m.

We have updated the test to be more general here in the introduction and more specific in the methods. See comments below.
L88-90: "CRNPs estimate the area-average SWC because neutrons are well mixed within the footprint of the sensor which typically has a radius of several hundred meters and depths of tens of decimeters (Desilets and Zreda 2013, Köhli et al., 2015)."

L91: Baatz et al. (2014) is more appropriate here. This paper deals with CRNP calibration, whereas Baatz et al. (2015) describes a method for biomass correction of CRNP count rates.

The citation was changed.

L94: Add a citation, e.g. Baatz et al. (2015)

The citation was added.

L96: "exploit" instead of "harness"

The text was changed.

L103: “instead” instead of “in lieu”

The text was changed.

L109: CONUS was explained in the abstract, but it would be good to explain it here again because of readers ignoring the abstract.

The text was changed.

L133: “Köhli”

The text was changed.

L144: see comment L78

The text was changed.

L147: “Köhli”

The text was changed.

L147-148: Köhli et al. also investigated effects of vegetation and SWC.

Thank you, we have updated the citation and added more description about the (Köhli et al., 2015) footprint calculations.

L152: Change into “Baatz et al. (2014)”

The citation was changed.

L170: The geomagnetic latitude is not a factor for the neutron counts correction. It is only used for the scaling of neutron counts to a specific location.

From rover calibration across Nebraska we have found that the estimate of p0 (reference pressure) and scaling factor must be consistent for a single rover calibration function at different locations. In order to estimate a site's p0 and scale factor we use latitude, longitude, and elevation in the COSMOS scaling calculator (http://cosmos.hwr.arizona.edu/Util/calculator.php). This ensures that each new site or rover survey point has the same values and neutrons are corrected in the same way. We have added the language of scaling factor for completion (L209-212).

L212-213: To solve the calibration function, information on depth-weighted average soil water content is needed as well. In addition, the depth-weighted average of mentioned parameters should be used to account for the decreasing sensitivity of the CRNP with depth (see e.g. Köhli et al., 2015). Furthermore, below ground biomass can be an important hydrogen pool for certain vegetation types especially during dry conditions, e.g. sugar beet, spruce forest etc. (see Bogena et al., 2013).

Perhaps it is unclear but we only trying to solve for the average soil water content from neutron counts. The issue of depth sensitivity may indeed be important, particularly during infiltration events where a step function of water content may exist. In addition, these step functions may also be present in soil horizons or root development, making vertical integration challenging for a nonlinear sensitivity function. We will mention these issues but prefer to deal with the challenge of horizontal measurements only in this paper instead of the more complex issue of horizontal and vertical variability of parameter data. We believe this will keep the focus of the paper on global datasets clearer. In addition, we note the collected in-situ datasets did not always vertically resolve the calibration datasets. Finally we not that the GSDE and SSURGO datasets do allow for depth information to be extracted and we recommend future research using this and more complete and vertically resolved calibration datasets. This is highlighted in the discussion.

The following text was added here: L264-271: " In the simplest form, the calibration function summarized in equations (1-4) requires depth-average estimates of three soil parameters, θ_{LW}, θ_{SOC}, and ρ_b, and two vegetation parameters SWB and SDB. We note that depth-weighted average parameters, belowground biomass and depth-weighted SWC are needed to fully understand the decreasing sensitivity of the CRNP with depth as recommended elsewhere (Bogena et al., 2013 and Köhli et al., 2015). As a first step, here we will only consider depth and area-average properties given the resolution of the global remote sensing products. We expect future work to improve on these analyses as regional datasets contain higher spatial resolution data.".

L217: "Köhli"

The text was changed.

L237: "Global Soil Dataset"

The text was changed.

L249: This step needs a better explanation.

This involves expert knowledge by a soil pedologist, here Prof. Mark Kuzila. The method follows expert knowledge and the NRCS soil taxonomy handbook. The reference to the NRCS handbook was added.

L258-259: In which cases "taking mean values" were preferred over "taking linear relationships"?

We only used the linear relationships where a significant p value was found (<0.05). The following text was added: L323-325: "A statistically significant p value (<0.05) was used to discriminate between using the mean values and linear relationship.".

L268: Actually, only one vegetation index is presented here.

The text was changed.

L271 "...65 ha large."

The text was changed.

L288-289: This information is not needed.

The text was changed.

L329: This is not the point. The problem actually is that the slope of the correlation strongly deviates from the 1:1 line in both cases. The error for soil organic carbon is larger than the organic carbon content of most of the samples. This questions the reliability of the GSDE data set for local applications like the cosmic-ray rover.

We agree the SOC data is very poor from the GSDE and in situ samples. Better estimates of SOC are needed. The following text was added for clarification L 406-409:" We note that the slope of the relationships for soil bulk density and soil organic carbon is different from 1 and can lead to biased results. Caution should be used for using these estimates as opposed to local in-situ sampling.".

L348: add an adjective like e.g. reasonably

The text was changed.

L362: "the" instead of "these"

The text was changed.

L428-430: Better data sets are not only needed for higher resolution applications, but also to increase the reliability of the calibration function.

The text was changed.

L434-435: The impact of soil organic carbon (SOC) on the calibration strongly depends on the total SOC amount and on the vertical distribution. For arable land SOC are relatively low and homogeneously distributed in the A-horizon due to land management activities. However, in grassland and forest sites, high SOC amounts and strong SOC gradients typically exist in the top soil (e.g. Bogena et al., 2013).

Thank you. The following text was added: L531-543: "For arable land we note that organic carbon has a relatively small impact on the calibration function as it is multiplied by several factors in the calibration equation, and relatively low and homogeneously distributed in the A-horizon due to land management activities. However, in grassland and forest sites, high SOC amounts and strong SOC vertical gradients typically exist in the top soil and may need to be quantified with local in-situ sampling (e.g. Bogena et al., 2013). For rover survey experiments in these areas, we suggest that SOC be sampled with composite samples, particularly between sites with varying land use histories which can be identified using historical land cover maps."

L463-465: Actually, this is an argument for adding more vegetation types in the analysis to increase the relevance of the paper.

We added the following text: L578-579: "We refer to the reader to Duncan et al. (2015) and Kumar et al. (2015) for a recent review of vegetation indices in remote sensing.".

L501-517: This section is not a conclusion and thus should be moved to the discussion section.

Thank you. The text was moved to subsection 4.3 in the discussion on best rover practices.

Literature

Baatz, R., H. Bogena, H.-J. Hendricks Franssen, J.A. Huisman, Q. Wei, C. Montzka and H. Vereecken (2014): Calibration of a catchment scale cosmic-ray soil moisture network: A comparison of three different methods. J. Hydrol. 516: 231-244, doi: 10.1016/j.jhydrol.2014.02.026.

Bogena, H.R., J.A. Huisman, C. Hübner, J. Kusche, F. Jonard, S.Vey, A. Güntner and H. Vereecken (2015): Emerging methods for non-invasive sensing of soil moisture dynamics from field to catchment scale: A review. WIREs Water 2(6): 635–647, doi: 10.1002/wat2.1097.

Duncan J.M.A. et al. (2016): The potential of satellite-observed crop phenology to enhance yield gap assessments in smallholder landscapes. Front. Environ. Sci., http://dx.doi.org/10.3389/fenvs.2015.00056

Korres, W., T.G. Reichenau, P. Fiener, C.N. Koyama, H.R. Bogena, T. Cornelissen, R. Baatz, M. Herbst, B. Diekkrüger, H. Vereecken, and K. Schneider (2015): Spatio-temporal soil moisture patterns - a meta-analysis using plot to catchment scale data. J. Hydrol. 520: 934-946, doi:10.1016/j.jhydrol.2014.11.042.

Kumar, L, Sinha, P. Taylor S. et al. (2015): Review of the use of remote sensing for biomass estimation to support renewable energy generation. J. Appl. Remote Sens. 9(1), doi:10.1117/1.JRS.9.097696

Peichl, M., Leava, N. A. and Kiely, G. (2012): Above- and belowground ecosystem biomass, carbon and nitrogen allocation in recently afforested grassland and adjacent intensively managed grassland. Plant and Soil, 350, 281-296.

Anonymous Referee #2
Received and published: 8 April 2016
General comments
The manuscript focuses on the mobile application of cosmic-ray neutron soil moisture probes (CRNP) and tests the reliability and accuracy of globally/continentally available data sets to provide information to support the calibration procedure. The relationship between CRNP measured low-energy neutron concentration and soil moisture can be strongly affected by changes in soil texture/soil type, surrounding vegetation, organic carbon content in the upper soil layer. Therefore, an operational procedure to provide information about CRNP calibration parameters for larger scales is of critical importance and relevance for the mobile application of CRNP. The paper is generally well written and easy to follow. However, especially the overview of CRNP and its calibration in the method section (chapter 2.1 - 2.3.) require a deeper revision. In 2015, Köhli et al. revised the footprint characteristics for soil moisture monitoring with cosmic-ray neutrons substantially. Although the authors cite Köhli et al. (2015) several times, key insights of the Köhli paper are omitted or reported incorrectly. By improving the physical representativeness of the underlying neutron transport model, Köhli et al. (Ibid.) revealed the highly dynamic nature of the CRNP footprint (horizontal and vertical) and redefined the footprint radius to range from 130 to 240 m. Furthermore, Köhli et al. revealed the high sensitivity of the CRNP to soil moisture (and other affecting properties) in the first tens of meters around the probe resulting in the need for a dynamically weighted average of CRNP-affecting properties within the probe's footprint (very recently applied and successfully tested by Heidbüchel et al. (2016)). While the manuscript mentions results of "recent neutron transport modeling" (l 145-146), the only given number for the CRNP support volume is the outdated "circle of ~ 300 m radius" (l 144). Although the authors mention the need for an adjustment of the sampling pattern for in-situ calibration ("in the light of recent modelling", 217-219), the sampling scheme presented in detail in the paper is based on results from 2012. Also here it would be desirable to provide a more detailed discussion of the importance of a weighted sampling scheme. All these aspects impact the interpretation of the CRNP signal and are of critical relevance for mobile CRNP applications. Even though the aspects mentioned above did not affect directly the interpretation of the manuscript's main topic (evaluation of accuracy of globally available data sets for CRNP calibration), the reviewer recommends a more intense discussion of the current state of knowledge about the CRNP theory and its importance for the mobile CRNP application. More comments on this topic can be found in the "Specific comments" section of this review. Despite these critical remarks, the manuscript is of high interest for the CRNP community and the manuscript's topic is well suited for the journal and the journal readers. I recommend a moderate revision before the article is considered for publication.

We thank the reviewer for their comments and concerns. Per the issue of the footprint characteristics we have had detailed discussions with Darin Desilets of HydroInnova about its refinement following Köhli et al 2015. It seems there is some on going discussion within the community that should be a central topic for the upcoming COSMOS workshop in August 2016 in Denmark. We hope that this issue and others with the calibration function, sampling method, sampling frequency etc. will be resolved at that time. We have added more exact language to the introduction and summarize conclusions from the Köhli et al. 2015 paper. Please see responses to specific comments below.

Specific comments

1. L 50-52: Delete "(~36 km)" and "(e.g.~2-5 cm ... Entekhabi et al., 2010)" since this is repeated and described again with the same citations in the following paragraph.

We have deleted some of the superfluous text.

2. L 66: I assume that the footprint is given square kilometers.

We have updated the text to reflect 36 by 36 km.

3. L78-79: The authors mention here the footprint radius of "~300 m" and underpin this by a citation of Köhli et al (2015). Since Köhli et al. revealed a reduced footprint radius (see also comments above) this is a wrong citation and should be corrected using the correct numbers.

We have changed the language to several hundred meters and give more details in the methods section about the specific dimensions described in Desilets and Zreda 2013, Köhli et al., 2015.

4. L109: Since it is introduced for the first time (except from the abstract), "CONUS" should be written out here.

We have updated the text.

5. L132: The use of the term "energy levels" is unusual in unbound particle systems. Energies of free atmospheric neutrons can be approximated as a continuum throughout the elastic scattering spectrum. Better use "well-known energy spectrum" or "continuous energy spectrum".

Thank you. We have updated the language to continuous energy spectrum.

6. L135-136: "(i.e., the neutrons which are primarily measured by the moderated detector)" repeated information, compare line 130.

The text was removed.

7. L 145-148: The authors mention new findings regarding the CRNP footprint and its dependency upon vegetation, soil moisture, atmospheric water vapor, elevation, surface heterogeneity. Since Köhli et al. (2015) investigated all of these aspects the citation should be placed at the end of the sentence. Furthermore, it would be highly desirable to discuss the impact of the dynamic nature of the CRNP footprint on the applicability for mobile surveys.

We have added the following language and citations to be clearer. The changing footprint with respect to mobile surveys was not discussed. We hope discussions and outcomes from the next COSMOS workshop will help pave a way forward.

L172-178: "Recent neutron transport modeling has further refined the footprint area to be a function of atmospheric water vapor, elevation (Desilets and Zreda, 2013), surface heterogeneity (Köhli et al., 2015), vegetation (Köhli et al., 2015), and SWC (Köhli et al., 2015). Köhli et al. (2015) found the footprint to range between 130 and 240 m in radius depending on conditions. Despite the varying footprint characteristics, the large measurement area at tens of hectares make this non-invasive technique an ideal complement to long-term surface energy balance monitoring around the globe.".

8. L173: The term "correction factor" has been used four times in the last 5 lines, please rephrase.

We have removed some of the repetition (L209-213).

9. L217-L219: "In light of recent modelling ... reduced footprint area". How does this recent finding affect the mobile application of CRNP?

I am not really sure it does for simplistic applications. Currently, the corresponding author assumes the centroid of measurement location (middle point after driving 1 minute) is a point and then performs spatial interpolation on those series of survey points. However, the elliptical shape and weighting function could be considered in the geostatistical analysis more explicitly. This would require advanced spatial interpolation techniques not provided by standard software. Certainly this is an open area of research for a skilled scientist in computational and statistical methods. Unclear how important this will be in light of other errors in the calibration method.

The following text has been added for clarification L264-278:" In the simplest form, the calibration function summarized in equations (1-4) requires depth-average estimates of three soil parameters, θ_{LW}, θ_{SOC}, and ρ_b, and two vegetation parameters SWB and SDB. We note that depth-weighted average parameters, belowground biomass and depth-weighted SWC and needed to fully understand the decreasing sensitivity of the CRNP with depth as recommended elsewhere (Bogena et al., 2013 and Köhli et al., 2015). As a first step, here we will only consider depth and area-average properties given the resolution of the global remote sensing products. We expect future work to improve on these analyses as regional datasets contain higher spatial resolution data. In order to estimate depth and area-average soil parameters, Zreda et al. (2012) and Franz et al. (2012) recommended averaging 108 individual in-situ soil samples from 18 locations (every 60 degrees and radii of 25, 75, 200 m) and six depths (every 5 cm from 0-30 cm) within a CRNP footprint. In light of recent modeling work (Köhli et al. 2015), this sampling pattern may need to be adjusted to be more representative of encountered conditions (such as shorter sampling distances due to reduced footprint area). Given the mixture of previously published datasets and new datasets used here, we decided to use the original sampling location description.".

10. L260: Delete ",and lattice water" since the test for lattice water relationships is described above.

We have removed text.

11. L302-308: Excessive of the verb "use" - used six times within five consecutive sentences.

We have changed verb use to avoid excess usage.

12. L323-324: I recommend to delete the sentence "Other than 1 outlier..." here, since this is repeated and discussed in section 4.1.

We have removed text.

13. L330-333: Repetition of L 241-244

We have removed text to avoid repetition of Greacen citation.

14: L350: Change to "Figure 4a and 4b".

We have changed text.

15: L365: Instead of "MODIS product and derived equation" it might be better to write "MODIS product in combination with the derived equations".

We have changed text.

16: L381: Change the title since it is the same like the title for chapter 2.6

We have changed chapter to "Results of GSDE Soil Properties Error Propagation Analysis".

17: L393-394: Why is this sentence given in italic letters? Furthermore, I find the formulation misleading. "Future sampling efforts" probably won't "minimize the range of bulk densities". But it can certainly increase the accuracy of bulk density estimation.
Bulk density itself is affected by the land use and can be a very dynamic parameter (e.g. due to agricultural cultivation measures) and this dynamic nature it a further challenge for the mobile CRNP application. This issue should be mentioned. The incorporation of land use information can increase the accuracy of bulk density estimation.

This is a key point and area that the users of the cosmic-ray probe should be aware of. The impact of land use on bulk density or soil organic carbon will be better highlighted. Perhaps a better definition is identifying the 5 and 95% quantiles of bulk density at a survey location. Therefore, more samples may indeed resolve these quantile estimates by eliminating the influence of outliers.
We have added to the following text for clarification of this key point.
L484-486: "Therefore, future sampling efforts or evaluations of available datasets should seek to improve the accuracy of bulk density, meaning better estimates of the mean, standard deviation, quantiles, and impact of land use practices on bulk density.".

18: L405-407: "This strong correlation is significant because large portions or the ... regions are made up of mollisol soils". I did not understand this sentence. A "large portion" isn't an explanation for the significance, is it?

We mean that a majority of the collected samples came from the mollisol group. Therefore the correlation for all samples with clay percent will be more heavily weighted to the mollisol soil group, which is highly correlated to clay percent. Clearly more samples are needed to resolve this issue amongst soil groups.
We have changed the phrase large portion to large areas for clarification.

19: L477-479: "...given the relatively small change in BWE... in forests, we would expect small change in N0 through time". CRNP measurements in forest can be challenging for several other reasons. Bogena et al. (2013) revealed the importance of the litter layer and its dynamic water content for CRNP calibration. Heidbüchel et al. (2016) found strong deviations in N0 calibrations for different times of the year and recommend a two-time calibration to catch seasonal variations in aboveground biomass. Furthermore, they found a considerable influence of root biomass on the CRNP signal.

The additional citation and discussion was added for forest areas. Reviewer 1 also points out that the vertical distribution of SOC or bulk density may be more important there.
L594-596:"For a more complete discussion of CRNP calibration in forests and estimates of time varying changes in N_0 please see Bogena et al., 2013 and Heidbüchel et al., (2016)."

20. L503: "minimum of 7" is a strong recommendation for a value which should be dependent on the individual site heterogeneity. Since there is no statistical proof for this statement, I suggest to avoid a concrete number.

This is more of a rule of thumb found as good practice used by the authors. We have removed reference to 7.

21. L505: Why is N0 a correction factor? Please clarify to which function and which parameters you are referring to.

N0 is not a correction factor but calibration parameter dependent on vegetation conditions that may change through time. We have changed language for clarity.

1) *L601-603:" Collect a series of full calibration datasets (θ_{LW}, θ_{SOC}, ρ_b, SWB, SDB) in differing land use and soil types to estimate the instrument specific slope and intercept for dependence of N_0 with BWE.".*

22. L507: The influence of road type has not been discussed in this work. Please explain the reasons for this recommendation.

This is briefly discussed in Chrisman 2013 and Franz 2015. The asphalt will be much drier than say a dirt road and influence the neutron counts. The reference to Chrisman and Zreda 2013 was added.

23. L507: replace “in missing areas” by “data gaps”.

The text was changed.

References: Bogena H.R., Huisman J.A., Baatz R., Franssen H.J.H., Vereecken H. (2013) Accuracy of the cosmic-ray soil water content probe in humid forest ecosystems: The worst case scenario. Water Resources Research 49:5778-5791. DOI:10.1002/wrcr.20463.
Heidbüchel I., Güntner A., Blume T. (2016) Use of cosmic-ray neutron sensors for soil moisture monitoring in forests. Hydrol. Earth Syst. Sci. 20:1269-1288. Köhli M., Schrön M., Zreda M., Schmidt U., Dietrich P., Zacharias S. (2015) Footprint characteristics revised for field-scale soil moisture monitoring with cosmic-ray neutrons. Water Resour. Res. 51:5772-5790.

Anonymous Referee #3

General comments
The paper covers many of the issues facing those currently using, or planning to use, roving CRNPs and as such is very timely. It is well written and the results are well presented. I suggest only minor revisions before the paper is acceptable for publication in HESS. I think the title might best be modified to ensure the reader knows this is about the roving CRNP method rather than about the static CNRP method where the variables in question will likely be assessed directly and in detail.

We have changed the word probe to rover in the title to reflect the mobile technology and emphasis of this paper. The reviewer is correct in that fixed probes should still rely on best local calibration practices.

Some discussion on the likely relative influence of the different pools of hydrogen would also be useful. As it stands now the reader has no idea if the relative impact of BWE or lattice water or SOC are as important or far less that the SWC which I imagine actually dominates the count rate. There is some discussion later in the paper but maybe this could be raised earlier in the paper too to set the scene. The importance of some of the poorer correlations diminishes somewhat when you bear this in mind.

Indeed. The quantification of the relative hydrogen pools in McJannet et al. 2014 does a nice job. The introduction makes this point in L158-163. We have added the phrase “somewhat” to help emphasize the lesser importance of the other pools.
L164-169: “Water in the near surface soil (i.e. SWC) is one of the largest sources of hydrogen present in terrestrial systems (McJannet et al. 2014). Thus, relative changes in the intensity of epithermal neutrons are overwhelmingly due to changes in the SWC. However, the shape of the calibration function (see section 2.2) is somewhat modified by local soil and vegetation parameters (Zreda et al. 2012) reflecting the variation of background hydrogen levels across landscapes.”

Can you standardise the terminology around neutron energy. The terms ‘epithermal’ and ‘low energy’ have been used interchangeably.

We have replaced all instances with low-energy, save the first reference (L156). Details about the detector response and isolation of certain energies is currently being investigated by Mie Andreasen and the University of Copenhagen group. Supporting manuscripts are anticipated to be out later this year.

Specific comments

L24 delete ‘using’

The text was changed.

L33 including forests too as a biomass source

The text was changed.

L34 the signal is accounted for not minimised

The text was changed.

L75 ‘measure’ not ‘measures’

The text was changed.

L77 CRNPs

The text was changed.

L130 low energy or epithermal – can you stick with one

The text was changed to low-energy

L201 is fwe not equivalent to (18.01528 * 5) /162.1406 = 0.5556?

The fwe=0.494 was updated in Franz et al. 2015 GRL, per the reviewer instructions.

L230 chosen from one

The text was changed.

L371 I think some discussion is warranted here (or later) about the actual water equivalent (kg/m2 or mm) that is held in the crop. I suggest this because this helps to give the reader an idea about the magnitude of this correction. If biomass water equivalent of 1 mm is equal to only 0.0033 cm3/cm3 for a soil depth of 300 mm then corrections for many less dense crops may not be needed or fall within the noise of CRNP measurements. Maybe it is also true that the highest BWE coincides with highest moisture and vice versa so the effects are further minimised in relation to SWC estimates.

We have added the following text for clarification.
L463-467:" We note that 1 kg/m^2 is approximately equal to 1 mm of water or about 0.0033 cm^3/cm^3 of SWC over 300 mm. This indicates that for relatively small changes in BWE it will be nearly indistinguishable from the noise in the CRNP measurements.".

L471 BWE at these levels of moisture must be very small and are probably insignificant in the corrections. Can you add these to strengthen this section?

We have added the following text for clarification.
L585-586:"By the end of senescence before harvest, the canopy water contents were down to 25-35 wt. %, and thus very low BWE and minimal impact on low-energy neutron intensity.".

L493 "statistically significant different mean values" do you mean "statistically different mean values"?

The text was changed.

L503 where does the 7 come from?

The exact number of 7 was removed but is a general rule of thumb.

Incorporation of globally available datasets into the roving cosmic-ray neutron probe method for estimating field scale soil water content

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Keywords: Cosmic-ray neutron probe; soil moisture; calibration parameters; remote sensing; maize; soybean

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Abstract

The need for accurate, real-time, reliable, and multi-scale soil water content (*SWC*) monitoring is critical for a multitude of scientific disciplines trying to understand and predict the earth's terrestrial energy, water, and nutrient cycles. One promising technique to help meet this demand is fixed and roving cosmic-ray neutron probes (CRNP). However, the relationship between observed low-energy neutrons and *SWC* is affected by local soil and vegetation calibration parameters. This effect may be accounted for by a calibration equation based on local soil type and the amount of vegetation. However, determining the calibration parameters for this equation is labor and time intensive, thus limiting the full potential of the roving CRNP in large surveys and long transects, or its use in novel environments. In this work, our objective is to develop and test the accuracy of globally available datasets (clay weight percent, soil bulk density, and soil organic carbon) to support the operability of the roving CRNP. Here, we develop a 1 km product of soil lattice water over the CONtinental United States (CONUS) using a database of *in-situ* calibration samples and globally available soil taxonomy and soil texture data. We then test the accuracy of the global dataset in the CONUS using comparisons from 61 *in-situ* samples of clay percent (RMSE = 5.45 wt. %, R^2 = 0.68), soil bulk density (RMSE = 0.173 g/cm^3, R^2 = 0.203), and soil organic carbon (RMSE = 1.47 wt. %, R^2 = 0.175). Next, we conduct an uncertainty analysis of the global soil calibration parameters using a Monte Carlo error propagation analysis (maximum RSME ~0.035 cm^3/cm^3 at a *SWC* = 0.40 cm^3/cm^3). In terms of vegetation, fast growing crops (i.e. maize and soybeans), grasslands, and forests contribute to the CRNP signal primarily through the water within their biomass and this signal must be accounted for accurate estimation of *SWC*. We estimated the biomass water signal by using a vegetation index derived from MODIS imagery as a proxy for standing wet biomass (RMSE < 1 kg/m^2). Lastly, we make recommendations on the design and validation of future roving CRNP experiments.

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1. Introduction

By the year 2050, over nine billion people are predicted to inhabit the Earth (United Nations, 2015). The monumental task of feeding the projected global population will require a near doubling of grain production (FAO, 2009). As of today, the majority (~2/3) of water consumption by humans is used for agriculture, where approximately half of all global food production comes from irrigated agriculture (Mekonnen et al., 2011). As such, an increase in food demand will put an even greater demand on fresh water resources, particularly an increasing reliance on groundwater (Mekonnen et al., 2011). The ability to model and forecast the hydrologic cycle will continue to play a major role in effective water resource management in the coming decades. Currently, most land surface models (LSM) aimed at characterizing the fluxes of water, energy, and nutrients, have relied on either sparse point scale *SWC* monitoring networks (Crow et al. 2012) or remote sensing products with large pixel sizes (~36 km) and shallow penetration depths (Kerr et al., 2010 and Entekhabi et al., 2010). A critical scale gap exists between these methods requiring innovative monitoring strategies (Robinson et al., 2008). Moreover, as LSMs continue to move towards highly refined spatial resolutions of 1 km or less (Wood et al., 2011), the need for accurate and spatially exhaustive *SWC* datasets continues to grow (Beven and Cloke, 2012).

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Estimating and monitoring *SWC* at the appropriate spatial and temporal scale for effective incorporation into LSMs has proven to be a difficult task. On one hand, monitoring networks at the regional (e.g., Nebraska Automated Weather Data Network; AWDN, Oklahoma Mesonet) and continental scales (Climate Reference Network; CRN, Soil Climate Analysis Network; SCAN) have continuously recording point sensors. However, these sparse networks are difficult to place in the context of the surrounding landscape given the multifractal behavior that soil moisture fields exhibit (Korres et al. 2015). Techniques such as temporal stability analysis (Vachaud et al., 1985) can help improve the representativeness of the monitoring networks but require *a priori* spatial information. On the other hand, remote sensing satellites using passive microwaves can monitor global *SWC* data every few days albeit with large spatial footprints (~36

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by 36 km, Entekhabi et al., 2010 and Kerr et al., 2010). In addition, passive microwaves lack significant penetration depths (~ 2-5 cm Njoku et al., 1996), limiting their effectiveness as a remote sensing input for full root zone coverage in LSMs.

Alternatively, the field of geophysics offers a variety of techniques to help fill the spatial and temporal gaps between point sensors and remote sensing products (Bogena et al., 2015). Bridging this gap requires both novel geophysical techniques and integrated modeling strategies capable of merging both point and remotely sensed data into a unified framework (Binley et al., 2015). One promising geophysical technique to help fill this need is fixed (Desilets et al., 2010, Zreda et al., 2012) and roving cosmic-ray neutron probes (CRNP; Chrisman et al., 2013, Dong et al., 2014), which measure the ambient amount of low-energy neutrons in the air. The low-energy neutrons are highly sensitive to the mass of hydrogen, and thus *SWC*, in the near surface (Zreda et al., 2012). CRNPs estimate the area-average *SWC* because neutrons are well mixed within the footprint of the sensor which typically has a radius of several hundred meters and depths of tens of decimeters (Desilets and Zreda 2013, Köhli et al., 2015).

To date, the CRNP method has been mostly used as a fixed system in one location to continuously measure *SWC* as part of a large monitoring network (Zreda et al., 2012, Hawdon et al., 2014). Recent advancements have allowed the CRNP to be used in mobile systems to monitor transects across Hawaii (Desilets et al., 2010), monitor entire basins in southern Arizona (Chrisman et al., 2013), compare against remote sensing products in central Oklahoma (Dong et al., 2014), and monitor ~140 agricultural fields in eastern Nebraska (Franz et al., 2015). In order to accurately estimate *SWC*, the CRNP method relies on a calibration function to convert observed low-energy neutron counts into *SWC* (Desilets et al., 2010, Bogena et al., 2013, see Sec. 2.2 for full details). The calibration procedure requires site specific sampling of both soil

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and vegetation data in order to determine the required parameters. While the calibration of a fixed CRNP is fairly standardized (Zreda et al., 2012; Franz et al., 2012; Iwema et al., 2015, Baatz et al., 2014), the heterogeneous nature of soil and vegetation characteristics across a landscape makes the pragmatic calibration of the roving CRNP a significant challenge. Specifically, the presence of water within vegetation and the soil minerals may alter the shape of the local calibration function and thus accuracy of *SWC* (Baatz et al., 2015). The need for reliable, accurate, depth-dependent, and localized soil and vegetation spatial information for use in the calibration function is critical in order to fully exploit the potential of the roving CRNP to monitor landscape scale *SWC* across the globe.

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The objective of this study is to explore the utility and accuracy of currently available global soil and vegetation datasets (soil organic carbon, soil bulk density, soil clay weight percent, and crop biomass) for use in the calibration function. To accomplish our objective, we aimed to answer the following questions:

1) Can global datasets of soil bulk density, soil organic carbon, and soil clay weight percent be used instead of *in-situ* sampling within reasonable error for use in the roving CRNP calibration function?

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2) Can the use of remotely sensed vegetation products, specifically the Green Wide Dynamic Range Vegetation Index (GrWDRVI) be used to quantify fresh biomass with reasonably low error (< 1 kg/m^2) for use in the roving CRNP calibration function?

To answer these questions, we tested the accuracy of these datasets against *in-situ* sample datasets of the same parameters. Existing *in-situ* datasets from across the CONtinental United States (CONUS) were combined with *in-situ* datasets from eastern Nebraska, which focused on

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fast growing crops of maize and soybean. Specifically, we tested the accuracy and use of a ~1 km global soil dataset (Shangguan et al., 2014). In addition, we examined the use of the Green Wide Dynamic Range Vegetation Index (*GrWDRVI*, Gitelson, 2004) derived from NASA's MODIS sensor aboard the Terra satellite for use in estimating the amount of fresh crop biomass.

The remainder of the paper is organized as follows: In the Methods section, the CRNP method is first presented, with emphasis on the integration of the calibration function and soil and vegetation parameters to convert observed low-energy neutron counts into *SWC*. Next, *in-situ* methods for estimating the soil and vegetation calibration parameters are discussed, which is followed by discussions on the soil and vegetation products available globally at ~1 km resolution. In the Results section, we first compare the *in-situ* soil sampling against the global datasets. Next, we develop a 1 km CONUS soil lattice water map using *in-situ* samples. We then compare the *GrWDRVI* against *in-situ* samples from Nebraska to estimate the changes in maize and soybean fresh biomass. Lastly, we present an error propagation analysis investigating the potential uncertainty of using the global soil calibration data vs. local *in-situ* sampling. The paper concludes with a discussion on best practice recommendations for calibrating and validating a roving CRNP experiment.

2. Methods

2.1 Overview of Cosmic-ray Neutron Probe

The CRNP estimates area-averaged *SWC* via measuring the intensity of low-energy neutrons (i.e. ~epithermal) near the ground surface (Zreda et al. 2008, 2012). A cascade of neutrons with a continuous energy spectrum are created in the earth's atmosphere when

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incoming higher energy particles produced within supernovae interact with atmospheric nuclei (Zreda et al., 2012 and Köhli et al., 2015). After fast neutrons are created, they continue to lose energy during numerous collisions with nuclei in air and soil, and become low-energy neutrons that are detected with the probe. The abundance of hydrogen atoms in the air and soil largely controls the removal rate of low-energy neutrons from the system (Zreda et al. 2012). Water in the near surface soil (i.e. *SWC*) is one of the largest sources of hydrogen present in terrestrial systems (McJannet et al. 2014). Thus, relative changes in the intensity of low-energy neutrons are overwhelmingly due to changes in the *SWC*. However, the shape of the calibration function (see section 2.2) is somewhat modified by local soil and vegetation parameters (Zreda et al. 2012) reflecting the variation of background hydrogen levels across landscapes.

Using a standard neutron detector with a 2.54 cm layer of plastic, Zreda et al. (2008) first described the support volume the detector measures to be a circle of ~300 m in radius with vertical penetration depths of 12 to 76 cm depending on *SWC*. Recent neutron transport modeling has further refined the footprint area to be a function of atmospheric water vapor, elevation (Desilets and Zreda, 2013), surface heterogeneity (Köhli et al., 2015), vegetation (Köhli et al., 2015), and *SWC* (Köhli et al., 2015). Köhli et al. (2015) found the footprint to range between 130 and 240 m in radius depending on conditions. Despite the varying footprint characteristics, the large measurement area at tens of hectares makes this non-invasive technique an ideal complement to long-term surface energy balance monitoring around the globe. Currently, there are >200 fixed CRNP (personal communication with Darin Desilets of HydroInnova LLC, Albuquerque, NM) functioning in this capacity around the United States of America (Zreda et al., 2012), Australia (Hawdon et al., 2014), Germany (Baatz et al., 2014), South Africa, China, and the United Kingdom. The real-time *SWC* data provide critical

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infrastructure for use in weather forecasting and data assimilation in LSMs (Shuttleworth et al., 2013, Rosolem et al., 2014, Renzullo et al., 2014).

In addition to the fixed CRNP measuring hourly *SWC*, a roving version of the CRNP has been used to reliably measure *SWC* at temporal resolutions as low as 1 minute (Chrisman et al., 2013; Dong et al., 2014) providing the ability to make *SWC* maps over hundreds of square kilometers in a single day. Moreover, Franz et al. (2015) found that a combination of fixed and roving CRNP data in a statistical framework has the ability to form an accurate, real-time, and multiscale monitoring network. With the continued increase in observation spatial scales, the use of *in-situ* sampling in the traditional CRNP calibration procedure is no longer practical, thus requiring the use of alternative available datasets to improve its operability. The remainder of this work will first describe the availability of such global datasets and then test the accuracy of using the datasets in the CNRP calibration function.

2.2 The Cosmic-ray Neutron Probe Calibration Function

In order to convert observed low-energy neutron measurements into *SWC*, a series of scaling factors, correction factors, and calibration functions have been developed. Zreda (2012) describes in detail the affects from changes in geomagnetic latitude, changes in incoming high-energy cosmic-ray intensity, and atmospheric pressure. Rosolem et al. (2013) further describes changes in absolute air humidity near the surface. Following these four scaling and correction factors, the corrected low-energy neutron counts can be converted into *SWC*. Desilets et al. (2010) proposed the original calibration function (Eq. 1) valid for mass based gravimetric measurements which Bogena et al. (2013) further expanded for volumetric water content. The

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calibration function has been successfully tested against direct sampling and point sensor measurements with RMSE < 0.03 cm^3/cm^3 across the globe including arid shrublands in Arizona, USA (Franz et al., 2012), semi-arid forests in Utah, USA (Lv et al., 2014), to humid forests in Germany (Bogena et al., 2013), and across ecosystems in Australia (Hawdon et al., 2014). The original calibration function proposed by Desilets et al., (2010) is:

$$\theta_T = \left(\frac{a_0}{\frac{N}{N_0} - a_1} - a_2\right) \tag{1}$$

where θ_T (g/g) is the total gravimetric water content, a_0 = 0.0808, a_1= 0.3720, a_2 = 0.1150 (see Desilets et al., (2010) for details), N(counts per time interval) is the aforementioned low-energy corrected neutron count rate, and N_0 (counts per time interval) is the theoretical counting rate at a location with dry silica soils. Zreda et al. (2012) illustrated that:

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$$\theta_T = \theta_p + \theta_{LW} + \theta_{SOC} \tag{2}$$

where θ_p (g/g) is the gravimetric pore water content in the soil, θ_{LW} (g/g) is the soil lattice water, and θ_{SOC} (g/g) is the soil organic carbon water equivalent. The volumetric soil water content, SWC, (cm^3/cm^3) is found by multiplying θ_p by $\frac{\rho_b}{\rho_w}$, where ρ_b (g/cm^3) is dry soil bulk density and ρ_w = 1 g/cm^3 is the density of water.

To account for effects of time varying above-ground vegetation on the low-energy neutron counts (Franz et al., 2013; Coopersmith et al., 2014), Franz et al. (2015) proposed the following additional correction factor to N_0:

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$$N_0(BWE) = m * BWE + N_0(0) \tag{3}$$

where $N_0(0)$ is the instrument specific estimate of N_0 with no standing biomass, BWE is the biomass water equivalent (kg/m^2 ~ mm of water/m^2), and m is the slope of the relationship between N_0 and BWE, determined via *in-situ* calibration datasets. The BWE is further defined as:

$$BWE = SWB - SDB + SDB * f_{WE} \tag{4}$$

where SWB is the standing wet biomass per unit area (kg/m^2 ~ mm of water/m^2), SDB is the standing dry biomass per unit area (kg/m^2 ~ mm of water/m^2), and $f_{WE} = 0.494$ is the stoichiometric ratio of H_2O to organic carbon (assuming organic carbon is cellulose, $C_6H_{10}O_5$). Using nine *in-situ* calibration datasets for maize and soybean crops, Franz et al. (2015) found their roving CRNP had a statistically significant linear relationship between N_0 and BWE yielding $N_0(0) = 518.34$ counts per minute and $m = -4.9506$ ($R^2 = 0.515$ and p-value = 0.03). We note the coefficients are less suitable for forest canopies given the need for a neutron geometric efficiency factor described further in the supplemental material of Franz et al. (2013). We also refer the reader to Coopersmith et al. (2014) and Baatz et al. (2015) for further discussion of CRNP use in forest canopies, and Bogena et al. (2013) for a discussion of below-ground biomass and litter layers. In addition, plant specific root-shoot ratios (Peichl et al., 2012) or allometric relationships (Jenkins et al., 2003) may be used to derive a better understanding of the impact of time-varying below-ground biomass on N_0. This is an open and challenging research area and beyond the scope of the current work.

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2.3 ***In-situ*** Soil and Vegetation Calibration Parameters

In the simplest form, the calibration function summarized in equations (1-4) requires depth-average estimates of three soil parameters, θ_{LW}, θ_{SOC}, and ρ_b, and two vegetation parameters SWB and SDB. We note that depth-weighted average parameters, belowground biomass, and depth-weighted *SWC* are needed to fully understand the decreasing sensitivity of the CRNP with depth as recommended elsewhere (Bogena et al., 2013 and Köhli et al., 2015). As a first step, here we will only consider depth and area-average properties given the resolution of the global remote sensing products. We expect future work to improve on these analyses as regional datasets contain higher spatial resolution data. In order to estimate depth and area-average soil parameters, Zreda et al. (2012) and Franz et al. (2012) recommended averaging 108 individual *in-situ* soil samples from 18 locations (every 60 degrees and radii of 25, 75, 200 m) and six depths (every 5 cm from 0-30 cm) within a CRNP footprint. In light of recent modeling work (Köhli et al. 2015), this sampling pattern may need to be adjusted to be more representative of encountered conditions (such as shorter sampling distances due to reduced footprint area). Given the mixture of previously published datasets and new datasets used here, we decided to use the original sampling location description. Zreda et al. (2012) found that a composite sample of 1 g of material gathered from each of the 108 samples was adequate to estimate θ_{LW} and θ_{SOC}. These composite samples can be analyzed directly for lattice water (g/g), soil total carbon (TC, g/g), and inorganic carbon (TIC, g/g) determined by measuring CO_2 after the sample is acidified (e.g. by Actlabs of Ontario Canada, Analysis Codes: 4E-exploration, 4F-CO2, 4F-C, and 4F-H2O+/-). Franz et al. (2015) reported $\theta_{SOC} = (TC - TIC) * 1.724 * f_{WE}$, where 1.724 is a constant to convert total organic carbon into total organic matter and f_{WE} is given above. To estimate ρ_b at each location, Zreda et al. (2012) used a 30 cm long split tube auger, which

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contained six 5 cm diameter by 5 cm length rings. All samples were then averaged to get a composite value.

In order to estimate standing wet biomass (*SWB*) and standing dry biomass (*SDB*) in maize and soybeans, Franz et al. (2015) measured average plant density in 1 m^2 quadrats at each of the 18 sampling locations. In a subset of six sites (randomly chosen from one radius for each of the six transects) three plants were removed and placed in a paper bag for weighing within two hours (to minimize water loss). The plants were then dried for five days at 70^{o} C and weighed again. Using the density of plants, wet weight, and dry weight, *SWB* and *SDB* can be determined at each site and averaged across the CRNP footprint.

2.4 Global Datasets of Soil Properties

Shangguan et al. (2014) compiled a thirty arc second (~1 km) Global Soil Dataset (GSDE) with 34 soil parameters in 8 layers (0–0.045, 0.045–0.091, 0.091–0.166, 0.166–0.289, 0.289–0.493, 0.493–0.829, 0.829–1.383, and 1.383–2.296 m). In order to construct an average value relevant to the CRNP, we arithmetically averaged the top four layers in each grid location to form a composite value (~30 cm) over the CONUS. The GSDE contains estimates of soil bulk density and soil organic carbon. In order to construct a map of lattice water, we explored if any relationships existed between clay weight fraction and lattice water following the work of Greacen et al. (1981) using active neutron probe calibration procedures developed for Australian soils. In order to account for variations in chemical and physical weathering on lattice water (Zreda et al., 2012), we further partitioned the analyses based on soil order. A global soil order map with a resolution of five arc minutes (~ 8 km) containing 25 major soil classifications was

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first uploaded to ArcMap (ESRI, v. 10.2.2) and clipped to the CONUS. The 25 soil classifications were then categorized into 12 major classifications of U.S. soil taxonomy (see Fig. 1, personal communication with Prof. M. Kuzila, University of Nebraska-Lincoln, Soil Survey Staff, 1999). The reduction from 25 to 12 soil classifications allowed us to generate larger sample sizes for each classification from the available calibration datasets. Using the available lattice water samples from Zreda et al. (2012) and additional samples collected *in-situ* over 2014, we analyzed if any statistically significant relationships existed between GSDE clay weight percent and 61 *in-situ* lattice water samples for each of the US soil orders (Table S1). We note that this procedure could be used globally if *in-situ* lattice water samples were available for all 25 soil taxonomic groups. From these relationships, a map of the CONUS lattice water weight percent was developed by using either the mean value of the *in-situ* lattice water or the linear relationships between clay weight percent (from the GSDE) and the lattice water *in-situ* samples. A statistically significant *p* value (<0.05) was used to discriminate between using the mean values and linear relationship. Additionally, *in-situ* samples of soil organic carbon, bulk density, and clay weight percent were compared against the same parameters derived from the GSDE.

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2.5 Global Datasets of Vegetation Properties

In order to estimate *SWB* and *SDB*, we downloaded remotely sensed 500 m MODIS reflectance data from NASA's Terra satellite (http://earthexplorer.usgs.gov/). To calibrate and validate the *in-situ* vegetation data to the remotely sensed vegetation estimates, we sampled two different agricultural areas in eastern Nebraska. The MODIS reflectance data were used to generate a widely used vegetation index (see detailed information below), and then calibrated against historical biomass data (2003-2013) from 3 fields near Mead, NE. Each field is part of

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the AmeriFlux network (http://ameriflux.ornl.gov/) with data going back to 2001 (site description given in Suyker et al., 2005). Each field is approximately 65 ha in area. Field 1 (Mead Irrigated/US-Ne1, 41.1650°, -96.4766°) is irrigated with continuous maize. Field 2 (Mead Irrigated Rotation/US-Ne2, 41.1649°, -96.4701°) is irrigated with a rotation of maize and soybean. Field 3 (Mead Rainfed/US-Ne3, 41.1797°, -96.4396°) is rainfed with a rotation of maize and soybean. At these three fields, destructive biomass samples were collected approximately every two weeks at 6 different locations in the field, typically consisting of 30-35 individual plants per sampling bout. From the destructive sampling bouts, we were able to compute *SWB* and *SDB*. The sites, with their long sampling records consisting of both rainfed and irrigated soybean and maize, are an ideal location for calibrating the remote sensing reflectance data and vegetation indices. In order to validate the derived vegetation index and coefficients from the above mentioned three sites, we used 4 bouts of destructive biomass sampling at two fields (each approx. 65 ha.) during 2014 near Waco, NE (Franz et al. 2015). The fields were irrigated maize (40.9482°, -97.4875°) and irrigated soybean (40.9338°, -97.4587°). *SWB* and *SDB* were collected following the protocol described in section 2.3.

A total of 924 MODIS images over the growing seasons (May to October) between 2003 and 2014 were downloaded for calibration and validation of the corresponding destructive biomass samples at the five field sites in central and eastern Nebraska (note: MODIS images from the closest date to *in-situ* sampling were used with up to a 4 day offset). We extracted the MODIS reflectance data in the green and near-infrared electromagnetic spectrum range. Next, we removed any pixels that were skewed by incidental cloud cover (Nguy-Robertson & Gitelson, 2015). The resulting data were then transformed from separate reflectance images into the Green Wide Dynamic Range Vegetation Index (*GrWDRVI*; Gietelson, 2004):

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$$GrWDRVI = \frac{(0.1 * Near\ Infrared - Green)}{(0.1 * Near\ Infrared + Green)} \quad (5)$$

where near-infrared light (MODIS band 2) has wavelength between 841 and 876 nm and green light (MODIS band 4) has wavelength between 545 and 565 nm. The *GrWDRVI* has been shown to have better correlations with observed *in-situ* biomass as compared to other vegetation indices such as NDVI (Nguy-Robertson et al., 2012; Nguy-Robertson & Gitelson, 2015). We then investigated if any relationships existed between *GrWDRVI* and *SWB* and *SDB*. We note that a variety of vegetation indices exist in the literature (c.f. Kumar et al. 2015 and Duncan et al. 2015) and that this analysis is a first step for use with maize and soybean. We anticipate that other vegetation indices may be more appropriate with use in other crops or vegetation types and more research is needed in this area.

2.6 Error Propagation Analysis of GSDE Soil Properties

We used a Monte Carlo analysis to estimate the expected uncertainty if the GSDE parameters were used instead of *in-situ* estimates. The statistical metrics of root mean square error (RMSE), mean absolute error (MAE), and bias describe the error propagation in the Monte Carlo simulation experiment. From the 61 CONUS *in-situ* samples and the GSDE soil properties, we estimated the mean difference and the covariance matrix for θ_{LW}, θ_{SOC}, and ρ_b. With these data, we simulated 100,000 realizations of the "true" (i.e. from the *in-situ* sampling) and perturbed soil properties using a multivariate normal distribution. Using a range of observed neutron counts and solving equations (1-2) with the true and perturbed soil properties, we also estimated the true and perturbed *SWC*. In order to provide realistic constraints on the error propagation results, we assumed soil bulk density was constrained between 1.2-1.5 g/cm^3, lattice

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water between 1-8 wt. %, soil organic carbon between 0-8 wt. %, and *SWC* between 0.03-0.45 cm^3/cm^3. Simulated and calculated values outside of these bounds were either reset to the minimum or maximum value or removed from the Monte Carlo statistics. A minimum threshold of 70% of simulated cases was used to compute all error statistics for each case. We note that the effects of growing biomass were not included here given the lack of available calibration datasets at all sites, but could be incorporated in future work following a similar methodology.

3. Results

3.1. Comparison of *In-situ* and Global Soil Calibration Parameters

The comparisons between observed clay weight percent, soil bulk density, soil organic carbon and the GSDE values are summarized in Table S1 and Figure 2 a, b, c for the 61 sampling sites within the CONUS. Other than 1 outlier (see discussion in 4.1.), the comparison between the mean observed and GSDE clay weight percent (of sites that had clay weight percent) behaved well (RMSE = 5.45 wt. %, R^2 = 0.68) considering the difference in scale and methods. The comparisons between soil bulk density (RMSE = 0.173 g/cm^3, R^2 = 0.203) and soil organic carbon as it was during the various 2011-2014 sampling campaigns, (RMSE = 1.47 wt. %, R^2 = 0.175) generally followed the same positive trend. We note that the slope of the relationships for soil bulk density and soil organic carbon is different from 1 and can lead to biased results. Caution should be used for using these estimates as opposed to local in-situ sampling.

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In order to construct a map of the CONUS lattice water, we investigated if any significant relationships existed between GSDE clay wt. % and observed lattice water for each US soil taxonomic group (Table 1). We found that a significant linear relationship existed between clay wt. % and lattice water for all 61 sites ($R^2 = 0.183$, *p* value <0.001). However, after partitioning the sites into soil taxonomic groups, only the mollisol taxonomic group yielded a statistically significant relationship ($R^2 = 0.539$, p value <0.001). Therefore, in order to construct a CONUS lattice water map, we used the mean values for six taxonomic groups and neglected the remaining five taxonomic groups due to an inadequate number of samples (Figure 3). Figure 2d illustrates the comparison between the derived and observed lattice water for the 61 CONUS sites (RMSE = 1.299 wt. %, $R^2 = 0.315$). Table S1 summarizes the observed and GSDE values for all 61 sites and Table 2 summarizes the mean difference and covariance matrix between the *in-situ* values and GSDE values. The mean difference and covariance differences were used in the error propagation analysis described in section 2.6 and 3.3. We note that each of the mean differences followed a normal distribution (see Table S1 for *in-situ* and GSDE values).

3.2. Comparison of *In-situ* and Remotely Sensed Vegetation Calibration Parameters

Using the 11 years of destructive vegetation sampling from 3 fields near Mead, NE, we found that the *GrWDRVI* was able to reasonably predict *SWB* when partitioning the data into maize and soybean, irrigated and rainfed, and green-up/mature and senescence periods of crop development (Figure 4 and Tables S2 and S3). Figure 4a and 4b illustrate the logistic functions that were used to predict *SWB* for maize green-up (RMSE = 0.88 kg/m^2) and soybean green-up (RMSE = 0.47 kg/m^2). We note that *SWB* relationships with *GrWDRVI* indicate that *GrWDRVI* values less than 0.25 equated to the absence of *SWB*. During senescence, we found that a second order power law function fit the data well. We found the maize senescence functions (DOY> 210) needed to be further partitioned by irrigated and rainfed conditions as limitations in soil

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water will occur more quickly with mature plants that utilize the entire root zone. The resulting functions for irrigated maize during senescence (RMSE = 0.75 kg/m^2) and rainfed maize during senescence (RMSE = 0.92 kg/m^2) behaved well. For the soybean senescence function (DOY>230), we found a single function behaved reasonably well for both irrigated and rainfed conditions (RMSE = 0.45 kg/m^2). As expected from previous research (Ciganda et al, 2008; Peng et al. 2011), we found that the *GrWDRVI* was a poor predictor of *SDB*/percent water content of the vegetation. We will discuss the reasons and alternative strategies for estimating *SDB* in section 4.2.

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Using the derived relationships from the three study sites near Mead, NE, we applied the equations to our two study sites near Waco, NE (~ 88 km from Mead, NE, Figure 5 and Tables 3 and 4). Figure 5 illustrates the time series of *SWB* using the 8 day MODIS product in combination with the derived equations for both field sites. The figure also illustrates the observed destructive sampling for 4 different sampling bouts. With the limited data, we found the time series of *SWB* calculated from the MODIS data followed the expected green-up and senescence *SWB* behavior for both the irrigated maize and soybean. The *GrWDRVI* derived *SWB* largely captured the maximum observed value for both the irrigated maize (6.58 kg/m^2 vs. 6.2 kg/m^2) and irrigated soybean (2.61 kg/m^2 vs. 1.81 kg/m^2). The largest discrepancy was during the maize green-up period (DOY 183) where the observed value was 2.4 kg/m^2 and ~4.0 kg/m^2 calculated from the *GrWDRVI*. While the derived equations behaved well for this limited validation dataset, the equations should be tested at additional sites where other crop and soil types may influence the function coefficients. Overall, the equations and regression fits resulting in RMSE < 1 kg/m^2 are within the uncertainty of destructive biomass sampling in crops (Franz et al., 2013; 2015). We note that 1 kg/m^2 is approximately equal to 1 mm of water or about 0.0033

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cm^3/cm^3 of SWC over 300 mm. This indicates that for relatively small changes in *BWE* it will be nearly indistinguishable from the noise in the CRNP measurements. By having general *SWB* relationships (for eastern Nebraska) through time using the 8 day MODIS data, this could allow for reasonable biomass corrections to N_0 with minimal effects (<0.01 cm^3/cm^3) on the overall estimation of *SWC*.

3.3. Results of GSDE Soil Properties Error Propagation Analysis

In order to further assess the accuracy of our datasets, we synthetically altered the parameters via a Monte Carlo error analysis. This was done using the GSDE soil parameters (θ_{LW}, θ_{SOC}, and ρ_b) as compared to using local sampling (Figure 6). The analysis revealed that for the given bounds of θ_{LW}, θ_{SOC}, and ρ_b, the maximum RSME was around 0.035 cm^3/cm^3 at a *SWC* = 0.40 cm^3/cm^3. The asymmetric shape of all the curves is expected given the nonlinear calibration function given in Eq. (4) and the bounded nature of soil moisture. We found that ρ_b was by far the most sensitive parameter, followed by θ_{LW} and then θ_{SOC}. We expect the influence of vegetation changes to be small on the overall accuracy of *SWC* (<0.01 cm^3/cm^3) given the low RMSE described in section 3.2 (< 1 kg/m^2, which is ~1 mm of water or 0.0033 cm^3/cm^3 for a soil depth of 300 mm). We also note the critical factor in the error propagation analysis is the assumed range of ρ_b, given that it is directly multiplied by the gravimetric water content in the calibration function. Therefore, future sampling efforts or evaluations of available datasets should seek to improve the accuracy of bulk density, meaning better estimates of the mean, standard deviation, quantiles, and impact of land use practices on bulk density.

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4. Discussion

4.1. Global Soil Calibration Parameters

The correlation between observed and GSDE clay content was very strong (Figure 2a) for all 61 sites in the CONUS except for the site in south central Texas (29.9492^{o}, -97.9966^{o}). The site occurred near a transition from vertisol to alfisol soil taxonomic groups; the site may have been improperly categorized (Table S1) or may have straddled a sharp gradient in clay contents. The strong correlation of the GSDE clay content with the observed values allowed us to use the GSDE clay content in understanding the correlation between clay content and lattice water organized by US soil taxonomic groups (Table 1). A strong correlation was only found for clay content and lattice water for the mollisol soil taxonomic group (see Greacen, 1981; Zreda et al., 2012). This strong correlation is significant because large areas of the Midwest and Great Plains regions of the United States are made up of mollisol soils. Globally, mollisol soils comprise about 7% of the land surface (United Nations 2007) but contain some of the highest productive grassland and crop areas (i.e. Central USA, Argentina, Central Eurasia). As such, the roving CRNP method remains applicable within grassland agricultural settings. No significant linear relationships with clay content were found for alfisol, aridisol, entisol, inceptisol, spodosol, or ultisol. Instead the mean value was assigned to the alfisol, aridisol, entisol, inceptisol, spodosol, and ultisol soil taxonomic groups when generating the CONUS map. We found the differences in most of the soil taxonomic mean values were statistically significant among different taxonomic groups given the small standard errors of the means (not shown but can be calculated from data in Table 1). The current analysis did not contain enough samples for the soil taxonomic groups of andisol, gelisol, histosol, oxisol, or vertisol to perform a linear regression or assign a mean value. We recommend future work to consider repeating the analysis for a larger dataset using

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the FAO 2007 (United Nations 2007) soil classification of all 25 groups (also classified for our sites in Table S1). Given the widespread interest in both the fixed and roving cosmic-ray technology, a database of lattice water and clay content for each site could be developed. In addition, warehouses like the Natural Resources Conservation Service (NRCS) in Lincoln, NE contain stored samples from around the USA. This warehouse with others around the globe could be further sampled to help complete the global dataset for use by the cosmic-ray community. Finally, the NRCS regularly updates the Soil Survey Geographic Database (SSURGO), which contains higher spatial resolution and vertically resolved estimates of soil texture and structure (i.e. clay content and bulk density). With the defined regression relationships and soil taxonomic groups, better spatial maps of lattice water could be generated. This may become important for applications of the rover at scales less than 1 km, such as using it for applications in precision agriculture as well as increasing the reliability of the calibration function.

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The correlation between the observed and GSDE soil organic carbon was fairly poor, particularly at the high end (> 4 wt. %). The history of land use is critical in determining carbon pools and how they change through time (Post et al., 2000) and may not be well represented in the GSDE. For arable lands, we note that organic carbon has a relatively small impact on the calibration function as it is multiplied by several factors in the calibration equation, and is relatively low and homogeneously distributed in the A-horizon due to land management activities. However, in grassland and forest sites, high SOC amounts and strong SOC vertical gradients typically exist in the top soil and may need to be quantified with local in-situ sampling (e.g. Bogena et al., 2013). For rover survey experiments in these areas, we suggest that SOC be

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sampled with composite samples, particularly between sites with varying land use histories which can be identified using historical land cover maps.

Observed *in-situ* soil bulk density and GSDE bulk density exhibited a positive relationship, albeit with low R^2. The poor fit and sensitivity of the parameter in the calibration function increases the importance of identifying the range and variability of bulk density within the rover sample domain. The variability shown here by the standard deviation of the bulk density for the individual point samples within the 28 ha sample domain varied between 0.1 and 0.2 g/cm^3. Moreover, estimating the quantiles of bulk density at a site is key given the propagation of error analysis presented in section 3.3. Thus, this result supports direct sampling at key locations (along gradients of land use, soil taxonomic groups, etc.) to constrain the quantiles of expected bulk density values. We also suggest that for rover surveys in the USA (and regional elsewhere), additional higher resolution datasets like SSURGO, and its derivatives (e.g. Polaris, Chaney et al., 2016), be used instead of the 1 km GSDE (in particular bulk density data as a function of depth), as significant small scale variability may be averaged out. This may be critical to account for in future roving CRNP research areas, such as precision agriculture or small scale watershed monitoring where significant soil texture variation may exist at short length scales. We note that this analysis is a first step in the incorporation of existing soil databases that will no doubt continue to increase in spatial resolution and accuracy. Given the increasing use of the roving CRNP technology, we anticipate similar analyses and procedures will be undertaken on regional and local scales from existing and new databases as they become available.

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4.2. Global Remotely Sensed Vegetation Calibration Parameters

The comparison of 11 years of destructive vegetation samples from maize and soybeans at 3 sites in eastern Nebraska indicated that the *GrWDRVI* was able to predict *SWB* in agricultural fields, especially when partitioned into green-up vs. senescence and irrigated vs. rainfed (Figure 4). However, as expected the *GrWDRVI* was unable to predict *SDB*. The main reason is as the plants begin to dry out during the late summer and early fall, leaves lose their chlorophyll and leaf structure beings to collapse thereby increasing reflected green and reducing near-infrared light (Ciganda et al. 2008; Peng et al. 2011). This is exaggerated by a change in the allocation of resources by the plant from leaves to grain, shifting where the majority of mass is located and thus weakening the capacity for the *GrWDRVI* to predict *SDB*. This biological investment of resources is more pronounced for maize than soybeans. As additional crops are included in this analysis, the location and development of the fruit and seed will impact the predictive relationships using vegetation indices. We refer to the reader to Duncan et al. (2015) and Kumar et al. (2015) for a recent review of vegetation indices in remote sensing.

While the developed regression relationships for maize and soybean (Table S3) were tested against independent biomass estimates from Waco, NE (Figure 5), we note that further validation is needed. In terms of a strategy for estimating *SDB*, we suggest that proxies such as crop type and growth stage be used. Franz et al. (2013 and 2015) found that in early stages, maize and soybean had canopy water contents from 75-90 wt. %. By the end of senescence before harvest, the canopy water contents were down to 25-35 wt. %, and thus very low *BWE* and minimal impact on the low-energy neutron intensity. If growth stage is not directly known, local meteorological observations, planting date, and crop variety can be used to compute proxies (e.g. growing degree days) or simulated from crop models (Allen et al. 1998). We note that having a reasonably accurate estimate of *SWB* and thus *BWE* (within ~ 1 kg/m^2) is all that is

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required to have a relatively small impact (< 0.01 cm^3/cm^3) on the estimated *SWC*. Finally, we note that this methodology is not applicable to areas with woody biomass. Following Franz et al., (2013), Hawdon et al., (2014), Baatz et al., (2015), and Coopersmith et al., (2014) we suggest other vegetation relationships (i.e. *BWE* vs. N_0) be defined. However, given the relatively small changes in *BWE* over the year in forests, we would expect small changes in N_0 through time. For a more complete discussion of CRNP calibration in forests and estimates of time varying changes in N_0 please see Bogena et al., 2013 and Heidbüchel et al., (2016).

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4.3. Roving CRNP Survey Recommendations

With the continuing use of the roving CNRP we make the following recommendations on best calibration and use:

1) Collect a series of full calibration datasets (θ_{LW}, θ_{SOC}, ρ_b, SWB, SDB) in different land use areas and soil types in order to estimate the instrument specific slope and intercept for dependence of N_0 with *BWE*.

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2) In the rover sampling area, construct a map of land use including descriptions of: vegetation/crop type, planting date, variety, rainfed vs. irrigated, and gravel vs. paved roads vs. natural areas (see Chrisman and Zreda 2013 for a discussion of road influence on neutron counts).

3) Collect a series of aggregate soil samples for soil organic carbon and lattice water around the survey area. The samples should be collected across land use, soil texture, and soil taxonomic groups. The GSDE or more local datasets like SSURGO and Polaris (Chaney

et al., 2016) in the USA can be used to select sites, cross validate samples, and fill in data gaps.

4) Soil bulk density is the critical parameter in the calibration equations and overall accuracy of the cosmic-ray neutron method. Bulk density should be collected locally wherever possible to determine reasonable quantiles. More local datasets like SSURGO and Polaris in the USA will likely perform better at smaller scales than the 1 km GSDE.

5) *SWC* validation datasets should be collected to independently assess the accuracy of the rover survey results.

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5. Summary and Conclusions

In this work, we developed a framework using globally available datasets for estimating four (θ_{LW}, θ_{SOC}, ρ_b, SWB) of the five key soil and vegetation parameters needed by the roving cosmic-ray neutron method for estimating *SWC* in fast growing vegetation areas such as row crop production in agricultural areas. The remaining crop vegetation parameter (*SDB*) can be fairly well approximated by crop type, growth stage or simulated with crop models. The accuracy of the GSDE soil database was tested against 61 calibration datasets from the CONUS. We found that the 1 km GSDE compares well against observed clay content ($R^2 = 0.68$) but much poorer against soil bulk density ($R^2 = 0.203$) and soil organic carbon ($R^2 = 0.175$). Surprisingly, of the six soil taxonomic groups we investigated, only mollisols showed a statistically significant correlation with clay content. The remaining five soil taxonomic groups we investigated did show statistically different mean values. These mean values were used to generate a map (not complete) of lattice water for the CONUS. From 11 years of destructive

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sampling of maize and soybean fields in eastern Nebraska, we found that the 8-day 500 m resolution MODIS derived *GrWDRVI* was highly correlated to *SWB*, particularly when partitioning the fields into green-up vs. senescence and irrigated vs. rainfed (RMSE < 1 kg/m^2). A propagation of error analysis indicated that the range of bulk density values was the most sensitive calibration parameter. For the selected ranges, we found the GSDE vs. local sampling resulted in a maximum RMSE of 0.035 cm^3/cm^3 at a *SWC* = 0.40 cm^3/cm^3. Finally, a list of best practices for future roving CRNP experiments is provided.

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Acknowledgments

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Table Captions

Table 1. Summary of mean, standard deviation of *in-situ* lattice water samples organized by USA soil taxonomic groups. The table also summarizes a linear regression analysis using the GSDE clay percent and *in-situ* sample. The last column indicates how the 1 km CONUS lattice water map was generated. Note NA stands for not applicable because of a lack of data.

USA Soil Taxonomic Group	**Mean Lattice Water (Wt. %)**	**Std. Lattice Water (Wt. %)**	**Number of Samples**	**Linear Regression Slope**	**Linear Regression Intercept**	**Linear Regression R^2**	**Linear Regression p value**	**GSDE Derived CONUS Lattice Water Product**
Alfisol	4.31	1.36	9	6.09	-0.11	0.086	0.44330	Mean
Andisol	NA	NA	NA	NA	NA	NA	NA	NA
Aridisol	2.73	1.36	10	4.82	-0.15	0.095	0.38607	Mean
Entisol	1.47	0.93	5	2.48	-0.14	0.233	0.41064	Mean
Gelisol	NA	NA	NA	NA	NA	NA	NA	NA
Histosol	NA	NA	NA	NA	NA	NA	NA	NA
Inceptisol	4.98	0.28	2	NA	NA	NA	NA	Mean
Mollisol	3.18	1.22	24	1.03	0.11	0.539	0.00004	Linear
Oxisol	NA	NA	NA	NA	NA	NA	NA	NA

Spodosol	2.68	2.10	4	3.45	-0.11	0.020	0.85919	Mean
Ultisol	2.82	2.33	6	0.28	0.20	0.229	0.33672	Mean
Vertisol	5.18	NA	1	NA	NA	NA	NA	NA
ALL	3.16	1.58	61	1.68	0.09	0.183	0.00066	NA

Table 2. Top) Summary of mean difference between *in-situ* samples and GSDE values (Figure 3) for bulk density, lattice water and organic carbon. Bottom) Summary of covariance matrix of difference between *in-situ* values and GSDE values. The mean difference and covariance data were used in an error propagation analysis illustrated in Figure 6.

	Bulk Density (g/cm^3)	**Lattice Water (Wt. %)**	**Organic Carbon (Wt. %)**
Mean Difference of in-situ value - GSDE value	-0.10035	-0.05789	-0.07077
Covariance matrix of in-situ value - GSDE value			
	Bulk Density (g/cm^3)	**Lattice Water (Wt. %)**	**Organic Carbon (Wt. %)**
Bulk Density (g/cm^3)	0.0386	-0.0567	-0.2077
Lattice Water (Wt. %)		1.6745	0.3624
Organic Carbon (Wt. %)			3.5810

Table 3. Summary of 2014 *GrWDRVI* and calculated standing wet biomass for irrigated maize and irrigated soybean fields near Waco, NE. Note that the senescence equation was applied to DOY 209 for the irrigated maize field as planting date and development can vary locally. The drop in *GrWDRVI* between DOY 201 and 209 is a clear indicator of change in plant growth stage that can be used on a field by field basis.

DOY (2014)	GrWDRVI, Irrigated-Maize	GrWDRVI-Irrigated Soybean	Calculated Standing Wet Biomass-Irrigated Maize (kg/m^2)	Calculated Standing Wet Biomass-Irrigated Soybean (kg/m^2)
153	0.23	0.23	0.00	0.00
161	0.24	0.24	0.00	0.00
169	0.32	0.28	0.53	0.06
177	0.57	0.54	4.69	1.25
185	0.55	NA	4.33	NA
193	0.63	0.63	5.63	1.91
201	0.61	0.71	5.34	2.48
209	0.55	0.73	6.50*	2.61
217	0.57	0.74	6.58	2.67
225	0.50	0.73	6.27	2.61
233	0.47	0.74	6.07	NA
241	0.40	0.68	5.38	2.89
249	0.43	0.64	5.73	6.77
257	0.27	0.47	1.44	6.07
265	0.25	0.44	0.00	5.83
281	0.21	0.28	0.00	2.02
289	0.21	0.26	0.00	0.78
297	0.20	0.25	0.00	0.00

Table 4. Summary of 2014 observed standing wet biomass for irrigated maize and irrigated soybean fields near Waco, NE. The observations represent the aggregation of 18 plants collected at 6 different locations across the field on the sampling date.

DOY (2014), Irrigated Soybean	**Observed Standing Wet Biomass-Irrigated Soybean (kg/m^2)**	**DOY (2014), Irrigated Maize**	**Observed Standing Wet Biomass-Irrigated Maize (kg/m^2)**
167	0.19	161	0.13
196	1.63	183	2.40
211	1.81	217	6.22
259	1.63	259	0.30

Table S1. Summary of *in-situ* and GDSE soil information for 61 CONUS study sites (see supplemental material zip file).

Table S2. Summary of observed standing wet biomass and MODIS derived *GrWDRVI* for each of the 3 fields near Mead, NE (see supplemental material zip file).

Table S3. Summary of derived equations estimating standing wet biomass from *GrWDRVI* for maize and soybean partitioned into irrigated and rainfed areas and green-up (DOY< 210 for maize, DOY<230 for soybean) and senescence. Destructive biomass data is aggregated from 3 fields near Mead, NE between 2003-2013 (Table S2). We note that the maize and soybean functions were bounded to provide realistic behavior at the observed *GrWDRVI* and destructive vegetation sampling bounds. See main text for details.

Figure Captions

Figure 1. Map of soil taxonomic classification map over the Continental United States of America using the twelve USA soil taxonomic orders (data source FAO 2007 and personal communication with M. Kuzila). Note gelisols are not present in the CONUS. Black dots indicate 61 locations where we have *in-situ* composite/average samples for soil bulk density, soil lattice water, soil organic carbon, and clay weight fraction collected over a 12.6 ha circle and averaged over the top 30 cm (Table S1).

Figure 2. Comparison between 61 *in-situ* composite sample and GSDE value from the closest pixel for a) clay weight percent b) soil bulk density, and c) soil organic carbon. d) Comparison between *in-situ* lattice water and derived values using GSDE clay weight fraction and soil taxonomic orders. See Table 1 for summary of data by taxonomic group, Table S1 for raw data, and Table 2 for statistical summary of differences between *in-situ* and GSDE product. Note error bars denote +/- 1 standard deviation.

Figure 3. Derived 1 km resolution lattice water weight percent map using the GSDE clay percent and regression analyses organized by soil taxonomic classification. See Table 1 for estimates of the mean, standard deviation, and linear regression vs. clay percent organized by taxonomic

group. Black dots indicate 61 locations where we have *in-situ* composite/average samples for soil bulk density, soil lattice water, soil organic carbon, and clay weight fraction collected over a 12.6 ha circle and averaged over the top 30 cm (Table S1). Missing areas indicate surface water bodies or soil taxonomic groups with no or limited *in-situ* lattice water sampling (see Table 1).

Figure 4. Relationship between *GrWDRVI* and observed standing weight biomass for maize (a, c) and soybean (b, d) partitioned into green-up (DOY< 210 for maize, DOY<230 for soybean) and senescence. Destructive vegetation data is aggregated from 3 fields near Mead, NE between 2003-2013 (Table S2). The regression coefficients and equations are summarized in Table S3. Note that the maize and soybean functions were subject to the constraints in order to provide realistic behavior at the observed *GrWDRVI* and destructive vegetation sampling bounds. See main text for details.

Figure 5. Time series of standing wet biomass for two study sites (irrigated maize and irrigated soybean) near Waco, NE over the 2014 growing season. The graph contains the observed *in-situ* sampling in addition to the *GrWDRVI* estimates using the equations summarized in Table S3. See Table 3 for *GrWDRVI* values and Table 4 for *in-situ* estimates.

Figure 6. Propagation of error analysis using Monte Carlo simulations of 100,000 soil parameter datasets of true soil parameters (i.e. soil bulk density, lattice water, soil organic carbon) and perturbed parameters with matching mean differences and covariance matrix between *in-situ* samples and GSDE derived parameters (see Table 2). Three error metrics are presented across a

range of neutron counts (and thus *SWC* values). Note that soil bulk density was constrained to 1.2-1.5 g/cm^3, lattice water was constrained from 1-8 wt. %, soil organic carbon was constrained from 0-8 wt. %, and soil water content was constrained from 0.03-0.45 cm^3/cm^3. Simulated and calculated values outside of these bounds were either reset to the minimum or maximum or removed from the Monte Carlo statistics. A minimum threshold of 70% of simulated cases were used to compute error statistics.

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With the continuing use of the roving CNRP we make the following recommendations on best calibration and use:

Collect a series (minimum of 7) of full calibration datasets ($\theta_{LW}, \theta_{SOC}, \rho_b,\ SWB,\ SDB$) in differing land use and soil types to estimate the instrument specific slope and intercept for correction factor N_0.

In the rover sampling area, construct a map of land use including: vegetation/crop type, planting date, variety, rainfed vs. irrigated, and gravel vs. paved roads vs. natural areas.

Collect a series of aggregate soil samples for soil organic carbon and lattice water around the survey area. The samples should be collected across land use, soil texture, and soil taxonomic groups. The GSDE or more local datasets like SSURGO in the USA can be used to select sites, cross validate samples, and fill in missing areas.

Soil bulk density is the critical parameter in the calibration equations and overall accuracy of the cosmic-ray neutron method. Bulk density should be collected locally wherever possible. More local datasets like SSURGO in the USA will likely perform better at smaller scales than the 1 km GSDE.

SWC validation datasets should be collected to independently assess the accuracy of the rover survey results.