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# Examining the variation of soil moisture from cosmic-ray neutron probes footprint: experimental results from a COSMOS-UK site

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## Abstract

Utilising cosmic-ray neutron probes is a relatively new approach in obtaining larger area soil moisture and various operational monitoring networks have been established worldwide utilising this technology to measure operationally this parameter. One such network located in the United Kingdom (UK) is the Cosmic-ray Soil Moisture Observing System, so-called COSMOS-UK, established in 2013. The present study aims at investigating the true footprint and the variations within the footprint detectable area at the COSMOS-UK sites using as a case study one such site located in Riseholme, UK. At the selected experimental site extensive fieldwork was conducted in July 2017 that allowed examining the agreement among the soil moisture data retrieved by the Time Domain Transmissometer (TDT) sensors and the corresponding estimates from the COSMOS-UK network station probe. The COSMOS-UK site footprint was compared using GPS-aided information from ground instrumentation, assisted by drone imagery acquisition and the implementation of geospatial interpolation methods in a Geographical Information System (GIS) environment. Altogether, this information was used for assessing the soil moisture footprint extent from the COSMOS-UK site. The COSMOS-UK station footprint was representative for an area shorter in size than the alleged footprint of 600 m diameter, as generally proposed in various relevant investigations. The COSMOS network slightly overestimated soil moisture content measured by the TDT sensor probes installed in the area. Our study findings although concern specifically the studied experimental site contribute towards efforts aiming at assessing the COSMOS-UK soil moisture measurement footprint showcasing the added value of geospatial analysis in this direction.

**Keywords** COSMOS UK · Soil moisture monitoring · Spatial analysis · Remote sensing · Geoinformation

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## Introduction

Soil moisture constitutes an utmost importance component in sustaining the life-supporting activities of an ecosystem at a micro and macro scale. Obtaining accurate spatiotemporal estimates of surface soil moisture (SSM) is a topic of key interest and priority today, particularly in the context of climate change and the global food and water security crisis (Ireland et al. 2015; Deng et al. 2019; Petropoulos et al. 2020a). SSM has a central role in Earth's surface physical processes such as the hydrological cycle but also in human and plant growth, (Silva-Fuzzo et al. 2019; Louka et al. 2020). Retrieving highly accurate spatiotemporal SSM data can assist in the sustainable management of global water resources and in the study of ecosystems and ecological processes (Srivastava et al. 2019; Petropoulos and Hristopoulos 2020). Moreover, information on SSM can be used in precision agriculture accurately estimating the plant's irrigation

needs, thus ensuring plant growth and productivity, and as early monitoring of drought indication. Furthermore, accurate estimation of soil's moisture before large rainstorms can assist in assessing and mapping the flood risk of the affected areas enabling the on-time briefing of the competent authorities (Petropoulos et al. 2018; Piles et al. 2016; Maurya et al. 2021).

Thus, precise knowledge of the spatiotemporal variability of moisture on the soil's surface at a range of geographical scales is essential for several practical applications and research investigations alike (Petropoulos et al. 2018, 2020b). Yet, information on SSM spatial variability at dissimilar scales over large extents are still a matter of research having to do with the challenges related to the constant spatial and temporal changes of the water content in the soil surface constant. SSM can be directly measured using a wide range of ground instruments (Petropoulos et al. 2018). Traditionally soil moisture measurement is conducted in situ via different instruments that perform point measurements, with one of the most widely used being the Time Domain Reflectometry sensor (TDR). However, such point-based ground instrumentation is not representative of the soil moisture variability at large scales. On the other hand, remote sensing (RS) techniques can estimate SSM systematically, inexpensively, and rapidly at a worldwide scale (Petropoulos et al. 2018). In this respect, the synergistic use of remote sensing (RS) alongside Geographical Information systems (GIS) and spatial interpolation techniques has enabled the provision of highly accurate spatial continuous data at regional and local scales, prerequisites for environmental monitoring such as soil moisture (Srivastava et al. 2019).

Cosmic-ray neutron probes consisting of a neutron source, a neutron counter and a compiler/readout instrument are a special group of ground-based techniques for measuring SSM on larger-than-point scales are based on (Zreda et al. 2012). Neutron probes measure a larger area instead of point measurements, known as footprints, which may vary in size. The measurement footprint of a sensor does not depend on soil moisture content, but it is inversely proportional to the atmospheric pressure. This is because in a flat area with no hedgerows or protruding vegetation, thinner air allows for neutrons to travel further. The inclusion of any hedgerows or protruding vegetation will affect the results for soil moisture as these features will hold moisture themselves. Köhli et al. (2015) have demonstrated how the area closest to the probes contributes the highest number of neutrons. Their study showed that 63% of neutrons are emitted between 50 and 90 m from the probes depending on the actual soil moisture. This fundamental fact drastically affects the robustness of a neutron probe. Yet, to our knowledge, very few studies so far have been concerned with an examination of the COSMOS neutron probe extent and the determination of the factors that affect the measurement

footprint representativeness. Thus, an investigation into this direction of the urgent need to be conducted, as it will allow to map the variations within this footprint and better understand the factors that affect the footprint area extent determination. This need is further demanded, given that there are operational networks operating today globally based on this neutron probe technology, with one such developed in the United Kingdom, for the measurement of soil moisture, named COSMOS-UK (Stanley et al. 2021). The currently implemented COSMOS-UK method is capable of measuring soil moisture at several sites across the country and has been reported to provide accurate soil moisture estimates for the given area around the installed neutron probe station location (CEH 2017).

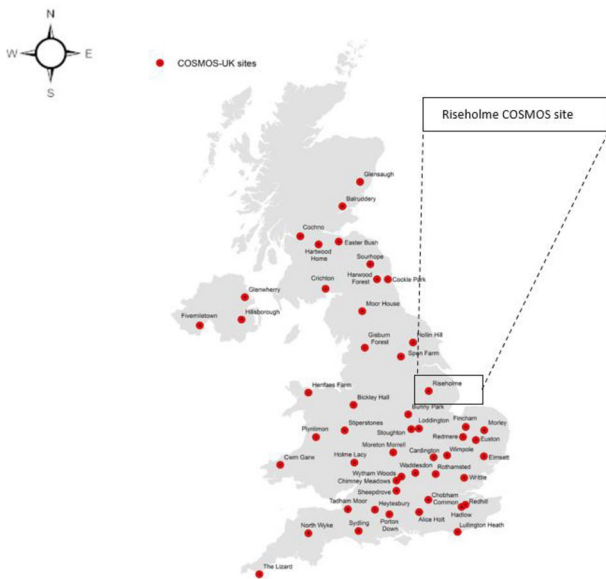
In this context, the present study aims at helping to understand the true footprint of a COSMOS-UK neutron probe and the variations of soil moisture within this footprint. For this purpose, ground measurements supported by unmanned aerial vehicle (UAV) image data acquired during a field campaign that took place in July 2017 at one COSMOS-UK agricultural site are acquired, which is used as a case study. To facilitate the study objectives, appropriate geospatial data analysis methods carried out in a GIS environment are also implemented herein. As a result, the paper is structured as follows: the experimental set up description is provided in Section “**Materials and methods**” and the data collection and their pre-processing—including the UAV imagery analysis and spatial interpolation of point measurements—is made available in Section “**Results**”. This is followed by the key results description and their discussion in Section “**Discussion**” and finally the main study conclusions in Section “**Conclusions**”.

## Materials and methods

### Study site

Since 2013, the UK Centre for Ecology & Hydrology (UKCEH) has deployed 51 COSMOS-UK environmental monitoring sites across the UK (Fig. 1). It is the most spatially dense national network worldwide to monitor soil moisture across the UK in near-real time (<https://cosmos.ceh.ac.uk>, last access: 21/09/2022). The spatial distribution of COSMOS-UK sites was appropriately selected to improve understanding of UK soil moisture conditions by representing key land cover and soil types as well as the soil moisture variability across the country.

Riseholme, East Midlands is the site of a COSMOS-UK network installed in 2016. The Riseholme site is situated at Riseholme College Agricultural Centre in Lincoln. The COSMOS-UK site is in a livestock grazed grassland, on calcareous mineral soil. Figure 1 presents all the stations of



**Fig. 1** A map of the COSMOS-UK stations around the UK (adopted from Boorman et al. 2020)

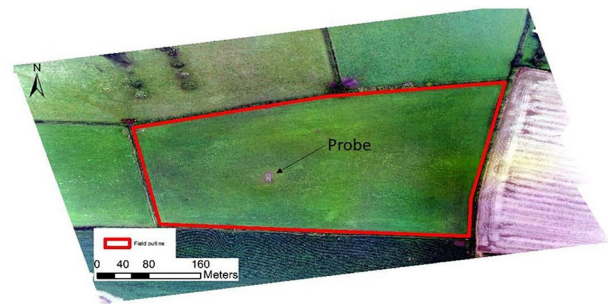
COSMOS-UK across the country, covering different areas with diverse geophysical properties. The COSMOS-UK system uses a neutron probe consisting of a neutron source, a neutron counter, and a compiler/readout instrument. The probe part, which is surrounded by a casing, is lowered into an aluminium tube that has been inserted in a bored hole to the desired soil depth. The radioactive source emits "fast neutrons" which bounce off the hydrogen atoms present in soil water. With each collision, the neutrons lose energy and speed. The number of deflected "slow neutrons" is then detected by the counter, and this number of slow neutrons is correlated with the soil water content. The compiler/readout instrument calculates and displays the results in Volumetric Water Content (VWC). The resulting measurements are measured using Volumetric Moisture Content (VMC) as this can be indexed to the contribution of hydrogen if the derived rock type of the soil is known.

**Datasets and methods**

The fieldwork for this study was carried out on July 26th, 2017. As part of the fieldwork and to assist the study implementation, a series of spatial and ancillary data was collected which are described below together with the pre-processing that was also carried out.

**Ground measurements**

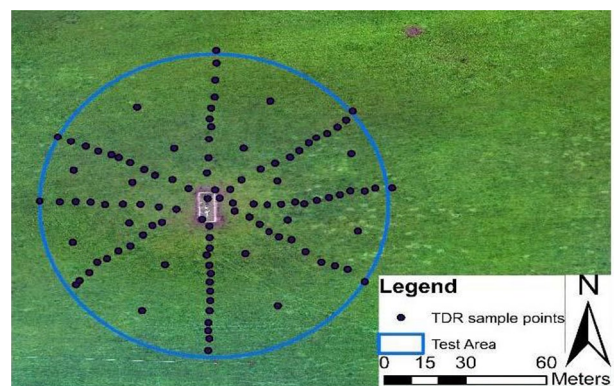
In our study, fieldwork was carried out on the Riseholme COSMOS-UK neutron probes site (Fig. 2) to understand how the soil moisture varies within the footprint of a probe.



**Fig. 2** A map of the Riseholme experimental site. The probe within it shown in the figure is the COSMOS-UK neutron probe

The fieldwork was set up on transects on a central pivot point, being the probe, and soil moisture recordings were taken using a Time Domain Reflectometry sensor (TDR) and a Trimble Geo 7 series GPS unit to accurately retrieve locations of the data collection points. The main aim was to detect the soil moisture variation within the immediate area around the probe. Using a transect at every 22.5° from the North, samples were taken every 5 m. The TDRs were inserted into the ground 12 cm deep, to ensure true ground penetration. The TDR's work by passing a current from one probe to another. The two probes were placed into the ground, and the soil moisture was determined by the conductivity of the soil. The higher the soil moisture content, the more conductive the soil will be (Topp and Davies 1985). Soil temperature was also collected as soil temperature correlated with soil moisture (Bao et al. 2016). Five measurements were taken at every sampling point and then averaged to get the representative value.

Using a transect at every 22.5° from North, the TDR's VWC at the locations were displayed. Figure 3 illustrates



**Fig. 3** The study site with the geographical locations of the sample points on which measurements were taken during the field data collection. The radius of the circle was 60 m as shown, giving it an area of 11.31m<sup>2</sup>. The image was derived from a drone during the time period when the field campaign was conducted

how the transect was laid out and where the sampling points were taken. Five readings were taken from every point and the readings from the TDR were averaged. Samples were taken every 5 m to the 60 m radius of the sampling area and repeated every 22.5° from the north (starting at 0°). Two samples were also taken between the transect. A 60 m testing field was selected as Zreda et al. (2012) claim that 80% of the free neutrons that a cosmos probe detects come from the first 50 m.

### Spatial interpolation

The resulting TDR readings were logged digitally and then interpreted using ArcMap. As the accurate location of each reading was taken, the data were then interpolated. Different methods of spatial interpolation are developed with different terminologies used to classify them, including “interpolating” and “non-interpolating” methods or “interpolators” and “non-interpolators” (Kourgialas et al. 2016). The most common used spatial interpolation methods applied in soil-related studies can be briefly classified into three categories: (1) non-geostatistical methods, (2) geostatistical methods, and (3) combined methods.

One of the important requirements for large-scale variability analysis is the continuous representation of parameter of interest for e.g., in this case is SSM. For the estimation of SSM values at a particular location, spatial interpolation of ground measurements is vital to achieve continuous spatial information. Sometimes it is very much needed when the surface has a spatial mismatch in terms of grid size, or when the available datasets do not cover the regions of interest completely (Srivastava et al. 2019).

Herein, the Inverse Distance Weighting (IDW) interpolation was used to produce the soil moisture interpolated maps from the previously collected point data. IDW approach uses a linear combination of values from selected sites, weighted by an inverse function of the distance between the point of observation and the sampled sites to estimate the values of an attribute at unsampled sites (Hutchinson 1996). IDW is a simple yet highly accurate deterministic method, non-parametric method that is based on Tobler’s first law (Tobler 1970). The principle of that law states that sampled points with values that are closer to the unsampled point are more comparable to them than those with values that are further away. The weights are stated as follows:

$$\gamma_i = \frac{1/d_1^p}{\sum_{i=1}^n 1/d_i^p} \quad (1)$$

where  $d_i$  is the distance between  $x_0$  and  $x_i$ ,  $p$  is a power parameter, and  $n$  represents the number of sample sites used for the estimation.

The main factor affecting the IDW method prediction accuracy is the value given to the power parameter. As distance rises, weights decrease, especially as the value of the power parameter grows, thus close samples have a higher weight and have a greater effect on the estimation, and the spatial interpolation that results is local (Isaaks and Srivastava 1989). The power parameter and neighborhood size are chosen at random (Webster and Oliver 2001). The most common value for  $p$  is 2, therefore the approach is typically referred to as inverse square distance or inverse distance squared. The power parameter can also be selected based on the measurement of the error (e.g., minimum average absolute error, resulting in optimal IDW) (Bárdossy and Lehmann 1998). The estimated surface smoothness increases with increasing power parameter, and we find that the estimation results are unsatisfactory when  $p$  is 1 and 2 compared to  $p$  equal to 4 (Ripley 1981). IDW is referred to as “moving average” when  $p$  is zero (Kourgialas et al. 2016), “linear interpolation” when  $p$  is 1, and “weighted moving average” when  $p$  is not equal to 1. (Zhou et al. 2007). IDW works well with well-spaced data, but clustering cannot be considered (Isaaks and Srivastava 1989).

### High-resolution area mapping and DEM extraction

In addition, during the field campaign UAV imagery was acquired simultaneously with the ground data collection. A DJI Phantom 3 professional drone was used that allowed mapping at a very high spatial resolution of the heterogeneity of the area on which the fieldwork was conducted. The drone imagery was acquired in a 50 m a.g.l. altitude with an average Ground Sampling Distance (GSD) of 3 cm. Standard pre-processing was applied to the acquired imagery using Agisoft Photoscan software and a standard photogrammetric/SfM approach (e.g., Harwin and Lucieer 2012) that allowed generating an orthomosaic image and a Digital Elevation Model (DEM) of the area.

### Statistical analysis

The evaluation was performed by comparing the spatiotemporal variability of the derived maps between the COSMOS-UK footprint and the interpolated maps produced by truth data of the TDT soil moisture sensors. The results were also compared with the drone orthomosaic and DEM products. In addition, point-by-point comparisons were performed between the COSMOS-UK predictions and the TDR ground measurements, and this formed the main validation

**Table 1** Statistical parameters used to evaluate the agreement between the COSMOS data and the TDR in-situ observations

Name of test	Equation
Mean of difference (Bias)	$bias = MBE = \frac{1}{N} \sum_{i=1}^N (P_i - O_i)$
Standard deviation of difference (scatter)	$scatter = \frac{1}{N-1} \sum_{i=1}^N \left( P_i - O_i - (\overline{P_i - O_i}) \right)^2$
Root mean standard error	$RMSE = \sqrt{bias^2 + scatter}$
Mean absolute error	$MAE = N^{-1} \sum_{i=1}^N  P_i - O_i $
R squared linear correlation coefficient	$R^2 = \left[ \frac{\sum_{i=1}^N (P_i - \bar{P})(O_i - \bar{O})}{\sum_{i=1}^N (O_i - \bar{O})^2 \sum_{i=1}^N (P_i - \bar{P})^{0.5}} \right]^2$

Subscripts  $i = 1 \dots N$  denotes the individual observations, P and O denote the predicted and observed values, obtained from field measurements. The horizontal bar in Scatter/MSD ratio equation denotes the mean value

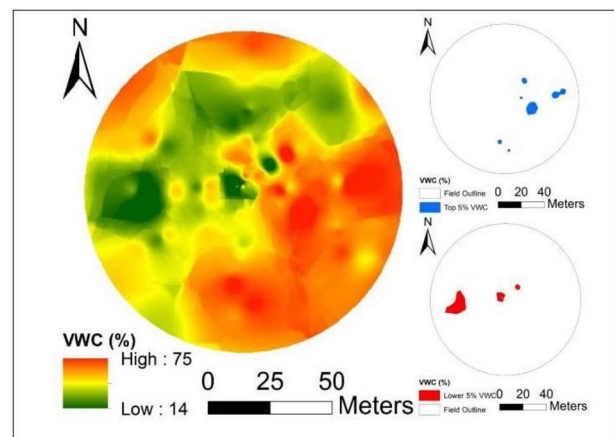
approach. A series of statistical scores were computed to quantify the agreement between predictions and observations (Table 1). The selected statistical metrics have been already used in analogous verification exercises (e.g., Petropoulos et al. 2014, 2015a, b; Piles et al. 2016; Deng et al. 2019; Petropoulos and Hristopoulos 2020). The mean of difference (bias) refers to the average difference between the estimator and the true values, and scatter has shown the true spread of the data. The bias shows how the possibility that the investigation could improve, whether the process was over or underestimating. The mean absolute error percentage shows this in percentage form. All these tests have shown the COSMOS products compared to the in-situ TDT readings.

### Results

The key study objective has been to understand the true footprint of a COSMOS-UK neutron probe and shed some light on the factors that determine its variability. These probes are used to detect soil moisture in the surrounding areas, yet this area will have some variability within it. TDR probes were used on the site at Riseholme on Wednesday 26th July 2017. The main study aim was to detect the soil moisture variation within the immediate area around the probe.

There were noticeable patterns from the interpolation (Fig. 4). The higher VWC readings were mostly to the south-east of the probe (middle of the sample area) and the drier were to the North-west-west of the sample area. However, a statistical test of the VWC values relative to their spatial distribution was required. The TDR readings were identified by their distance from the probe and banded into 10 m categories. Table 2 shows the statistics of the VWC relative to their distance from the probe. The key statistic here was the standard deviation, as the true footprint of the COSMOS-UK probe should be relatively uniform. The two lowest standard deviation readings were up to 10 and 20 m. To determine the true footprint of the sensor, an area with a standard deviation lower than the overall standard deviation of the  $r = 60$  m test

area was selected. The summarizing statistics of the fieldwork carried out in Riseholme presented the following values: mean 57.12%, maximum 75%, minimum 14%, standard deviation 12.31, COSMOS reading 37.07%. An area of  $r = 50$  m has a standard deviation less than the overall standard deviation of 12.31. Therefore, the advised footprint for the Riseholme sensor was  $r = 50$  m.



**Fig. 4** An interpolated map of the TDR results taken from the test site in Riseholme during the fieldwork that was conducted at the site

**Table 2** The spatial statistics of the data of the fieldwork carried out in Riseholme

Distance from the probe, $r$ (m)	Mean VWC (%)	Standard deviation VWC (%)	Number of readings
10	61.16	4.97	21
20	58.34	7.52	56
30	57.5	9.35	113
40	56.85	10.25	160
50	57.29	10.77	194
60	56.5	14.64	298

## Discussion

For this investigation, the true footprint of the COSMOS-UK needed to be evaluated. Howells et al. (2021) investigated the potential use of Synthetic-Aperture-Radar Soil Water Index (SCAT-SAR SWI) as a tool for soil moisture retrieval across the UK by comparing its outputs with the COSMOS-UK soil moisture observations. Results depicted the underestimation of the soil moisture content using the SCAT-SAR alongside a higher bias than the COSMOS-UK sites. Moreover, according to the CEH website, the neutron probe can measure soil moisture for an area with a 700 m diameter (CEH, 2017). Shuttleworth et al. (2010) agree that a neutron probe could have an area diameter of 700 m, depending on geophysical characteristics. As this investigation, has shown, Fig. 4 shows a high level of variability in VWC within 60 m of the probe. Zreda et al. (2012) describe the true footprint of a COSMOS-UK as the area from which 86% of counted neutron arises from, which is said to be around 600 m around the probe. Table 2 shows that the standard deviation was highest at 60 m away from the probe, showing that the variation of the TDR VWC % readings was increasing the further away from the probe the readings were. The test area did not go to this extent mainly because the present study aimed at determining the variation of soil moisture within the immediate vicinity of the probe. Figure 3 showed the field's location, one contributing factor to the design of the data collection was the fact there is a large hedgerow separating the fields. Some investigations have found that the inclusion of some geophysical features affect the size of the footprint dramatically. Köhli et al. (2015) demonstrated how bodies of water and vegetation can affect the soil moisture readings from the probe. The inclusion of the hedgerow would affect the readings of the probe, as the vegetation here would hold moisture which would contribute and skew the results of the neutron probe. However, the suggested footprint for the Riseholme probe should not be used for other sites. Some probes can be representative of very large areas. Large flat fields can have very uniform neutron counts, and the footprint can be an area with a radius of 400 m. This is a very good example of how the neutron footprint will change according to the type of geophysical barriers within the probe area.

Furthermore, after detecting the large soil moisture variability in the small area around the COSMOS probe at Riseholme, the question should be asked whether RS will ever become accurate enough to detect these variabilities to such a fine spatial resolution. For agricultural practices, only RS product with very high resolution can be applied for common practices, on a centimetre basis instead of a meter basis (Hijmans et al. 2005). A spatial resolution

of  $500 \times 500$  m cannot be used for finite measuring (i.e., measuring the soil moisture variability in one field only), it can only be used regionally (Jiang and Islam 1999). However, the present study aimed at assessing COSMOS for a national monitoring system, rather than a tool specifically to measure field variations. Evidently, the current product, if the bias was refined, could be used to monitor soil moisture for the whole UK, which could have practical implications for example in agriculture.

The selection of the IDW interpolation, which was adopted in our study, is a factor that should also be considered as well when analyzing the obtained results. To our knowledge, there are not many studies focusing on evaluating the capability of different geospatial interpolation methods for soil moisture retrievals. In a recent such study, Srivastava et al. (2019) compared in an agricultural setting in India several interpolation techniques like kriging with external (KED), ordinary kriging (OK), inverse distance weighting (IDW) and Spline methods. Their results showed that the KED is performing marginally better than the other techniques particularly so when other soil properties information were provided such as organic carbon was added. Although further analysis is required in future studies repeating the present study adopting other interpolation methods as well, on the basis of studies such as that of Srivastava et al. (2019) it can be argued that results that would be obtained would be similar in trends if not in absolute terms. However, this is something requiring further investigation.

Figure 4 shows an interpolated map of the sample area around the probe. There were some soil moisture variability patterns, the higher VWC readings were mostly to the south-east of the probe (middle of the sample area) and the drier area to the North-west-west of the sample area. However, as shown in Table 2, the number of points was also larger the further away the probe it was. This is because the experiment was conducted without excluding the previous points. For example, for the 60 m probe test the sample from the 10 m, 20 m, 30 m 40 m and 50 m test were also included. This was done as the probe works in a similar way, the closer points will always contribute, and the uncertainty comes the further away from the probe the sampling gets. Furthermore, as the samples were taken in situ using a TDR, the samples were taken individually and not simultaneously. The time between the first samples taken and the last was around 3 h. This indicates there could be a temporal change in the soil moisture. Flanagan and Johnson (2005) hourly change in soil moisture in some areas can be as drastic as annual changes in other areas. This must be factored in, especially when considering the COSMOS-UK neutron probe product as immediate readings.

One key asset of this study's approach is the potential transferability across different COSMOS sites not only in the UK but also in other sites of the world. The presented

herein methodological approach can easily be implemented in other similar sites as it does not require any highly sophisticated device and software making it cost effective. Another key asset is the selection of the interpolation method. By choosing IDW there was no need for any further pre-process of the collected dataset, as this technique does not require any sophisticated statistical transformation to be conducted. This facilitates the implementation of this approach to non-experts of the field, making it accessible to a variety of users. On the other hand, this approach has several crucial limitations each one related to different factors. In particular, a very important limitation is the fact the suggested approach cannot be fully automated as extensive fieldwork is needed to be executed. Another limitation is the sampling design of the field measurements. Sampling design heavily influences the study results and accuracy. By applying different sampling patterns, the results could be further improved in terms of accuracy and uncertainty. All in all, the methodological approach, proposed by this study, examining the COSMOS footprint is simple, robust, and highly accurate with its assets like its high transferability overpassing its limitation.

## Conclusions

In this study, an assessment of the soil moisture variability of the COSMOS-UK site was performed to evaluate the area footprint of these probes. As the case study the Riseholme COSMOS site was selected on which an extensive field campaign took place in July 2017. The obtained results suggested that the true footprint of this COSMOS-UK station was representative of an area smaller than 600 m in diameter as generally used in many relevant studies. Results showed that the COSMOS network had shortcomings, mainly in the inconsistencies of the footprint, as it was found that at Riseholme the footprint could be as small as  $R = 50$  m when Zreda et al. (2012) places the footprint of COSMOS probes at around  $R = 200$  m. However, it should be noted that this revised footprint was only applicable to the Riseholme probe. Yet, it should be noted that the key findings reported in this study are specific to be Risehold site and the experimental setup of our study and their generalisation is subject to further studies that should be carried out involving other COSMOS sites and implementation settings. Indeed, further evaluation of the applicability in different areas, ecosystems and extents of the proposed technique is needed. Such an investigation would require validating the applied technique for other test sites taking into consideration differentiation of factors related to the geomorphology, land use/land cover differentiation and the vegetation species which could drastically affect the footprint of the probes. Other highly sophisticated machine learning techniques

combined with ancillary data could be exploited to further improve the study's results. All the above findings are of key importance to be taken up by future studies exploiting neutron probe data in the context of soil moisture retrievals and their potential synergies with other data collected for example from remote sensing sensors.

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## Declarations

**Conflict of interest** The authors have not disclosed any competing interests.

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