Revealing pore connectivity across scales and resolutions with X-ray CT

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Abstract

Connectivity is one of the most important parameters to quantify pore structure and link it to soil functions. One of the great challenges in quantifying connectivity with X-ray microtomography (X-ray μCT) is that high resolution, as required for small pores, can only be achieved in small samples in which the connectivity of larger pores can no longer be quantified in a meaningful way. The objective of this study was to investigate the changes in pore connectivity with changing sample size, covering a range of analysed pore diameters of more than three orders of magnitude. With this approach, we wanted to address whether pore types formed by different processes in an agricultural chronosequence leave characteristic traces in certain connectivity metrics. The Euler number, χ, and the connection probability of two random points within the pore system, that is, the Γ-indicator, were determined as a function of minimum pore diameter. The results show that characteristic signatures of certain pore types overlap with scale artifacts in the connectivity functions. The Γ-indicator, gives highly biased information in small samples. Therefore, we developed a new method for a joint-Γ-curve that merges information from three samples sizes. However, χ does not require such a scale fusion. It can be used to define characteristic size ranges for pore types and is very sensitive to the occurrence of bottle necks. Our findings suggest a joint evaluation of both connectivity metrics to disentangle different pore types with χ and to identify the contribution of different pore types to the overall pore connectivity with Γ. This evaluation on the chronosequence showed that biopores mainly connect pores of diameters between 0.5 and 0.1 mm. This was not coupled with an increase in pore volume. In contrast, tillage led to a shift of pores of diameter >0.05 mm towards pores of diameter >0.20 mm and thus increased connectivity of pores >0.20 mm. This work underlines the importance of accounting for the scale dependence of connectivity measures and provides a methodological approach for doing so.

Highlights

- Scale dependence of connectivity metrics needs to be accounted for.
Connectivity metrics can be used to disentangle different pore types across scales.

Roots mainly connect the pore system between 0.1 and 0.5 mm.

A joint $\Gamma$-connectivity function can be constructed that is free of scale artifacts.

**KEYWORDS**

biopores, connection probability, connectivity, Euler number, scale, tillage, X-ray CT

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**1 | INTRODUCTION**

Important soil functions are defined or influenced by soil structure. Soil properties and processes such as hydraulic conductivity, gas exchange and water retention, as well as erosion, are controlled by the spatial structure of pores and solids (Bronick & Lal, 2005; Rabot, Wiesmeier, Schlüter, & Vogel, 2018). Besides porosity and pore size distribution, one of the most important parameters for soil functions is pore connectivity (Rabot et al., 2018). It affects both air permeability (Paradelo et al., 2016) and saturated hydraulic conductivity (Luo, Lin, & Schmidt, 2010; Sandin, Koestel, Jarvis, & Larsbo, 2017; Zhang et al., 2019). Moreover, the connectivity of different pore size classes is also essential for soil as a habitat for a myriad of organisms and for the accessibility of soil organic carbon (SOC) for these organisms and their aeration status (Kravchenko, Negassa, Guber, & Rivers, 2015; Negassa et al., 2015; Rabbi et al., 2016).

Digital imaging techniques, such as X-ray microtomography (X-ray $\mu$CT), have developed rapidly in recent years and are used to visualize and quantify the 3D pore space. This provides an impressive insight into the complexity of soil structure. It shows how pore structure is shaped by soil management or biological activity (Helliwell et al., 2013; Lucas, Schlüter, Vogel, & Vetterlein, 2019), how different characteristic pores or pore types form the overall soil architecture (Pagliai & Vignozzi, 2002) and suggests a hierarchy of pores of different size and origin (Elliott & Coleman, 1998). Pores can be divided into textural pores, defined by the arrangement of soil primary particles and larger structural pores. The latter are mainly shaped by biological activity and soil cultivation. A challenge in analysing the resulting complex structure is that pores of various sizes, shapes and origin cannot be disentangled by simple metrics. Currently, there are two promising approaches to tackle this problem.

1. Identification and segmentation of structural pores by their characteristic shape. This differentiation enables the linking of pores to their processes of formation. One example is those structural pores created by plants, which form a dense network of cylindrically shaped pores (biopores) (Leue et al., 2019; Lucas et al., 2019; Zhang et al., 2018). Also, different tillage systems lead to characteristically formed pores (Pires et al., 2017; Pires, Roque, Rosa, & Mooney, 2019).

2. Using a hierarchical sampling scheme and combining the information from images from different sample sizes and resolution to derive a complete description of multiscale heterogeneity (Bacq-Labreuil et al., 2018; Dal Ferro, Sartori, Simonetti, Berti, & Morari, 2014; Karsanina, Gerke, Skvortsova, Ivanov, & Mallants, 2018; Leuther, Schlüter, Wallach, & Vogel, 2019; Schlüter et al., 2018; Schlüter, Weller, & Vogel, 2011; Vogel, Weller, & Schlüter, 2010). By merging the pore size distribution (PSD) of several sample sizes (Vogel et al., 2010) a joint pore size distribution can be created while increasing the size range of visible porosity ($\phi$-vis).

These two approaches lead to the open question of whether pore connectivity metrics are sensible enough to disentangle different pore types across different scales and whether a scale fusion of these metrics, that is, to combine the information from different scales, is possible and helpful, as has been demonstrated for the PSD.

We calculated connectivity for different pore sizes of an existing X-ray $\mu$CT dataset of a lignite mining reclamation site (Garzweiler, Germany) from Lucas et al. (2019). The dataset consists of around 500 samples of different diameters (10, 3 and 0.7 cm) scanned at different resolutions (57, 19 and 5 $\mu$m). The development of the pore network during the chronosequence was mainly affected by tillage and by the formation of biopores, reflected by a steady increase of biopore density over time. For this study, we pooled samples with vastly different macroporosities, partly due to inherent differences in bulk density directly after reclamation and partly due to different ages and types of management. The rationale for this pooling is that the processes which shape characteristic pore types are universal; for example, biopores look the same in all samples. The samples only differ vastly in the volume proportion of these characteristic pore types. The objective of this paper is to find generally applicable features in connectivity measures that can be used to distinguish pore types despite this large variability.
the dataset covering multiple scales and structures provides an excellent basis to investigate how measures of connectivity as a function of both pore size and sample size can be used to disentangle different pore types and to characterize the entire pore system with regard to its formation.

1.1 Theoretical consideration

There are several mathematical approaches to characterize 3D connectivity in porous media (Renard & Allard, 2013). We here focus on two different connectivity metrics, which are often used in soil hydrology: (a) the Euler number \( \chi \), a topological measure from integral geometry and (b) the \( \Gamma \)-indicator or connection probability based on pore cluster size distribution. The metric \( \chi \) is the result of the total number of unconnected clusters (N) minus the total number of redundant loops (C) plus the total number of closed cavities (H) (Vogel, 1997). The latter are typically negligible in soil pore systems (Vogel, 2002):

\[
\chi = N - C + H. \tag{1}
\]

When neglecting H, \( \chi \) becomes negative if the number of redundant connections exceeds the number of unconnected clusters and positive if it is the other way round. The \( \chi \)-number is a global metric that can be efficiently calculated from the frequency of local pixel configurations within \( 2 \times 2 \times 2 \) voxel neighbourhoods (Renard & Allard, 2013; Vogel, 2002). It is not sensitive to the size of connected clusters. Thus, a negative \( \chi \) does not necessarily mean that there is a long-range connection through a connected pore cluster. In contrast, the dimensionless \( \Gamma \)-indicator is sensitive for long-range connectivity; that is, it is higher if a large fraction of the porosity belongs to a large, connected cluster. It is obtained from calculating the second moment of cluster size distribution (Renard & Allard, 2013):

\[
\Gamma_p = \frac{1}{N_p^2} \sum_{k=1}^{N_i} n_k^2, \tag{2}
\]

where \( N_p \) is the number of all pore voxels \( p \), \( N_i \) the number of all clusters and \( n_k \) the number of pore voxels in cluster \( k \). \( \Gamma \) reflects the probability of two randomly chosen pore voxels belonging to the same pore cluster and is highly affected by the largest pore cluster \( n_k \) (Jarvis, Larsbo, & Koestel, 2017). It can range from 0 (many unconnected clusters) to 1, when all pore voxels belong to a single connected cluster. The \( \Gamma \)-indicator typically increases with increasing porosity in an s-shaped curve without a clear percolation threshold (Renard & Allard, 2013). The slope of this curve reflects how connected pore clusters vary in size; that is, it is a measure of the variability of the percolation among samples of the dataset (Renard & Allard, 2013). We here use \( \phi \)-vis and the slope of this curve at the inflection point to characterize connectivity. In summary, \( \Gamma \) reflects the probability of finding a continuous path through the pore system and \( \chi \) reflects the number of internal connections without considering their lengths (Herring, Andersson, Schlüter, Sheppard, & Wildenschild, 2015).

There is typically a fixed factor of 1,000–2,000 between CT image resolution and sample size (Rabot et al., 2018). This means that on the one hand high resolution can only be obtained within small samples, but on the other hand this small volume cannot be regarded as a representative elementary volume (REV) with respect to soil structure anymore (Page-Dumroese, Brown, Jurgensen, & Mroz, 1999; Timm et al., 2005). The range of scales that is captured representatively for a given sample size is further reduced by the fact that (a) pore objects typically need to have a diameter larger than the actual voxel resolution and (b) the sample volume must be much larger than the typical size of pore objects to detect connectivity features. Consequently, the size range of objects that can be quantified based on a given sample size is very narrow (i.e., the factor between smallest and largest objects is about 10 at most). However, it can be extended substantially when combining pore structure information obtained from different sample sizes scanned at different resolutions (Vogel et al., 2010). We calculate the connection probability, \( \Gamma \), and the Euler number, \( \chi \), as a function of pore sizes based on the maximum inscribed sphere method. This allows us to continuously add smaller pores, starting from the largest unconnected pores and ending at pore diameters slightly larger than the voxel resolution. This can be done for samples of different size and resolution and allows investigation of how different pore sizes contribute to the connectivity of the pore space (Vogel, 2002), and thus also how bottle necks connect pore bodies. Bottle necks are the relatively narrow pore sections that connect wide pore bodies. In soils where textural pores dominate (e.g., sands), pore bodies or packing pores are between the particles and are typically slightly smaller than these (Nimmo, 2013).

Based on the definitions of \( \Gamma \) and \( \chi \), different scaling behaviours of the two metrics can be expected when changing sample size and resolution. Subsampling of an intact soil core cuts off long-distance connections, which leads to an underestimation of \( \Gamma \). In the following we will refer to this scaling artefact as the “REV artefact” because the sample size falls below a representative elementary volume in terms of pore connectivity. In addition, we
assume that the connectivity metrics are very sensitive to the total volume of investigated pores. This decreases considerably when only the largest pores are considered for a given sample size by removing smaller pores with the maximum inscribed sphere method. In this case, the connectivity metrics are based on very limited information, up to the point where only one isolated pore remains and $\Gamma$ and $\chi$ approach one. In the following, we will refer to this scaling artifact as a “low-count artifact.”

**FIGURE 1** X-ray $\mu$CT-derived pore size distribution within different sample sizes. (a) A cross-section through one sample at three sample sizes to illustrate the relation in size (right) and the change in resolution (left). (b) Cumulative pore size distribution of the 12-year-old field at 0–20 cm depth (dashed line) and corresponding distribution of the different sample sizes (decreasing intensity of blue = decreasing sample size). Inset shows the frequency distribution of the corresponding curves. The intersection points reflect the transition between two sample sizes to calculate the joint cumulative distribution [Color figure can be viewed at wileyonlinelibrary.com]
Small-scale features contribute to $\chi$ in the same way as large-scale features, but small-scale features are typically much more abundant and are captured more representatively. Reducing sample size while increasing resolution continuously adds smaller pores for which $\chi$ is highly sensitive. Accordingly, a continuous change of $\chi$ is expected. Thus, with regard to the open question, we hypothesize that scale fusion while analyzing connectivity across different sample sizes is only necessary for $\Gamma$.

2 | MATERIALS AND METHODS

A description of the reclamation procedure and field management, together with a detailed site characterization of the space-for-time chronosequence, can be found in Pihlap et al. (2019). In short, a 20-m-thick layer of loess, including about 2.2 m of developed Luvisol, is excavated, thoroughly mixed and deposited as an at least 2-m-thick layer of new topsoil. In this way, reclaimed soils developed from the same loess substrate, characterized by a loess material with high CaCO$_3$ content and weakly alkaline pH. Crop rotation consists of 3 years of alfalfa (*Medicago sativa*) in a pioneering phase without any mechanical disturbances. Afterwards, the fields are ploughed and the crop rotation consists of *Triticum aestivum* L. (wheat) and *Hordeum vulgare* L. (barley), *Brassica napus* L. (rapeseed) and *Zea mays* L. (maize) in the years after the pioneering phase. Three intact soil cores were taken from three plots from fields at 0 (directly after first seeding), 1, 3, 6, 12 and 24 years, at two different depths (0–20 cm and 40–60 cm), as described in Lucas et al. (2019). The field for 0 years was not sampled at the second depth. The 99 soil cores (10 cm Ø, 20 cm height, ~1,500 cm$^3$ volume) were scanned at a resolution of 57 μm with an X-ray microtomograph (X-Tek XCT 225, Nikon Metrology, Brighton, MI, USA). The obtained images are used to describe the pores larger than 200 μm, assuming that pores smaller than 4 voxels in diameter cannot be properly captured and are very sensitive to the choices made during image processing. This is shown in the frequency distribution of pore sizes (Figure 1), which in the case of the distribution derived from 10 cm Ø columns at 200 μm intersects the corresponding curve of the 3 cm Ø columns and then drops below it at smaller pore sizes (Figure 1). Subsamples of 3 cm Ø, 3 cm height, ~21 cm$^3$ volume (three per core, 297 in total) and 0.7 cm Ø, 1 cm height, ~0.6 cm$^3$ (one per core, 99 in total) were taken to enhance the resolution to 19 μm and 5 μm, respectively. Thus, the pore sizes of ~50–200 μm could be described with the 3-cm samples and pore sizes from 10 to 50 μm were described using the 0.7-cm samples. Images of all sample sizes were processed and segmented into binary images of visible pores and matrix voxels and pore size distribution was computed as described by Lucas et al. (2019) using Fiji/ImageJ (Schindelin et al., 2012) and associated plugins (Legland, Arganda-Carreras, & Andrey, 2016; Ollion, Cochain, Loll, Escudé, & Boudier, 2013). Subsamples of 3 cm Ø were also used to separate all cylindrical pores (biopoires) from all visible pores by a shape-based tubeness algorithm in Fiji (Version 1.3.3), as described in Lucas et al. (2019). Biopore length was not determined for the other sample sizes, because either the sample volume was too small or the voxel resolution too coarse to capture them representatively. A joint pore size distribution of the different sample sizes was created by considering the maximum frequency of all three pore size distributions at each pore diameter (Vogel et al., 2010), as shown in Figure 1b (inset). The scale transitions, that is, the pore diameters at which the frequency distributions cross, varied between 0.04 mm and 0.07 mm (for Ø 0.7 cm and 3 cm) and 0.19 and 0.304 mm (for Ø 3 cm and 10 cm). A joint cumulative pore size distribution (PSD, Figure 1b) is constructed from this joint frequency distribution by integration, starting with the largest pore diameters (from right to left).

In analogy to $\phi$-vis (Figure 1b), $\Gamma$ and $\chi$ were calculated, for pores larger than a certain pore diameter $g$ at all resolutions, using the MorphoLibJ plugin (Legland et al., 2016) in Fiji, which is based on the maximum inscribed sphere method. In the following we will refer to this pore size threshold as the “minimum pore diameter.” For each sample size, only pores larger than 4 voxels in diameter were considered, to minimize misclassification and noise, because $\chi$ is highly sensitive to such errors (Armstrong et al., 2019). To compare the results from different sample sizes we normalized the $\chi$-numbers by the sample volume, which in the following is referred to as $\chi$-density (cm$^{-3}$).

2.1 | Measuring water retention

Additional undisturbed samples (10 cm × 10 cm height, one cylindrical soil core per plot and depth) were taken to measure the water retention curve using the HYPROP evaporation method (Hydraulic Property Analyzer; METER, formerly UMS, München, Germany). In this way the experimentally obtained PSD derived from the water retention curves can be used to validate the image-derived PSD after scale fusion. The soil cores were saturated with water prior to evaporation. The gravimetrically measured air contents were
analysed without parametric model adaptation to compare water-retention data with image-derived pore size distributions. The air-filled porosity was calculated by subtracting the water content at a given matrix potential from the water content at saturation. In the following, only the retention curves of the ploughed fields (3, 6 and 12 years after reclamation) are presented.

**FIGURE 2** Scatterplots for $\chi$-density (a) and $\Gamma$-indicator (b) as a function of $\phi$-vis for all minimum pore diameters. Plotted curves are examples of a linear model for $\chi$-density (distorted by the non-linear axis) and a logistic model for the $\Gamma$-indicator. The image C shows a 125-$\mu$m thick section from a 7-mm sample (12-year-old field, 40–60-cm depth). The two parts of the same image section reveal how pores of >30 $\mu$m diameter (dark blue) get connected at various locations through pores <30 $\mu$m diameter (light blue), thus causing a shift towards more negative $\chi$-densities [Color figure can be viewed at wileyonlinelibrary.com]
2.2 | Statistics

To evaluate the relation between $\phi$-vis and $\chi$, a linear model was fitted using R (version 3.5.3). The s-shaped relation between $\phi$-vis and the $\Gamma$-indicator was described by a logistic function fitted with non-linear least squares using a Gauss-Newton algorithm in R:

\[
\Gamma(\phi) = \frac{a}{1 + e^{-k(\phi - \phi_0)}},
\]

where $a$ is the asymptote, $k$ the growth factor, and $\phi_0$ is porosity $\phi$ at the inflexion/midpoint. The slope at the midpoint is then obtained by:

\[
\frac{d}{d\phi} f'(\phi = \phi_0) = a \cdot \frac{k}{4}.
\]

The assumptions of the different models were visually assessed by evaluating plots of residuals (residuals vs. residuals, QQ plot of standardized residuals). For the linear models, $R^2$ as a measure of goodness of fit is also assessed by evaluating plots of residuals ($\text{residuals vs. residuals, QQ plot of standardized residuals}$). For the non-linear model of $\Gamma(\phi)$.

3 | RESULTS

3.1 | General behaviour of Euler number and $\Gamma$-indicator

The $\chi$-density across the minimum pore diameter reveals a huge standard deviation, which is related to a high variability of $\phi$-vis in the pooled dataset (Figure 2a, Figure S1). Moreover, three salient features emerge. (a) The $\chi$-density always decreased linearly with increasing $\phi$-vis at any given minimum pore diameter. The slopes of these linear trends are reported in Table S1. (b) The addition of certain pore size classes, represented by the minimum pore diameters of 0.11 mm, 0.05 and 0.03 mm, caused a vast increase towards positive $\chi$-densities. Apparently, a new pore type must have emerged at this pore diameter of 0.03 mm, where many randomly distributed, isolated pore bodies appeared located between apparent secondary pores (Figure S2). (c). The gain in redundant connections was most dramatic when the smallest-considered pore diameter of 0.02 mm was added, which dramatically improved pore network connectivity, as shown in Figure 2c. The observations (2) and (3) became even more salient when showing average values of $\phi$-vis and $\chi$, as discussed below.

The scatterplot of $\Gamma$ and $\phi$-vis exhibits two major patterns (Figure 2b, Figure S3). (a) The logistic relationship between both metrics seems to hold except for the largest pore size classes (<1 mm), with an RMSE for $\Gamma$ varying between 0.11 (pore diameter > 0.513 mm) and 0.16 (pore diameter > 0.03 and >0.04 mm), as shown in Table S1. The largest pore size classes (<1 mm) are affected by the low count artefact, as discussed below. (b) The same level of clustering represented by $\Gamma$ was reached at very different $\phi$-vis for different minimum pore diameters. The average $\phi$-vis and slope $f'$ ($\Gamma'/\phi$-vis) at the inflexion point are reported in Table S1. Obviously, the smallest pores were distributed very uniformly in space (Figure 2b) and, therefore, it took a rather high $\phi$-vis to reach good long-range connectivity through that disperse network ($\phi$-vis at the inflexion point: 12.2%). In contrast, $\phi$-vis was low (5.8% and 7.2%) at the inflexion point for minimum pore diameters of 0.11 mm and 0.23 mm, respectively, with a high slope at the inflection. Thus, these pores must be shaped in a way that facilitates long-range connectivity with only little $\phi$-vis.

3.2 | Secondary pores: Biopores

The pore shape effect on the $\Gamma$-indicator becomes obvious when only the extracted network of biopores is analysed. This is demonstrated for the two fields 3 and 12 years after reclamation at a depth of 40–60 cm, which had the same pore size distribution (Figure S4) but very different biopore volumes. The total biopore volume was more than doubled on the 12-year-old field (Figure 3a). The highest contribution to total biopore length density occurs in a pore diameter range of 0.1–0.5 mm. 

The steady increase in biopore length density with decreasing pore diameter did not cause a steady increase in $\Gamma$. The mean values of $\Gamma$ jumped towards lower $\Gamma$-indicators at the transition from one sample size to the next smaller sample size (Figure 3b, Table S1). This indicates that large pore clusters were disrupted in the smaller sample size due to the “REV artefact.” In order to get a continuous, smooth trajectory at the scale transition, corrected for the REV-artefact, we suggest a joint-$\Gamma$-curve: large samples contain a well-connected pore network that is composed of long-reaching large pores (e.g., cm-dm in the case of biopores) and short-reaching smaller pores (e.g., mm in the case of primary pores). When looking at the same pore size threshold in smaller samples at higher resolution, the larger pores are not captured representatively due to the smaller volume. This inevitably leads to lower $\Gamma$-indicators and,
thus, to a bias with respect to the entire pore system. In contrast, the change in $\Gamma$-indicators for changing pore size thresholds within a single sample size is assumed to be not biased. We therefore calculated the joint-$\Gamma$-curve by correcting for the offset. For the largest pores of a subsample, we took the corresponding $\Gamma$-value of the larger sample and then considered only the slope between $\Gamma$-indicators within each subsample. Interestingly, the joint-$\Gamma$-curve adds up to about one (Figure 3c).
The joint-Γ-curve reveals different trends between the 3 and 12-year-old fields in the typical biopore diameter range of 0.1–0.5 mm (Figure 3c). The values of the 3-year field were almost constant at $\Gamma = 0.2$ in that range as the biopore volume is too low for the emergence of well-connected biopore clusters. The values of the 12-year field increased towards $\Gamma = 0.4$ when adding the entire range of typical pore diameters (>0.1 mm) as the critical

**Figure 4** Relation between pore size distribution and connectivity metrics for the ploughed topsoils (0–20 cm) and subsoils (40–60 cm) of the 6-, 12- and 24-year-old fields. Shown are pore size distribution measured by an evaporation method (d) and by X-ray μCT (c), such as the connectivity metrics Γ-indicator (b) and χ-density (a). The different intensities of grey in the background reflect the range of sample sizes. Inset in D shows the range of the sample sizes without a logarithmic x-axis [Color figure can be viewed at wileyonlinelibrary.com]
volume fraction for a well-connected macropore cluster decreased to 7% (Table S1). In other words, only approximately 1 Vol-% of the elongated shaped biopores led to good long-range connectivity; that is, high $\Gamma$-values through slightly oriented pores that connect the otherwise randomly distributed pore space at rather low volume fractions. The most significant contribution to long-range connectivity came from biopore diameters around 0.2 mm and decreases towards smaller biopore diameters (Figure S5).

### 3.3 Secondary pores: Tillage induced

Figure 4 shows both connectivity metrics as a function of minimum pore diameter as well as volume fractions derived from X-ray $\mu$CT and from the evaporation method for the ploughed topsoil (0–20 cm) and subsoil (40–60 cm) of the 6, 12 and 24-year-old field.

The mean of the corrected $\Gamma$-indicator of the tilled fields, that is, average of three plots at a depth of 0–20 cm, revealed a steady increase beginning at a pore diameter of 1 mm to $\Gamma$-indicators close to 1 at about 0.08 mm (Figure 4b). Like the 12-year-old field, the $\Gamma$-indicators of the 6- and 24-year-old subsoils (40–60 cm) increased constantly, but only starting at 0.5 mm, as larger pores are almost absent without ploughing and reaching values close to 1 at 0.02 mm. The increase was especially high between pore diameters of 0.03 mm and 0.02 mm.

Similar to the mean values of all fields (Table S1), the $\chi$-density in the subsoil (40–60 cm) of the three fields (6, 12 and 24 years) decreased with decreasing minimum pore diameter towards highly negative values, but positive values occurred at 0.11 mm and 0.03 mm (Figure 5a, note the non-linear y-axis), suggesting the emergence of a new pore type. With the exception of pore diameters of 0.076 mm and 0.02 mm, the $\chi$-densities of the ploughed soil layers (0–20 cm) were lower at all pore sizes than in undisturbed subsoil (Figure S1, Figure 4a), indicating an overall improvement in connectivity (both in terms of $\Gamma$ and $\chi$) due to the periodic soil loosenning by ploughing. The $\chi$-densities in the 0.7-cm Ø samples were higher compared to those in 3-cm Ø directly at the scale transition (minimum pore diameter of 0.08 mm). At this pore size, which is located at the scale transition of 0.7-cm Ø and 3-cm Ø samples (Figure 1), especially the $\chi$-densities of the subsoil showed a “low count artefact.” The reason

![Figure 5](https://wileyonlinelibrary.com)

**Figure 5** 3D visualization of pores with a minimum diameter of 0.1, 0.2 and 0.3 mm of a 3-cm column from topsoil (top row), which is ploughed, and a column from subsoil (bottom row), reveals the differences in structure and shows the shift of narrow macropores (<200 μm) towards macropores (>200 μm) during ploughing, as described in Lucas et al. (2019) [Color figure can be viewed at wileyonlinelibrary.com]
for this was the particularly small volume of pores of the subsoil at this minimum pore diameter (Figure S1). In the topsoil the volume fraction of the largest pores in the smallest sample size was still high enough to be captured representatively so that it matched the more trustworthy χ-values for the same minimum pore diameter in the next largest sample size. In summary, the Euler number was continuous across scales unless the remaining pore volume at large minimum pore diameter reached a critically low value.

The macropore volume was higher within the topsoil with both types of measurement techniques, evaporation method and X-ray μCT. The two layers mainly differed by the increase of ϕ-vis for macropores >0.2 mm and a decrease between 0.05 mm and 0.2 in the tilled layers (Lucas et al., 2019). These differences can be also seen in the visualized pore systems at a minimum diameter of 0.1, 0.2 and 0.3 mm for one selected, representative sample out of approximately 80 each (Figure 5). The curves from the measurements of topsoil and subsoil slowly converge around a minimum pore diameter of 0.2 mm, due to the lower amount of pores between 0.05 and 0.2 mm in the topsoil (Figure 4c). Yet the pore size distribution, measured by the evaporation method, only showed a clear increase of pore volume in the subsoil for pores <0.03 mm (Figure 4d). This is because the evaporation method in fact does not measure the size distribution of pores per se, but the size distribution of pore bottle necks.

4 DISCUSSION

The results of this study indicate that the χ-number and the Γ-indicator together are suitable for disentangling different pore types and describing their effect on connectivity. The reason for this is that the two connectivity metrics reflect different pore characteristics. One of the issues that emerges from these findings is that scale artifacts have different impacts on the two measures: Because Γ as a percolation-based characteristic is strongly related to the biggest pore cluster (Jarvis et al., 2017), it is highly underestimated in samples that are too small to capture these clusters (Figure 3). This is in good agreement with the findings of two recent publications. Koestel, Larsbo, and Jarvis (2020) showed that typically used soil samples of 100 cm³ volume are not large enough to describe processes that depend on pore network connectivity. In addition, Piccoli, Schjønning, Lamandé, Zanini, and Morari (2019) revealed that gas transport measured by parameters such as air permeability increased with increasing sample volume, as small sample volumes were less dominated by continuous and tube-like macropores, that is, biopores. We proposed a new method for a joint-Γ-curve, integrating information obtained from various sample sizes (i.e., scales). Therefore less-biased information on how the connection probability changes as a function of minimum pore diameter and at which point the pore system connects into one percolating system can be obtained (Figure 3). This curve increases drastically when ϕ-vis approaches the inflexion point. Thus, we demonstrated how this distribution can be used to estimate the influence of management practices (i.e., tillage) and biological activity (i.e., biopores) on the connectivity of the pore space (Figure 4).

The hypothesis raised by this study was that χ does not need such a scale fusion. We could show that cutting of long-range connections when reducing the sample size had indeed a minor effect on χ. In addition, the sensitivity to small-scale features enabled us to link drastic changes in χ-density across the pore size distribution to a transition between different types of pores having different origin. However, both χ-density and Γ-indicator were affected by the “low count artefact” (Figure 4). This underlines that both connectivity measures require a sufficient number of pores larger than a certain pore diameter in the sample to provide reasonable information on their connectivity.

Our findings about changes in volume fractions of specific pore types and connectivity metrics of the entire pore system (and biopores only) with changing minimum pore diameter revealed some common trends that are summarized in the conceptual scheme in Figure 6.

Growing roots and other biota such as earthworms form biopores of different sizes. Consistent with the literature, this study showed that these sizes vary extremely from several μm, formed by fine roots, to several mm in diameter, formed by earthworms or tap roots (Yunusa & Newton, 2003). Smaller biopores between 0.03 and 0.3 mm are formed by first- and second-order lateral roots of cereals (Yunusa & Newton, 2003) and are adequately captured within 3-cm Ø samples, and these contribute to the majority of biopores (Figure 3). We could show that due to the high biopore length between 0.1 and 0.5 mm, long-ranging pores are able to connect the existing pore system at low ϕ-vis (Figure 3, Figure S5). Similar to this, Tippkötter (1983) could link an interconnected network of biopores between 0.1 and 1 mm in a loess subsoil, with a maximum between 0.15 and 0.25 mm, to the morphology of living root systems. In addition, Koestel et al. (2020) found that connectivity increases with increasing pore volume, mainly due to pores between 0.08 mm and 0.25 mm that connect otherwise isolated macropores (Koestel et al., 2020).

The differences of the joint-Γ-distribution of the 3-year and 12-year-old fields (Figure 3), which share
almost the same joint pore size distribution (Figure S4), in combination with the decrease of the percolation threshold at pore diameters at 0.11 and 0.23 mm (Table S1), show that growing roots do not necessarily increase $\phi$-vis or change the PSD over time. Instead, in the examined reclaimed soil, they rearranged the existing macropore system and thus reduced the percolation threshold without changing $\phi$-vis (Table S1).

On the other hand, tillage leads to an increase in $\phi$-vis for pores $>$0.2 mm (Figure 4c, Figure 5). By this, the increase in the joint-$\Gamma$-curve was shifted towards larger pore diameters. Thus, connection probabilities of the topsoils already reached values close to 1 at pore diameters around 0.05 mm, as compared to values of approx. 0.5 in the subsoil (Figure 4b). Different X-ray $\mu$CT studies, which examined the influence of tillage on the connectivity of macropores, showed both that tillage increases (Pihlap et al., 2019; Pires et al., 2017; Pires et al., 2019; Schlüter et al., 2018) or decreases (Dal Ferro et al., 2014; Lucas et al., 2019; Zhao et al., 2017) the connectivity of the pore space. This inconsistency may be due to the differences in the resolution of the images analysed, which ranged from around 0.003 mm to 0.06 mm. Thus, the connectivity metrics may have reflected different pore types.

Studies that examined $\chi$ in soil as a function of pore size often showed positive and increasing values for $\chi$ in the macroporous range ($>$0.2 mm), but these then became negative at a certain threshold and continuously decreased to a minimum (Bacq-Labreuil et al., 2018; Schlüter et al., 2011;
Vogel et al., 2010). In contrast, however, in the investigated loess substrate, the \( \chi \)-density showed that even the pores >0.5 mm were well connected and had slightly negative values. At minimum diameters >0.5 mm the pore system mainly consisted of big biopores in untilled soils (Figure 4), but also in the tilled topsoil many fragmented biopores existed (Lucas et al., 2019), which were able to connect more randomly distributed pores created by tillage (Figure 6).

However, deriving \( \varphi \)-vis with the evaporation method, showed the highest increase at equivalent diameters <0.03 mm in the subsoil (Figure 4d). In contrast to the pore size distribution derived by X-ray \( \mu \)CT, the evaporation method is only capable of showing the pore neck distribution. At pores >0.03 mm more isolated pores than new connections emerged, as \( \chi \)-densities become positive (Figure 4a). These pores with a diameter of approx. 0.03 mm apparently correspond to sparsely distributed secondary pores (dark blue in Figure 2c, red in Video S1), which tend to be isolated from the network of larger macropores formed by biological activity and tillage (Figure 6). At pore diameters between 0.03 mm and 0.05 mm several pore types overlap (Figure 6); therefore, the heterogeneity between samples is rather high and the explained variance by the linear model of \( \chi \) is rather low (Table S1, Figure S1). These samples are composed of different volumes of well-connected secondary and unconnected textural pores. The subsoil contains a relatively high amount of unconnected pores of approximately 0.05 mm (Figure 4b). At the smallest pore diameter of 0.02 mm, the \( \chi \)-density decreases again massively towards the minimum of \(-2,115.80\) \( \text{mm}^{-3} \) as even smaller pore necks emerge (light blue in Figure 2c, cyan in Video S1). Through them the entire pore network becomes connected and \( \Gamma \) reaches values of around 1. As a result, at the corresponding tension also the water of the unconnected pores >0.3 mm is drained and causes the shift between PSD and bottle-neck distribution (Figure 4).

5 CONCLUSION

This study examined the nature of the connectivity metrics Euler number (\( \chi \)) and the connection probability (\( \Gamma \)) in terms of their sensitivity to different pore types across scales.

The most obvious findings to emerge from this study are as follows. (a) Different scale artifacts overlap with actual pore features, which must be carefully considered during the interpretation of connectivity across scales. (b) \( \Gamma \) is highly sensitive for long-ranging pore clusters and thus prone to the “REV-artefact”, which occurs when subsampling of an intact soil core cuts off long-distance connections. Therefore, a scale fusion between subsamples of different sizes is needed. We showed that this is possible by integrating information obtained from various samples into a joint-\( \Gamma \)-curve. The Euler number (\( \chi \)) as a local metric does not need this scale fusion. It is dominated by small-scale features (i.e., small pores) leading to a smooth transition between scales. (c) By combining the information of \( \chi \) and \( \Gamma \) the contribution of different pore types to the overall pore connectivity can be described and disentangled across scales. The Euler number as a function of pore size can be used to detect transitions from more continuous pore types (e.g., biopores) to packing voids between particles characterized by pore necks. The joint-\( \Gamma \)-curve provides valuable information on the overall connectivity across scales and reveals how much different pore types contribute to this overall pore connectivity.

We showed that biopores mainly connect the pore system of diameters between 0.5 and 0.1 mm. For the specific soil investigated in this study this was not necessarily coupled with an increase in pore volume. In contrast, tillage could be seen as a shift of pores of diameter >0.05 mm towards pores larger than 0.2 mm, which went along with an increase in pore volume and thus also in connectivity.

Overall, the current data highlight the importance of choosing an appropriate sample volume to identify effects of soil management or the creation of biopores with X-ray \( \mu \)CT. To cover the relevant scales of structural pores we therefore suggest combining at least two sample sizes.

ACKNOWLEDGEMENTS

We thank the German Research Foundation (Deutsche Forschungsgemeinschaft—DFG) within the framework of the research unit DFG AOBJ: 628683 for funding. Julius Diel, Erik Rittmüller, Bernd Apelt and John Maximilian Köhne were a great help during the sampling campaign and laboratory work. We are thankful to Manuel Endenich and Gerhard Dumbeck (Department of Reclamation, RWE Power AG) for selection and providing of the sites and support during the sampling campaigns. We thank the anonymous reviewers who helped improve the manuscript.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

AUTHOR CONTRIBUTION

All authors listed have made a direct and intellectual contribution to the work and approved it for publication.
M.L. made substantial contributions to the design and acquisition of data. M.L. and S.S. analysed the data.

**DATA AVAILABILITY STATEMENT**
Data available on request from the authors.

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**How to cite this article:** Lucas M, Vetterlein D, Vogel H-J, Schlüter S. Revealing pore connectivity across scales and resolutions with X-ray CT. *Eur J Soil Sci.* 2021;72:546–560. https://doi.org/10.1111/ejss.12961