Cosmic-Ray neutron Sensor PYthon tool (crspy): An open-source tool for the processing of cosmic-ray neutron and soil moisture data

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Abstract.

Understanding soil moisture dynamics at the sub-kilometre scale is increasingly important especially with continuous
10   development of hyper-resolution land-surface and hydrological models. Cosmic Ray Neutron Sensors (CRNS) are able to
provide estimates of soil moisture at this elusive scale and networks of these sensors have been expanding across the world
over the previous decade. However, each network currently implements its own protocol when processing raw data into soil
moisture estimates. As a consequence, this lack of a harmonized global dataset can ultimately lead to limitations in the global
assessment of the CRNS technology from multiple networks. Here we present crspy, an open-source python tool that is
15   designed to facilitate the processing of raw CRNS data into soil moisture estimates in an easy and harmonized way. We outline
the basic structure of this tool discussing the correction methods used as well as discussing the metadata that crspy can create
about each site. Metadata can add value to global scale studies of field scale soil moisture estimates by providing additional
routes to understanding catchment similarities and differences. We demonstrate that current differences in processing
methodologies can lead to misinterpretations when comparing sites from different networks and having a tool to provide a
20   harmonized dataset can help to mitigate these issues. By being open source, crspy can also serve as a development and testing
tool for new understanding of the CRNS technology as well as being used as a teaching tool for the community.

1 Context and Background

Soil moisture exerts a large influence on hydrological (Van Loon et al., 2015), biogeochemical (Schlesinger et al., 2015), and
climatic processes (Dobriyal et al., 2012; Koster et al., 2004), agricultural systems (Fontanet et al., 2018; Dutta et al., 2014),
25   landslide modelling (Zhuo et al., 2019) and earth system sciences (Fang and Lakshmi, 2014; Bonan, 2008). Its accurate
measurement is important to advance our understanding of these areas of research. In-situ point scale soil moisture estimates,
such as Time Domain Reflectometry (TDR), can provide higher temporal resolution; however spatial resolution is still limited,
on the order of centimetres. Soil heterogeneity can lead to uncertainties when upscaling to the field scale (Western et al., 1999),
which would be required for regional or larger scale hydrological modelling. Alternatively, satellite remote sensing products
30   such as Soil Moisture Active Passive (SMAP) and Soil Moisture and Ocean Salinity (SMOS) can provide global estimates of
soil moisture at a coarser spatial (~40km resolution) and temporal (~3 days) scale, and at much shallower depths (~5cm)

(Entekhabi et al., 2010; Kerr et al., 2001). It is accepted that we will require a finer spatial resolution than currently achievable through remote sensing estimates for tasks such as increasing our understanding of sub-kilometre land-atmosphere interactions, or towards the improvements of farming practices (such as through the process of irrigation scheduling), and so there is a need

35   for additional processing of ancillary data for the downscaling of these products (Portal et al., 2020; Alemohammad et al., 2018). In addition, the recent push for hyper resolution global modelling means we require measurements at a finer spatial resolution, on the order of sub-kilometer scales (Wood et al., 2011). Bierkens et al., (2015) discussed the implications of moving from a more standard resolution ~50km model to a hyper-resolution model that is sub-kilometre. The study further discussed the need to move from sub-grid paradigms, that represent a conceptualized form of earth system dynamics from

40   within the standard 50km resolution model, to explicit dynamics of earth system processes at scales < 50km. This requires a greater understanding of environmental functions at sub-kilometre, spatial scales, which in turn requires accurate measurements of environment states at the same scales.

Cosmic-Ray Neutron Sensors (CRNS) is a relatively new technology that allows estimates of soil moisture at the field scale

45   (~600m diameter) at hourly temporal resolution. Zreda et al., (2008) demonstrated that fast neutrons are mainly moderated by hydrogen atoms, which allows us to infer changes in water content in the soil profile. A tube attached to the sensor, filled with a gas such as helium or boron trifluoride, is able to detect fast neutrons that pass through it by inducing a voltage difference. Desilets et al., (2010) introduced an equation used to convert neutron counting rates into gravimetric soil moisture which has been further improved upon by Dong et al., (2014) and Hawdon et al., (2014) (equation 1). This equation forms the core to

50   using cosmic-ray neutron sensors for, now, volumetric soil moisture estimates in the field:

$$\theta_{vol} = \left[\frac{a_0}{\frac{N_{raw} \cdot f_p \cdot f_i \cdot f_h \cdot f_v}{N_0} - a_1} - a_2 - LW - WSOM \right] \rho_{bd} \qquad (1)$$

where θ_{vol} is volumetric soil moisture (cm^3/cm^3); $a_0, a_1, and\ a_2$ are coefficients obtained from neutron particle physics

55   modelling (Zreda et al., 2008; Desilets et al., 2010) and assumed to be constants; LW is the lattice (chemically-bounded mineral) water (%), $WSOM$ is the water equivalent of soil organic carbon (g/cm^3), and ρ_{bd} is the bulk density of the dry soil (g/cm^3). N_{raw} is the measured raw, uncorrected, neutron count identified over the given integration time, usually set to one hour. f_p, f_i, f_h, and f_v represent correction factors applied to N_{raw} to account for additional influences on the neutron signal other than soil moisture; they are correctios for air pressure, incoming neutron intensity, atmospheric water vapour and above

60   ground biomass, respectively. N_0 is the theoretical neutron count found in absolutely dry conditions (i.e., the maximum number of neutrons that can be found at the site without the direct presence of hydrogen). This term is unique to each site and is found through the calibration process, explained in detail in Section 2.2.

The detection of background neutrons in the atmosphere, as a method to infer estimates of field scale soil moisture, was first
65   described in Zreda et al., (2008). In that study, the authors demonstrated that neutron intensity above the surface was inversely
correlated with the amount of moisture in the soil below. This was developed further in Desilets et al., (2010), where the initial
form of equation 1 was first described and applications of this technology continued to be explored within the earth sciences
community (Desilets 2011; Franz et al., 2012; Rivera Villarreyes et al., 2011). A large-scale network of these sensors was
subsequently deployed across the United States leading to the Cosmic-Ray Soil Moisture Observing System (COSMOS)
70   (Zreda et al., 2012).

After the establishment of the first national-scale network in the US (Zreda et al., 2012), other countries such as in Australia
(Hawdon et al., 2014), Germany (Bogena et al., 2013), and the UK (Evans et al., 2016) established their individual national
networks, as well as additional sensors located in smaller networks or individual sites. Sensors from these networks have in
75   some cases been running for up to 10 years, which can be potentially valuable for the understanding of soil hydrology. As
these networks have grown so has the literature surrounding best practices for calibration and correction of the sensor signals,
allowing us to have a lower uncertainty in CRNS soil moisture estimates (Franz et al., 2012; Rosolem et al., 2013; Hawdon et
al., 2014; Baatz et al., 2015; Schrön et al., 2017). As consequence of improvements to the signal correction and sensor
calibration, a divergence in methods is noticeable among different networks. Each network inevitably implements its own
80   protocol when correcting the neutron signal to give soil moisture estimates leading to a less harmonized dataset among
networks.

This lack of a harmonized global dataset can ultimately lead to limitations in the global assessment of this technology from
multiple CRNS networks. Discrepancies in processing methodology can leave questions around information obtained, and
85   uncertainty propagated, from analysis and comparison of sensors in different networks, such as whether soil moisture signals
can be attributed solely to environmental differences or processing differences. By not necessarily following all recommended
correction steps, the estimated soil moisture products from these sensors or even networks can be seen as sub-optimal,
potentially undermining their true value. An example of the impact of evaluation sub-processed cosmic-ray soil moisture data
from the US network against land surface models is presented by (Dirmeyer et al. 2016). There is a consensus to follow certain
90   steps and guidelines which are not uniformly applied across all networks. Known corrections to account for changes in
atmospheric pressure, neutron intensity, atmospheric water vapour and aboveground biomass are applied differently and on
occasion not at all on some networks which could lead to different estimates of soil moisture (Zreda et al., (2012), Hawdon et
al., (2014), Evans et al., 2016). For example, Rosolem et al., (2013) demonstrated the influence on the neutron signal that
occurs from changes in atmospheric water vapour over time. When comparing processed soil moisture estimates with, and
95   without this additional signal correction, they demonstrated a difference of up to 0.1 cm^3/cm^3 at a site at Park Falls, USA.
Additionally, Hawdon et al., (2014) demonstrated the different approaches available in correcting neutron counts for incoming
cosmic-ray intensity and showed that there is a noticeable difference in neutron counts and ultimately soil moisture depending

on the chosen method. Schrön et al., (2017) provided an improved approach to CRNS calibration demonstrating that their revised approach improves accuracy of soil moisture estimates. For example, at the UK site, the authors found that the Root-

100 Mean-Squared-Error (RMSE) of soil moisture estimates from the CRNS was reduced from 5.3% volumetric, using the conventional calibration approach, to 1.4% volumetric, using the revised calibration approach. Improvements in accuracy were identified at all the sites they analysed, however currently this revised approach is not applied across the networks.

In order to mitigate this ongoing issue of lack of harmonization in the soil moisture estimates from the CRNS technology, we

105 present here an open-source python tool to process raw CRNS data into soil moisture estimates, using the most current methods identified in the literature. It is designed to allow a user to apply consistent data processing methods across sensors that may be located in different networks. Section 2 will describe the structure of the tool along with the relevant correction and calibration methods. It will also describe the site metadata creation process which is an additional aspect to crspy that is built to facilitate data analysis of many sites. Section 3 will discuss the implications of differing processing methodologies on soil

110 moisture estimates, as well as the benefits of creating detailed metadata for post processing analysis.

2 The crspy tool

The **C**osmic **R**ay neutron **S**ensor **Py**thon tool (crspy, pronounced "crispy"): is a tool written in Python3 that has been developed to facilitate the processing of the global networks of CRNS data in a uniform and harmonized way. It is available through an open-source repository and can be installed into a user's python environment. The tool is designed to allow the easy

115 implementation of the most up to date correction factors and calibration processes to any CRNS site globally, ultimately allowing for any user to access a harmonized dataset. Although it is designed for multiple sites from varied networks, crspy is versatile enough to process a single site as well. It is being provided to help facilitate research in the CRNS community and is not intended to state whether one networks processing methods are superior to another. It is the authors' opinion, however, that it is important for the community to consider creation of a best practice, as this will allow comparison of sensor data

120 around the world in the future. In addition, crspy is structurally designed to accommodate new corrections and processing steps that may become available in the future in an easy manner. By being open source, crspy can also serve as a development and testing tool for new understanding incorporating to the CRNS technology as well as used as a teaching tool for the community.

Figure 1 is a visual representation of the processes within crspy that converts raw sensor data into corrected soil moisture

125 estimates. Due to the varied nature of input data, such as when different networks label data differently, it is first necessary for a user to correctly format input data following crspy's naming convention (see Table A1 in Appendix). Additionally, to organise the various input and output datasets a specific working directory folder structure is necessary. This allows crspy to automatically handle the numerous sources of data. After installing the package a user can build this folder structure easily with the function `crspy.initial(wd)` where `wd` is a string representing the working directory location.

130
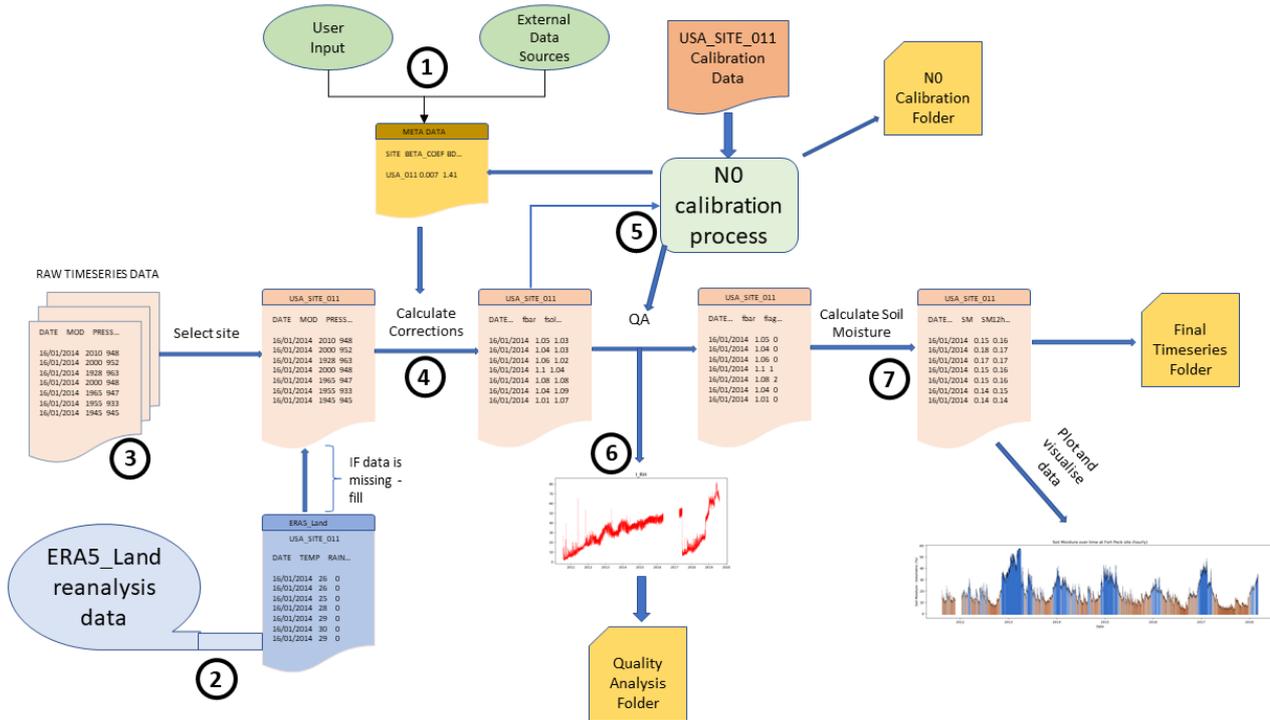
Figure 1. The structure of crspy demonstrating all the modules that are used in creating soil moisture estimates. (1) represents the metadata table which is a collection of site descriptors (e.g., soil texture, site elevation) (see section 2.4). (2), (3) and (4) corresponds to the ERA5-Land data collection and use for gap filling, data tidying and for the computation of correction factors (see Section 2.1).
135 **(5) represents the calibration process (if this option is selected) (see Section 2.2). (6) highlights the quality assessment steps undertaken (see Section 2.3). Finally, (7) represents the step where soil moisture estimates are calculated from the neutron counting rates (refer to equation 1).**

2.1 Data processing and correction

140   To obtain soil moisture estimates, we need to apply equation 1 at each time step in the data. The values will be obtained from time varying sensor data, external data products, static site-specific values and static values that are not site-specific. The coefficients $[a_0 \; a_1 \; a_2]$ are constants with values of 0.0808, 0.372 and 0.115, respectively, defined in Desilets et al., (2010). These values are fitting constants that describe the shape of the relationship between neutron counts and soil moisture, obtained from neutron particle physics modelling, and are the same for all sites. These values are stored in the `name_list.py` file, 145   which stores constant values for crspy.

Site-specific soil properties

150 The site-specific soil parameters described in Equation 1 are LW, $WSOM$ (obtained from soil organic carbon) and ρ_{bd}. Due to the open data policies of many of the CRNS networks this data is usually available online (see data availability statement). These values should be defined prior to running the main crspy function and are stored and read from the metadata file.

The parameter LW corresponds to the lattice water (%), which represents the hydrogen contained in the mineral structures of the soil (Hawdon et al., 2014). As fast neutrons are mitigated by hydrogen atoms, regardless of their source, this will have an

155 overall impact on the neutron count rate. This value is usually obtained through analysis of soil samples taken from the footprint of the site sensor (Franz et al., 2012). The parameter $WSOM$ represents the water equivalent of soil organic matter (g/cm^3). Soil organic carbon (SOC) is obtained through analysis of soil samples and represents the total organic carbon in the soil at the site. Hawdon et al., (2014) discuss the need to convert this value into a water equivalent. This is completed on the assumption that organic matter in the soil is cellulose which means that proportionally the water equivalent of this can be found

160 by:

$$WSOM = SOC * 0.556 \tag{2}$$

The parameter ρ_{bd} represents the dry soil bulk density (g/cm^3) and is a site-specific static value. It is obtained through analysis

165 of soil samples and is used in the conversion of gravimetric soil moisture to volumetric soil moisture values. If dry soil bulk density data is unavailable for a site, crspy includes the option to obtain this value from the global data source SoilGridsv2 (see Section 2.4). In case of missing data, crspy takes advantages of built-in routines to fill out the information. In that case, if ρ_{bd} or SOC (used to calculate $WSOM$) are missing, then crspy will use the estimates collected from SoilGridsv2, which is collected in the metadata process. Currently there is no way to estimate LW at sites that we know and so here a user should

170 input a value of 0. Notice that the other site-specific static value is the N_0 number. This number is found through the calibration process which is described in greater detail in section 2.2.

Time varying values and correction methods

The remaining values required to obtain θ_{vol} are N_{raw} and f_p, f_i, f_h, f_v which all vary with time. It is ultimately the

175 relationship between N_{raw} and N_0 which gives us our ability to estimate volumetric soil moisture once the additional corrections have been applied. The parameter N_{raw} is obtained from the sensor data and will usually be representative of the number of neutrons counted over a one-hour time period. This is the measured raw (uncorrected) neutron count; however, we know that there are additional impacts on this count rate that require correction which are represented by the f factors in equation 1. Changes in atmospheric pressure impact the neutron counting rate, the f_p term corrects for this so that $N_{raw} * f_p$

180 gives the neutron count rate as if it were taken at the reference atmospheric pressure. Changes in incoming cosmic-ray intensity will directly influence neutron count rates as this is the source of fast neutrons and so the f_i term will correct this to match a

reference date in time. Atmospheric water vapour and above ground biomass are additional sources of hydrogen, outside of the soil moisture source we are interested in, and so the f_h and f_v terms adjust the count rate in consideration of this. These correction methods have been improved upon since the technologies first implementation with additional sources of
185 uncertainty identified and equations designed to mitigate their impact.

There are occasional data availability issues observed at some sites. For example, meteorological variables are a necessary part of converting neutron counts to soil moisture estimates because they are needed to account for the numerous impacts on the signal, such as pressure corrections and atmospheric water vapour corrections. On occasion, some of the sites do not measure
190 all the necessary variables considered to be essential to correct for additional sources on the neutron signal. External relative humidity sensors are essential in correcting for changes in atmospheric water vapour but are not always included in site data. When data is unavailable through in-situ site sensors, ERA5-Land (Muñoz Sabater, J., 2019) data are used to fill values. ERA5-Land is a dataset, based upon the ERA5 reanalysis data, that combines modelled data with real world observations, resulting in a gridded, global hourly product at 9km resolution, provided publicly by the European Centre for Medium-Range Weather
195 Forecasts (ECMWF). Previous iterations of the ERA reanalysis datasets (such as ERA-Interim) have proved useful by other global networks for the task of gap filling missing data, such as in the FLUXNET community (Vuichard and Papale, 2015). We are implementing a similar approach used by the FLUXNET community in crspy, and consequently to the global CRNS database, as we envision the potential to a merged database incorporating both flux tower and CRNS soil moisture data in the future. As the two measurement technologies show similar temporal and spatial footprints, their combined use can eventually
200 lead to a better understanding of land-atmosphere interactions at the field scale, for example (Iwema et al., 2017). It is important to note that although the resolution is spatially coarser when compared with CRNS sites, the ERA5-Land dataset was chosen as a source for gap filling for three main reasons: (1) it covers the lifetime of all the CRNS sites around the world which ensures all historical data to be used for gap-filling if necessary; (2) the dataset is produced at hourly resolution which matches the standard resolution of CRNS sites; (3) this is an open data source which aligns with our desire to develop a full open-source
205 tool for CRNS data processing.

The ERA5-Land dataset includes key variables such as precipitation, temperature, and dewpoint temperature which can be used to correct for influence on the neutron signal, such as using dewpoint temperature when relative humidity sensors are not available at the site (Rosolem et al., 2013). Our choice also follows previous studies that demonstrated that ERA-Interim tended
210 to perform best when compared with other global reanalysis products (Decker et al., 2012). ERA5, which ERA5-Land is derived from, has benefitted from a decade of research when compared to ERA-Interim and has been shown to be a great improvement (Hersbach et al., 2020).

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(i) Atmospheric Pressure correction (f_p)

Changes in atmospheric pressure can have an impact on neutron counting rates measured by the CRNS (Zreda et al., 2012, Hawdon et al., 2014). This is attributed to the fact that higher atmospheric pressure reduces neutron counting rates as there are
220   more particles in the air column that can slow fast neutrons down. In crspy this is corrected with the equation:

$$f_p = \exp\big(\beta(p - p0)\big) \tag{3}$$

where f_p is the pressure correction factor (defined in Equation 1), β is a coefficient to account for mass attenuation length at
225   the site, p is the atmospheric pressure at the site (hPa) and $p0$ is a reference atmospheric pressure (hPa) for the site, commonly taken as the mean pressure for the site's elevation. The β coefficient and the reference atmospheric pressure value are calculated for each location as a function of the latitude, elevation, and cut-off rigidity at the site as described in Desilets et al., (2021).

230   **(ii) Incoming High-Energy Neutron Intensity (f_i)**

It is important to correct for incoming neutron intensity as this will have a direct impact on neutron counting rates. Changes in the incoming cosmic-ray intensity will affect the number of fast neutrons in the atmosphere as increased cosmic-ray intensity will lead to an increased counting rate created through the cascade of reactions (Desilets et al., 2006). We use the data from the Neutron Monitoring Data Base (NMDB) available online, providing a collection of neutron monitoring sites from around
235   the world. The NMDB provides neutron counting rates at hourly resolution from monitoring stations around the world, its data is considered the official distribution from each site principal investigator. The correction method currently varies across networks. For example, the COSMOS (USA) originally corrected the data by comparing neutron intensity to a pre-defined reference date, in that case, assumed to be 01 May 2011. The Jungfraujoch neutron monitoring station in Switzerland was used as a reference site. The calculation for this is shown as follows:

240

$$f_i{'} = \frac{I0}{Im} \tag{4}$$

where Im is the incoming cosmic-ray intensity at sensor measurement time and $I0$ is incoming neutron intensity at the decided reference date and $f_i{'}$ here is used to define this particular incoming cosmic-ray intensity correction factor, to avoid confusion
245   with f_i from equation 1.

The default approach in crspy, however, is to use the approach outlined in Hawdon et al., (2014) where the Jungfraujoch monitoring station is used but an additional correction for differences in site cut-off rigidity is applied with:

250 $$Rccorr = -0.075(Rc - Rcjung) + 1 \qquad (5)$$

where $Rccorr$ is the correction for differences in cut-off rigidity (GV), Rc is the cut-off rigidity at the sensor location and $Rcjung$ is the cut-off rigidity at the Jungfraujoch monitoring station (which has a value of 4.49 GV). This is applied at each time step to give a final corrected value with:

255

$$f_i = (f_i' - 1)Rccorr + 1 \qquad (6)$$

The Australian CosmOz network uses a different approach which does not always use the Jungfraujoch as the reference monitoring station. Instead, this network will change the reference station based on the stations which has the closest cut-off
260 rigidity (GV) to the sensor site from the Neutron Monitor Database (Hawdon et al., 2014). This option is also available in crspy when running the main processing function `crspy.process_raw_data(fileloc, intentype="nearestGV")` by invoking intentype with the "nearestGV" option. This involves identifying the NMDB site with the nearest cut-off rigidity and applying equation 4.

265 **(iii) Atmospheric Water Vapour (f_h)**

Hydrogen atoms can slow down fast neutrons leading to a reduction in the count rate with increasing atmospheric water vapour. This signal needs to be removed to ensure that neutron counting rates are attributed to soil moisture and not moisture in the air. This is corrected at each time step with the following equation (Rosolem et al., 2013):

270 $$f_h = 1 + 0.0054 \times \rho v \qquad (7)$$

where f_h is the atmospheric water vapour correction factor and ρv is absolute humidity (g m^{-3}). Some sites do not have external relative humidity sensors that can be used to calculate vapour pressure, which can be used to calculate absolute humidity along with temperature. When this is the case then ERA-5 Land data can be utilised by converting dewpoint
275 temperature (ºC) to vapour pressure (kPA) (for further information on the steps to obtain absolute humidity from standard meteorological variables, please refer to the appendix section in Rosolem et al., 2013).

(iv) Above Ground Biomass (AGB) (f_v)

Similar to other sources of hydrogen, biomass can also affect the neutron counting signal. There have been numerous attempts
280 to identify the relationship between AGB and neutron count rates (e.g. Rivera Villarreyes et al., (2011), Baatz et al., (2015), Heidbüchel et al., (2016) and Tian et al., 2016). Unlike other sources of hydrogen, AGB is sometimes not available from local samples at each site. In order to reduce the impact of AGB on the measured neutron signal, crspy currently uses static estimated

for each site from the European Space Agency (ESA) Climate Change Initiative (CCI) global dataset and apply the correction method based on the work of Baatz et al., (2015), who found a linear relationship between above ground biomass and neutron
285 counting rates.

 The following equation is used:

$$f_v = \frac{1}{1-(0.009*agb)} \qquad (8)$$

290

where f_v is the above ground biomass correction factor and agb is the dry above ground biomass at the site (kg/m^2). The ESA CCI database provides above ground biomass estimates as a global gridded data product at 100m resolution (Santoro and Cartus, 2019). As the ESA CCI data currently used is a static value in time, it will not impact the soil moisture estimates, in principle, because the correction is applied on both the N_{raw} and N_0 numbers, hence mitigating any impact. Nevertheless, we
295 have included this routine in crspy in this form as we anticipate improvements to dynamical above ground biomass corrections in the future, at which point crspy can be updated to include the latest theory that can be applied across all sites (Wahbi et al., 2018; Vather et al., 2020; Fersch et al., 2020). Further improvements to be able to dynamically account for biomass changes at all CRNS sites will be important for reliable estimation of soil moisture dynamics, especially when analysing sites with land-use changes or cropping cycles.

300 **2.2 Sensor calibration**

The above steps give us all the values in equation 1 necessary to provide a soil moisture estimate, except for N_0. A required step in processing, and eventually using the data, is to calibrate the CRNS to the specific conditions found at the site of interest. Without this step, the soil moisture can potentially have significant biases and deemed unusable. Alternatively, the uncalibrated measurement can only give you a rough idea about the dynamics of the soil wetness conditions in relative terms. The calibration
305 step typically requires multiple soil samples (typically 100s) taken from within the sensor footprint and oven dried to get an accurate representation of soil moisture at the calibration time. These samples are then weighted and averaged to give a field scale soil moisture estimate of the sensor footprint (note that we use dry soil bulk density, ρ_{bd}, sampled within the footprint to estimate volumetric water content in cm^3 cm^{-3}). The crspy tool uses the soil moisture averaging method obtained from field samples proposed by Schrön et al (2017), which is based upon the original work of Köhli et al., (2015). The method provides
310 an updated approach for weighting soil moisture samples taken within the footprint that considered spatial distance from the sensor of each sample as well as the influences of pressure and humidity during the sampling period. This allows for a more accurate estimate of independent soil moisture within the CRNS footprint for the calibration step. Schrön et al. (2017) suggested improved sampling strategies which included samples closer to the sensor (< 5m radius from the sensor) and sample locations guided by knowledge of local hydrological features. The data required for the calibration step includes the date of

315 the sample, an integer to represent each soil moisture profile (a core of soil taken from within the sensor footprint), the depth of each sample within each profile, the distance from the sensor, and the volumetric soil moisture of the sample. Again, these should be named following the template requirements by crspy (see Table A2 in Appendix).

With regards to number of calibration days, crspy is flexible enough to process both single-day or multiple-day calibration
320 campaigns. Multiple calibration campaigns were shown to improve the CRNS signal (Iweema et al., 2015). For the case of multiple-day calibration, all calibration days should be presented in a single table, ensuring that the correct dates of each sample period are provided, and following the same formatting and naming requirements used for single-day calibration.

Finally, when running crspy for a single site, the user is able to turn on or off the calibration process. This is included because calibration only needs to be done once, as N_0 does not vary with time. When the calibration step is turned on, crspy will call
325 the calibration routine and write the output to the metadata table in the column 'N0'. If the calibration routine is turned off, crspy will skip this step and simply read the N_0 number for the site from the metadata. Alternatively, the user can provide the N_0 coefficient independently in the metadata table and skip the calibration step completely by always having it off in crspy.

2.3 Quality assessment

330 All data should be checked for quality to ensure that erroneous data is not included, and crspy includes some automated steps to begin this process. All networks implement quality assessment on neutron counts in order to remove poor quality data (e.g., Zreda et al., 2012; Hawdon et al., 2014; Evans et al., 2015). In crspy, we remove suspicious data points by applying flags to neutron counts that fall within four categories, the below rules are consistent with the application in other networks:

335 1. Counts that differ by 20% from the previous time step are removed
2. Counts below 30% of N0 are removed
3. Counts above N0 are removed
4. Battery voltages below 10V are removed

340 Additionally, crspy will output time series diagnostic plots of all variables used for identifying patterns in data that point towards potential issues which may require a small subset of the data to be removed manually (this, of course, depends on the quality of the data from individual sites and, therefore, cannot be fully automated).

2.4 Metadata

345 Metadata is an important piece of information that allows the user to better describe each site characteristics beyond its soil moisture dynamics. The information can be extremely useful especially when multi-site regional to global CRNS stations are

to be analysed simultaneously. The metadata of each site is stored in a tabular format within the folder structure of the working directory, a full description of the columns is given in the Appendix (Table A3 in Appendix). It serves two main purposes. Firstly, it stores static site-specific variables that are used in computing estimated soil moisture values (e.g., LW, SOC and ρ_{bd}

350   ). To provide an example, ρ_{bd} is necessary to convert gravimetric soil moisture estimates into volumetric soil moisture estimates in equation 1. The ρ_{bd} value is collected during the calibration campaign at each site and will vary between sites. It represents an averaged value taken from the soil samples and it is stored in the metadata. Each site is also be given a country code and a site number in the metadata, which is used by crspy to find any required values stored in the metadata. The country code is used to help identify geographic locations in analysis and helps when the site numbering of networks may overlap.

355   Raw time series data should be titled with the country code and number in the following format: $country\_SITE\_sitenum$.txt. Where $country$ is a capitalised letter code and the $sitenum$ is a 3-digit number. For example, sensor data for a site in the UK could be titled: UK_SITE_101.txt. This $sitecode$ (i.e., UK_SITE_101) is used to identify each site when organising the outputs, as well as a lookup code for constant variable values stored in the metadata.

360   A second purpose of the metadata is to act as a resource when analysing many sites together. The ability to classify catchments by physical characteristics can allow us to understand key similarities and differences between sites, an important direction in hydrological research (Wagener et al., 2007). To increase the value of the metadata, as well as including data collected at the site, global data products have been integrated. These products are all public products that a user can download and store within the folder structure of the working directory. We realize that these global datasets are not a direct replacement for the

365   invaluable information obtained at the site; however, in many cases, such pieces of information are not available, undermining any multi-site analysis. We believe the use of the datasets described in detail below can provide us key information at regional and global level. In crspy, a simple function is used to extract the information from the data products below when provided with the location of the CRNS (i.e., latitude and longitude):

370   (i)   **ESA CCI Land Cover and Above Ground Biomass data:** The European Space Agency (ESA) Climate Change Initiative (CCI) provides numerous global data products that are useful in the earth sciences community. Land cover data and above ground biomass data are obtained from ESA CCI and stored in metadata for each site for analysis through identifying site differences and similarities. Both products are spatial consistent with the CRNS sensor range (100m-300m) and are available globally. The usefulness of ESA CCI datasets in land surface

375   modelling continues to be established (Li et al., 2017).

            (ii)   **International Soil Reference and Information Centre (ISRIC):** The ISRIC provides a global data product that gives estimates of soil properties on a 250m resolution grid. This is available as SoilGridv2 which is an updated (as of May 2020) iteration of the original SoilGrid product (Hengl et al,. 2017). The properties are estimated from collections of ground measurements that are compiled by the World Soil Information Service (WoSIS). WoSIS

380   provide standardised soil profile data to facilitate the creation of products such as SoilGrid (Batjes et al., 2020).

(iii) **ERA5-Land:** As discussed previously meteorological variables from ERA5-Land data can be downloaded for each site. Mean annual precipitation and temperature data is stored, along with derived Köppen-Geiger classifications.

2.5 Running the tool.

385 Once the working environment has been prepared the data can be processed with `crspy.process_raw_data(fileloc, Calibration=True, intentype=None)`. Where fileloc is the location of the raw sensor data, the Calibration process can be turned on or off as a Boolean descriptor and intentype can be left as `None` to enact the default process for incoming neutron intensity correction or can be changed to "`nearestGV`" to utilise the alternative method.

3 Discussion

3.1 Benefits of data harmonization

As mentioned previously, one of the key purposes of crspy is the easy and harmonized processing of CRNS sites from around the globe, as there is currently no true consensus on what correction steps are implemented in different national networks. These technical differences can lead to changes in outputs which may result in non-optimal conditions for regional/global
395 analysis from multiple countries. Whereas some users may wish to understand changes at one particular site, inter-site comparisons are limited when each site could be processed in a different way. In this section, we highlight such impacts with one example related to the individual sensor corrections steps, and their impact on the final soil moisture estimates.

Table 1 outlines three identified methods that are currently employed across different networks. Method p_int1 is the method
400 employed at the COSMOS (USA) network, which lacks the atmospheric water vapour correction and applies an intensity correction using only the Jungfraujoch neutron monitoring site directly. Method p_int2_awv closely resembles the CosmOz (Australia) network methodology, which does apply the atmospheric water vapour corrections and an intensity correction that differs from method p_int. In this case, the neutron monitoring station used as an incoming neutron intensity reference is changed to the nearest station with a similar cut-off rigidity to the CRNS site being corrected. Method $p\_int3\_awv\_agb$ is the
405 default crspy method, and resembles the methods used by COSMOS-UK, while also allowing for the above ground biomass correction to the neutron signal. In this final case, the intensity correction uses Jungfraujoch as its reference site but with an additional correction to account for differences in cut-off rigidity between Jungfraujoch and the site (equation 5).

410

Table 1. The three identified methods of correcting neutron signals in use.

	Method p_int1	Method p_int2_awv	Method $p\_int3\_awv\_agb$
Atmospheric pressure correction	Yes	Yes	Yes
Incoming neutron intensity correction	Jungfraujoch NMDB (no GV correction)	Nearest GV NMDB (variable locations) (Hawdon et al., (2014))	Jungfraujoch NMDB **plus** additional correction for site GV (see equation (5) and Hawdon et al., 2014)
Atmospheric water vapour correction	None	Yes (Rosolem et al., (2013))	Yes (Rosolem et al., (2013))
Above ground biomass correction	None	None	Yes (Baatz et al., (2015))

With all these different correction approaches applied independently from each national network, we investigate both the impact on the measured neutron counts and consequently the propagated effects on the estimation of soil moisture. Figure 2

415 shows two sites with distinct hydroclimatic regimes, both taken from the COSMOS-USA network, that have been processed in the three identified methods (see highlighted star markers in Fig. 3 and Fig. 4). The Santa Rita Creosote site is shrubland dominated with a soil categorized predominantly by sandy loam type located in Arizona, USA. The site has a mean annual temperature of 19 ℃ and a mean annual precipitation of 335 mm, which primarily falls in winter storms and monsoonal summers (Köppen-Geiger climate classification BSh, a hot semi-arid climate). Climate data taken from ERA5-Land and

420 Köppen-Geiger classification derived from ERA5-Land data using the method outlined in Peel et al., (2007). The Wind River site is an old-growth mixed conifer forest site in Washington, USA. The site is much wetter than the Santa Rita Creosote site, with an annual precipitation of 2,200 mm, and much colder, with an average annual temperature of 8 ℃. Precipitation at Wind River tends to fall all year round but with slightly lower rates in the summer period (Köppen-Geiger classification is Csb, a Mediterranean climate mild with dry, warm summers). Climate data has been extracted from ERA5-Land and Köppen-Geiger

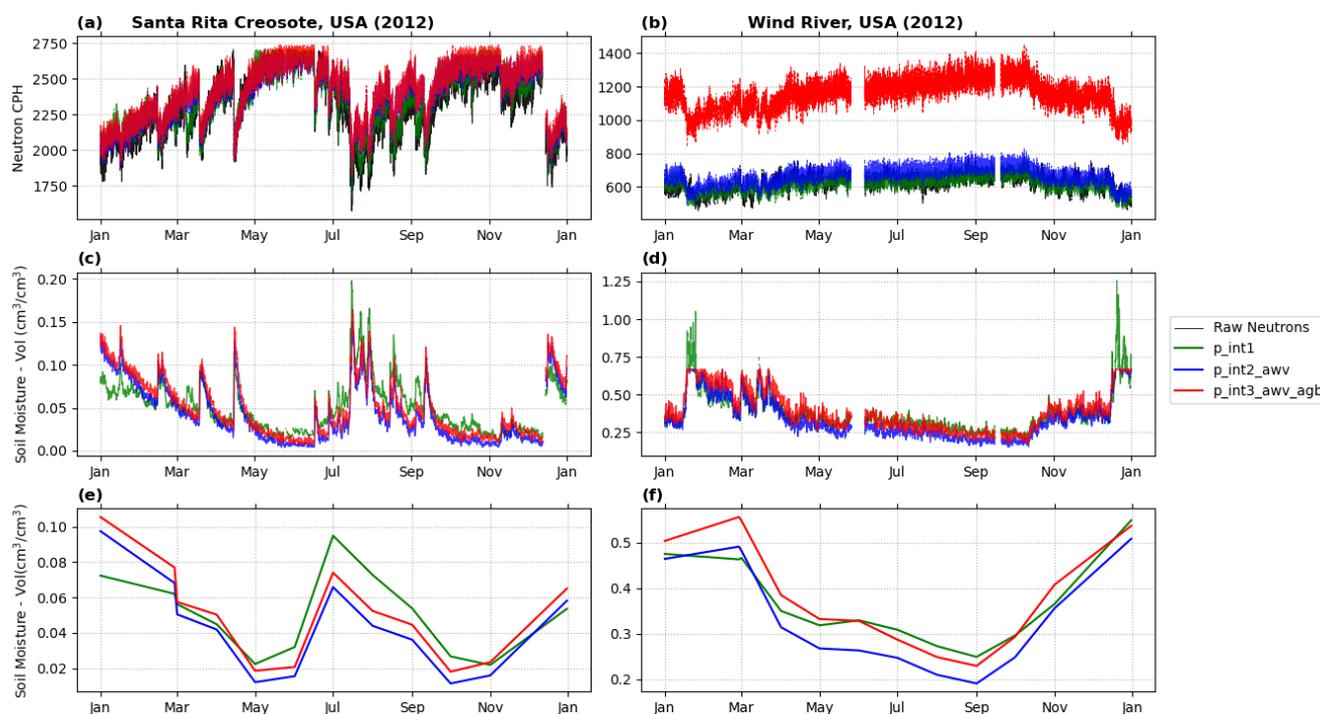
425 classification derived from 10 years of ERA5-Land data using the method outlined in Peel et al., (2007). The raw neutron data from both sites were obtained directly from the COSMOS network, representing the p_int case in Table 1. In addition, in order to compare the impact of the different correction approaches outlined in Table 1, the raw data from the CRNS at both sites, have been processed in crspy to give the corrected signals for methods p_int2_awv and $p\_int3\_awv\_agb$.

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Figure 2. Example of CRNS data obtained at two distinct sites: Santa Rita Creosote (a, c, and e) and Wind River (b, d, and f). Neutron counting rates (raw and corrected based on the different strategies outlined in Table 1) are shown in panels (a) and (b). Derived soil moisture estimates (cm³ cm⁻³) are shown at hourly and monthly timescales in panels (c) and (d) and panels (e) and (f), respectively.

435   It is clear to see the inverse relationship between neutron count rates and soil moisture, most noticeably at Santa Rita Creosote (Figures 2a and 2c). The soil moisture here tends to be low, such as in June when it was below 0.05 cm³ cm⁻³, which is to be expected in a hot semi-arid environment. Sudden spikes in soil moisture can be attributed to precipitation events, with the summer monsoonal precipitation causing a sudden increase in the mean soil moisture values for the months of July, August, and September (and, inversely, periods corresponding to decreases neutron counting rates). It is also clear that the method

440   chosen has an impact on soil moisture values. This is most notable when comparing the p_int1 method with both the p_int2_awv and $p\_int3\_awv\_agb$ methods. During the summer months, the p_int1 method appears to estimate higher soil moisture values compared to the other two methods (both appearing to be much more closely aligned to each other). This is likely due to the fact that the p_int1 method does not account for changes in atmospheric water vapour. As a consequence, during the monsoonal summers when there is more hydrogen in the atmosphere from increased humidity, the relatively high

445   water vapor in the atmosphere is incorrectly attributed to additional soil moisture. This is because the CRNS records wrongly attribute the decrease (attenuation) of neutron counts due to water vapor to an increase in soil moisture, causing an over

estimation. For example, even early in March there is a sudden rise in soil moisture from the p_int1 estimates which does not appear in the other two methods (Figure 2c). This suggests that rather than a sudden rise in soil moisture, this was actually a rise in atmospheric water vapour. This demonstrates the importance of removing external impacts on the neutron signal as they

450 could be incorrectly attributed to soil moisture dynamics. The negative effect of neglecting such correction, for example, can be pronounced even more on monthly estimates of soil moisture due to the aggregated nature of this error (Figure 2e).

The Wind River site is a much wetter site when compared to Santa Rita with its driest month matching Santa Rita Creosotes wettest month. It is worth noting in that in the case of Wind River there is a much larger difference between the neutron count

455 rate of method $p\_int3\_awv\_agb$ compared to the other methods (Figure 2b). This is because the $p\_int3\_awv\_agb$ method includes an above ground biomass correction, using the ESA CCI above ground biomass product to calculate a correction. Currently, as this correction is applied using a static aboveground biomass value (constant with time), the impact of the correction is not translated to differences in estimated soil moisture. This is due to the correction being applied to both the neutron counting rate and the N_0 term as well. With dynamic data, that represents changes in above ground biomass over time,

460 we would be able to improve our estimates of soil moisture, as the impact of changing above ground biomass could be removed from the neutron signal. One additional noticeable feature that crspy implements is the capping of soil moisture to more realistic values, in this case 0.68 cm³ cm⁻³. The p_int1 method does not do this and so there are physically impossible values of volumetric soil moisture in February and December, as seen in figure 2d. In crspy maximum values for soil moisture are estimated by inferring porosity of the soil:

465

$$sm\_max = 1 - \left(\frac{\rho_{bd}}{density}\right) \tag{9}$$

where sm_max is the maximum volumetric soil moisture value (cm³ cm⁻³), ρ_{bd} is soil bulk density (g/cm³) and $density$ is the density of ground material (estimated with an assumed density of quartz at 2.65 g/cm³).

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At the Wind River site, the differences between p_int2_awv and $p\_int3\_awv\_agb$ are much more noticeable, especially when the soil moisture estimates are aggregated to monthly timescales (Figure 2f). This observed difference is due the fact that these methods do not apply the same correction for incoming cosmic-ray intensity (f_i). Such differences are caused by the choice of correction rather than physical controls on soil water dynamics. This can lead to inaccurate comparisons across sites from

475 different national/regional networks. For example, identifying useful soil moisture signals that can be used to categorise the hydrology of sites will be an important tool for understanding differences and similarities with regards to hydrology. Branger and McMillan (2020) demonstrated this in their paper looking to identify useful soil moisture signals that can be robust, discriminatory, and representative, with research continuing in this area of developing useful diagnostic soil moisture signatures (Araki and McMillan, 2020). When reducing large time series data into signatures, such differences can be

480   aggregated which could begin to effect conclusions. However, the authors stress here that it is not within the scope of this work, nor the intention, to identify which method is better or worse than the other, but rather highlight the potential negative impacts of the lack of a harmonized dataset for large-scale global assessment of the CRNS technology.

3.2 Usefulness of crspy metadata

485   Metadata can be used to describe the network of CRNSs around the world geographically, climatologically, and hydrologically. To achieve this, crspy compiles relevant data obtained directly from the sensor, key data descriptors provided from each site or network, and from global data products. Wagener et al. (2020) discuss the need for high quality metadata to improve our ability to understand the knowledge accumulation in the field of hydrology. The metadata can be valuable in separating relevant sites in different groups, for example researchers may be interested in understanding how soil moisture behaves at sites above

490   2000m elevation with certain land use types and given particular weather events (Chen et al., 2020); or sites where mean annual precipitation is above/below a certain threshold; or even grouping sites by different land cover or soil types. So called meta-analyses can help a researcher identify which sites should be included in their studies and which can be excluded (Evaristo and McDonnell, 2017). The metadata provided by crspy allows the user to quickly obtain any grouping of interest in an easy and accessible way.

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In order to demonstrate some of the features that can be easily accessed with the help of metadata, we show an example using the compiled COSMOS network data for continental USA (CONUS). Some of this data are taken directly from the network website and then processed using the `crspy.fill_metadata()` function. This function collects information from global data products at specific site location (i.e., latitude and longitude), as well as using meteorological data from ERA5 Land to

500   produce annual meteorological summaries (e.g., mean annual temperature, mean annual precipitation, Köppen-Geiger climate classification, etc). Figure 3 gives an example of how the metadata can be easily used to show the location of each sensor in the continental USA domain (CONUS) based upon the supplied with additional information, in this case, main land cover classes obtained from the CCI ESA Land Use data. An important step here is that the user is not required to download and process the land cover data separately and individually. crspy incorporates that step for the user seamlessly.

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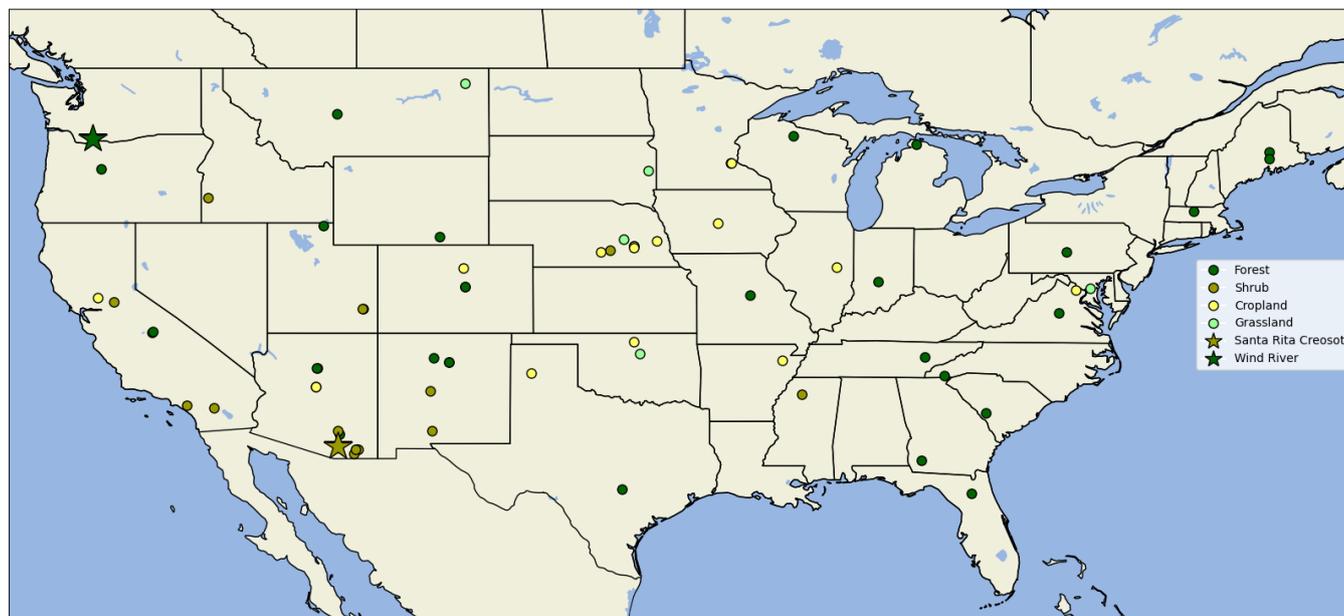
Figure 3. Map showing the location of CRNS sites from the COSMOS network across CONUS. The colours are representative of the land cover types obtained from the ESA CCI global database and the stars highlight the location of the two sites processed above (i.e., Santa Rita Creosote and Wind River).

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In addition to locating the CRNS stations and identified the main land cover type, Figure 4 shows a scatter-histogram of the sites across CONUS providing additional annual meteorological summaries, namely mean annual temperature and mean annual precipitation. The scatterplot still retains the information about the main land cover type obtained from the ESA CCI global database. In addition, both meteorological variables are shown as side-histograms and were computed using the ERA5 Land data. Initial analysis indicates that CRNS classified as shrublands tend to be relatively warmer and drier. Grassland and forests tend to be wetter while showing a wider range of temperatures. Croplands are slightly warmer than grassland and forests but still showing lower temperatures than those observed in shrublands. However, croplands also indicate a slightly wider range of wetness, when compared to the grassland and forest sites, as observed from the total annual precipitation. This could be useful when deciding which sites should be used in a particular study, such as a study on soil moisture dynamics in shrublands with low overall precipitation. Alternatively, it can be used in big data analytics when trying to identify the dominant mechanisms on soil moisture dynamics globally.
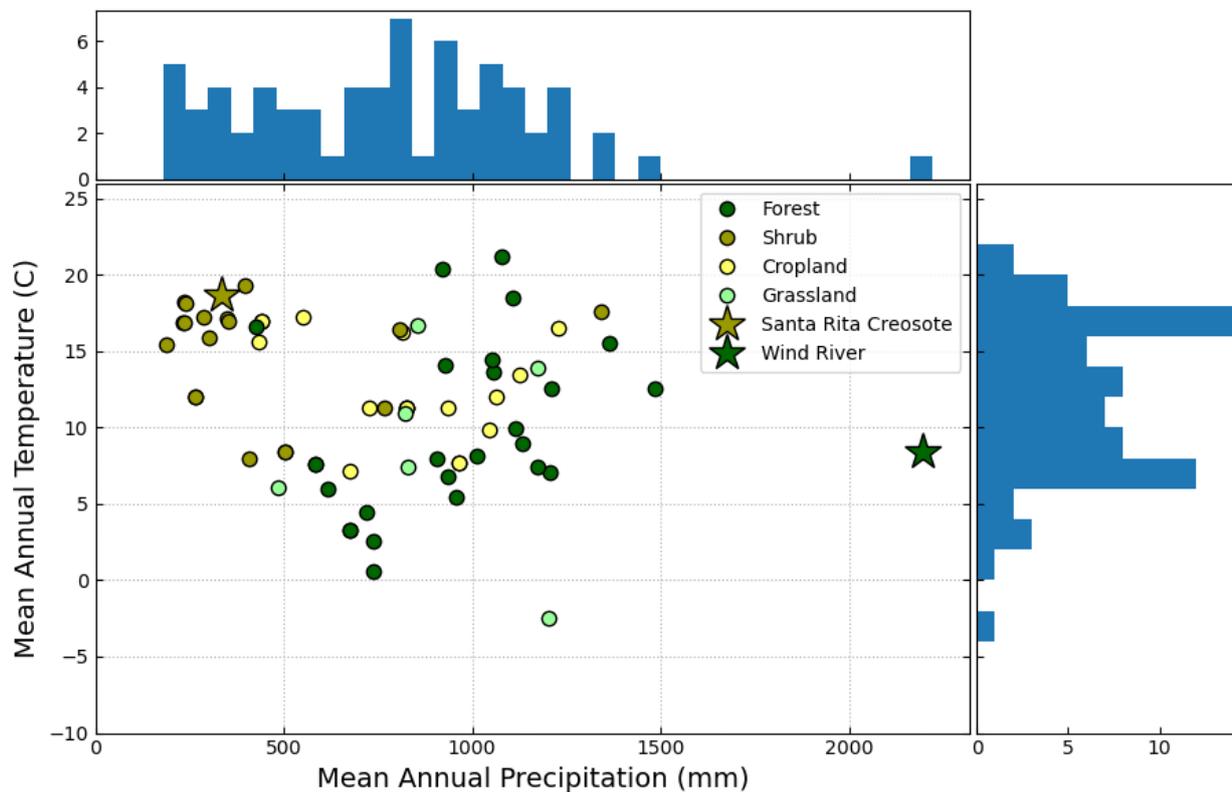
Figure 4. Scatter-histogram showing the Continental USA CRNS sites and some of their climatological characteristics. The colours represent land use types which has been identified from ESA CCI Land Use global data set. The stars
525 **highlight the location of the two sites processed above (i.e., Santa Rita Creosote and Wind River).**

4. Summary

Soil moisture is an important component of the hydrological cycle and understanding its dynamics at relevant spatiotemporal scales is critical especially with recent advances of global land surface and hydrological models. The CRNS technology is able
530 to provide estimates of soil moisture at the sub-kilometre scale and at hourly resolution. This is particularly relevant now as we continue to move towards hyper-resolution global modelling efforts. Over the years, with an increase of adoption to the technology, the CRNS community has acquired a better understanding about the benefits and limitations of this relatively novel technique. However, due to a lack of data harmonization across networks, undertaking global scale analyses is currently very limited and unexploited. Here, we introduced the crspy python package with the aim to facilitate users to process data
535 easily with the most current methods, and most importantly, in a harmonized fashion. crspy is an open-source tool aimed to

integrate the latest developed methodologies for CRNS to be used both for research and teaching activities. It integrates high-quality global data products (such as ERA5-Land) to ensure that all sites can be included in analysis. This is done in a similar way to other well-established global environmental networks such as the Ameriflux and Fluxnet.

Our examples of application demonstrated that when CRNS data is processed with different methodologies, it can ultimately
540 lead to divergences in soil moisture estimates. This could potentially have a negative impact on the analysis and overall findings, especially when sites across multiple networks are evaluated simultaneously. By harmonizing data processes, we envisage that CRNS data will be used more widely by the global modelling and experimental communities, leading to further adoption of the technology. The objective of crspy is to provide an open and easy-to-use data processing platform that can enable initially. Additionally, crspy data collection relies on the production of an extensive metadata archive. This archive can
545 be shared and used within the community to better understand key aspects about soil moisture from typical sampling locations, to inform on signature behaviour by different groupings. crspy has been developed to open up the debate and use of free and public open CRNS data, and we invite the general community to engage with us to improve this platform in future years.

5 Data availability statement

Raw CRNS data are publicly available from several sources, including the US COSMOS network
550 (http://cosmos.hwr.arizona.edu/), the Australian CosmOz (https://cosmoz.csiro.au/) and UK-COSMOS network (https://doi.org/10.5285/b5c190e4-e35d-40ea-8fbe-598da03a1185). We acknowledge the NMDB database (https://www.nmdb.eu), founded under the European Union's FP7 programme (contract no. 213007) for providing neutron count data. ESA CCI data including above ground biomass data and land cover data are available from (http://cci.esa.int/data last accessed 26/02/2021). The soil grids data are accessible online from https://soilgrids.org/. The ERA5-Land data are
555 provided by ECMWF and are available at https://doi.org/10.24381/cds.e2161bac.

6 Code availability

The code discussed in this paper can be found at https://doi.org/10.5281/zenodo.4585513. The GitHub repository, where future updates will be uploaded can be found at https://github.com/danpower101/crspy. The GitHub repository also includes a wiki page which goes into greater detail on how to run the package and includes a walkthrough jupyter notebook
560 (run_crspy_workthrough.ipynb) that will walk through processing an example site.

7 Author contributions

All authors were involved in the conceptualisation of this work. Data curation was undertaken by DD, SD, and DP. Investigation undertaken by RR, MRR, and DP. Software was written by DP. Manuscript drafted primarily by DP and subsequently written together with RR and MRR.

8 Competing Interests

The authors declare that they have no conflict of interest.

9 Acknowledgments

This work was funded by the Engineering and Physical Sciences Research Council (EPSRC) Water Informatics: Science and Engineering Centre for Doctoral Training (WISE-CDT) (grant number EP/L016214/1) with additional support from the Brazilian Experimental datasets for MUlti-Scale interactions in the critical zone under Extreme Drought (BEMUSED) (grant number NE/R004897/1) and the MOSAIC Digital Environment Feasibility Study (grant number NE/T005645/1), both projects both funded by Natural Environment Research Council (NERC); as well as with the support from the International Atomic Energy Agency of the United Nations (IAEA/UN) (project CRP D12014).

10 Appendix

The appendix section consists of 4 tables that outline the naming conventions required for crspy to run as well as the output table along with a description of each variable. When labelling input data, columns titles should match the styles below in the 'COLUMN NAME' column. This initial step will then allow crspy to run smoothly, as it uses column titles to identify relevant data sources.

Table A1. The naming convention for CRNS input data. Networks can occasionally have different naming conventions
590 **(e.g., temperature is referred to as t1). Changing the column titles to the following format will allow crspy to function**
correctly.

COLUMN NAME	UNITS	DESCRIPTION
TIME	datetime	Datetime of the observation. Format: "yyyy-mm-dd hh:mm:ss"
MOD	count	Moderated neutron count for time interval
UNMOD	count	Unmoderated neutron count for time interval
PRESS1	hPa	Pressure sensor number 1. Usually the older analogue version that is somewhat less accurate
PRESS2	hPa	Pressure sensor number 2. This will be used primarily and if unavailable PRESS1 will be used in place.
I_TEM	Celsius	Internal Temperature of the sensor box
I_RH	%	Relative humidity inside the sensor box
BATT	Voltage	Voltage of the battery
E_TEM	Celsius	External Temperature at the site. This would be an external reading. If not available then ERA5-Land data is used
E_RH	%	External Relative Humidity at the site. If not available then dewpoint temperature is used to find absolute humidity
RAIN	mm	Rainfall at the site. If local is available this is used - if not available it is obtained from ERA5-Land data

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Table A2. The naming convention for the calibration data. This format should be followed and will allow the calibration module to be utilised.

COLUMN NAME	UNITS	DESCRIPTION
DATE	Date. Format "dd/mm/yyy"	Date that the data was collected from the site
PROFILE	int	Integer to differentiate profiles. A profile being a single core. The core could then have multiple "layers".
LOC_rad	meters	Distance from the sensor for each sample in meters.
DEPTH_AVG	cm	The depth of the soil sample for each layer. Taken as the mid point of the layer.
SWV	%	The volumetric soil moisture of the sample. Should be given as decimal (i.e. 0.3). If it is given as a numeric percent (e.g. 30%) crspy will attempt to identify this and convert to decimal

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Table A3. The naming convention of the metadata table.

COLUMN NAME	UNITS	DESCRIPTION	Required at start?
COUNTRY	-	Country code for location of site e.g. "USA"	Yes
SITENUM	-	Assigned 3 digit number for site: e.g. 001	Yes
INSTALL_DATE	-	Date of site installation	No
LONGITUDE	degrees	Longitude of site	Yes
LATITUDE	degrees	Latitude of site	Yes
ELEV	m	Elevation above sea level of site	Yes
TIMEZONE	-	Time zone of the site	No
GV	gv	Cut-off Rigidity of site	Yes
LW	%	Lattice Water from site specific calibration data	Yes
SOC	%	Soil Organic Carbon from site specific calibration data	Yes
BD	g/cm^3	Bulk Density from site specific calibration data	Yes
N0	-	Theoretic maximum neutron count for site (dry conditions), calculated in tool and written.	No
AGBWEIGHT	kg/m2	Live woody above ground biomass estimates from ESA CCI biomass data	No
RAIN_DATA_SOURCE	-	Declaration of the source of rain data. Currently this will be either "Local" or "ERA5_Land"	No
TEM_DATA_SOURCE	-	Declaration of the source of temperature data. Currently this will be either "Local" or "ERA5_Land"	No
BETA_COEFF	-	Store of the calculated beta coefficient (see pressure calculations) for each individual site	No

REFERENCE_PRESS	hPa	Reference pressure calculated using elevation	No
BD_ISRIC	g/cm^3	Bulk Density estimates taken from the International Soil Reference and Information Centre (SoilGrids250m https://soilgrids.org/)	No
SOC_ISRIC	g/dm^3	Soil Organic Carbon estimates from ISRIC	No
pH_H20_ISRIC	pH	pH of water estimates from ISRIC	No
CEC_ISRIC	mmol(c)/kg	Cation exchange capacity at ph7 from ISRIC	No
CFVO_ISRIC	cm^3/dm^3	Coarse fragments from ISRIC	No
NITROGEN_ISRIC	cg/kg	Nitrogen in soil from ISRIC	No
SAND_ISRIC	g/kg	Sand in soil from ISRIC	No
SILT_ISRIC	g/kg	Silt in soil from ISRIC	No
CLAY_ISRIC	g/kg	Clay in soil from ISRIC	No
*_ISRIC_UC	varied	The uncertainty bounds of each of the ISRIC variables, in absolute terms.	No
TEXTURE	-	Soil texture identified from Sand/Silt/Clay percentages using the USDA soil texture triangle	No
WRB_ISRIC	-	World Reference Base (2006) soil class from ISRIC. Provided as a table of probable classes - this is the most probable class.	No
LAND_COVER	-	Land Cover type taken from Copernicus data set.	No

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625 **Table A4. crspy final output table from a given CRNS site. Note that there may be additional columns when run as different networks may have additional variables.**

COLUMN NAME	UNITS	DESCRIPTION
DT	datetime	Datetime of the observation. Format: "yyyy-mm-dd hh:mm:ss"
MOD	counts per hour	Moderated neutron count
UNMOD	counts per hour	Unmoderated neutron count
PRESS	hPa	Atmospheric pressure recorded by the sensors at the site
TEMP	Celsius	Atmospheric temperature - if sensors are missing ERA5-Land data is used
I_TEM	Celsius	Internal Temperature of the sensor box
I_RH	%	Relative humidity inside the sensor box
E_TEM	Celsius	External (atmospheric) temperature
E_RH	%	External (atmospheric) relative humidity
RAIN	mm	Rainfall recorded at the site. If local data is unavailable, then ERA5-Land data will be used in its place
BATT	Voltage	Voltage of the battery
fbar	-	The pressure correction factor
DEWPOINT_TEMP	Celsius	Dewpoint temperature - from ERA5-Land data
SWE	mm	Snow water equivalent - from ERA5-Land data
ERA5L_PRESS	hPa	Atmospheric pressure - from ERA5-Land data
VP	hPa	Vapour Pressure - calculated
NMDB_COUNT	counts per hour	Neutron count rate from neutron monitoring database - usually Jungfraujoch
pv	kg/m^3	Absolute humidity - calculated
fawv	-	The atmospheric water vapour correction factor
finten	-	The incoming cosmic-ray intensity correction factor
fagb	-	The above ground biomass correction factor
FLAG	-	The flag assigned to data in error (see Section 2.3 for definitions)
MOD_CORR	counts per hour	The corrected neutron count rate after the correction factors have been applied

MOD_ERR	counts per hour	The statistical error of the neutron count rate
SM	volumetric soil moisture cm^3 cm^{-3}	Estimated soil moisture
SM_PLUS_ERR	volumetric soil moisture cm^3 cm^{-3}	Estimated soil moisture error above the estimated value - this is calculated by subtracting the MOD_ERR value (due to the inverse relationship) to the MOD_CORR value and calculating what the SM would then be
SM_MINUS_ERR	volumetric soil moisture cm^3 cm^{-3}	Estimated soil moisture error below the estimated value - this is calculated by adding the MOD_ERR value (due to the inverse relationship) to the MOD_CORR value and calculating what the SM would then be
SM_12h	volumetric soil moisture cm^3 cm^{-3}	The SM value with a 12-hour rolling average applied to it. Minimum number of values to calculate the 12-hour average is 6 hours of data within the 12-hour window
D86avg	cm	The depth of the measurement - taken as the depth from which 86% of neutrons are estimated to be sourced from (Schron et al., 2017)
D86avg_12h	cm	The D86 value with a 12-hour rolling average applied to it. Minimum number of values to calculate the 12-hour average is 6 hours of data within the 12-hour window

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