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Fitting and comparing water retention curves for soils under contrasting experimental treatment: Examples from conservation agriculture trials in southern Africa

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ABSTRACT

Conservation Agriculture (CA) is proposed as a 'climate-smart' intervention for resilient crop production in dryland areas affected by climate change. Evidence is needed for how these practices affect fundamental properties of the soil. The soil water retention curve (SWRC) is a physical attribute of the soil which provides information on its porous structure and physical quality. It is also critical for modelling processes in the soil such as water movement, water availability for plants and infiltration into the soil during rainfall events. In this paper we estimate parameters of the van Genuchten model of the SWRC from experiments on CA interventions in southern Africa, using a linear mixed modelling framework. The method we use, stochastic approximation maximization, allows for maximum likelihood estimation of the parameters without use of linearizing approximation. We show how sequential fitting of model parameters, with marginal false discovery rate control, allows us to make robust inferences about differences in the SWRC between soils under contrasting experimental management. We also show how the method allows us to draw samples from distribution of SWRC parameters, reflecting the uncertainty which arises from variation within the management treatments. Indices of soil physical quality may be computed from the parameter estimates to compare treatments, and by computing them from the samples, the uncertainty in these indices can also be assessed. We use the estimated model parameters to simulate infiltration of water into the soils under different management during a rainfall event. Again, by using the samples from the joint distributions of the parameters the effects of uncertainty in these parameters as propagated through the model can be computed. We applied these methods to soils collected from experimental plots under CA and conventional tillage (CV) at sites in Zimbabwe, Zambia and Malawi. We observed differences in the SWRC for the CA and CV plots at the Zambian site where a physically vulnerable soil showed greater macroporosity under CA than CV. In contrast, a sandy and organic-poor soil at

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the site in Zimbabwe showed somewhat greater macroporosity under cultivation rather than CA management. There was no detectable treatment effect of the management system on the SWRC for the soils at the site in Malawi.

1. Introduction

Climate change is having significant impact on global food production, not least in Africa (Onyeaka et al., 2024). One critical effect of a changing climate is the increased frequency of extreme weather events, droughts and floods (WMO, 2025), and the resilience of a farming system to these challenges is largely dependent on soil physical quality, in particular the capacity of the soil to retain water and to sustain infiltration.

Conservation agriculture (CA) in which soil disruption by cultivation is minimized or avoided altogether, the soil is protected by organic mulch, commonly crop residues, and cropping systems are diversified is widely promoted in southern Africa and elsewhere as a resilient farming practice under climate change (e.g. Mkomwa and Kassam, 2022). There is some evidence that, in dryland agriculture, CA results in improved rainfall-use efficiency through increased water infiltration and decreased evaporation from the soil surface, with associated decreases in runoff and soil erosion (Steward et al., 2018; Corbeels et al., 2020). However, not all experiments have shown that CA improves soil water properties, relative to CV. Mbanyele et al. (2021) reported from Zimbabwe that soil water content under CV was larger than under CA by a factor of 9%–27% on sandy soil during a drought year. Esser (2017) found that infiltration rates between rip lines and basins, reduced tillage options widely used as part of a CA strategy, were smaller than in a ploughed or hoed field by a factor of 31%–37%. In consequence, CA fields showed a consistently shorter time for the start of surface water saturation, ponding, and runoff under artificial rain compared to conventionally-cultivated fields.

These inconsistent outcomes are likely to result from effects of local environmental conditions on the impact of CA. For example, CA entails increase organic carbon input to the soil through mulches, but Lal (2020) noted that soil texture, among other factors, could control the effects of increased soil carbon status on plant-available water. This is consistent with the 'socio-ecological niche' concept (e.g. Descheemaeker et al., 2019), which emphasizes the importance of matching interventions for agricultural improvement to the specific conditions of small-holder farmers, given the diversity of environmental, biophysical and socioeconomic circumstances in which they operate.

The discussion above shows that it is necessary to develop a better understanding of how CA practices impact soil functions in differing environments. Our contention is that this requires study of treatment effects on basic soil properties, and not just outcomes such as crop yield. One fundamental physical property of the soil, which determines key aspects of its physical quality, is the soil water retention curve (SWRC, also called the soil water release curve or soil water characteristic curve). This represents the volumetric water content of the soil (sometimes the gravimetric water content) as a function of the soil water tension or, equivalently pF or the matric potential (Hillel, 1980). One can think of it as showing how the soil water content is reduced on applying an increasing suction to water held in soil pores. The SWRC is an important descriptor of soil physical behaviour, it quantifies the capacity of the soil to hold water at different tensions, and so to drain excess water and to retain water against gravity, some which is available to plants and microbes and some of which is unavailable. Fundamentally the SWRC summarizes the structure and quality of the soil porous architecture, and so also expresses the capacity of the soil to provide a suitable environment for roots and microbes, and to sustain processes such as infiltration (e.g. Dexter, 2004; Reynolds et al., 2007)

The SWRC has been used to measure impacts of soil management practices on soil quality and function. In some studies SWRC parameters have been treated as soil properties for comparison between management practices or land uses. For example, Liu et al. (2011) fitted SWRC to measurements from aggregates in different size classes under different management practices. To assess the effects of inorganic fertilizer use on water retention they used the fitted SWRC to compute the water content at a specified pF, and then regressed this on soil organic carbon content.

A similar approach was taken by Eze et al. (2020) who fitted water retention curves to measurements from soils in experiments on CA practices across Malawi, and then used each to compute the plant available water capacity as the difference between the water retained at tension −33 kPa, treated as field capacity, and −1500 kPa, treated as the permanent wilting point. This showed that the available water under CA increased relative to CV, but remained suboptimal, which was attributed to the lack of evidence for increased soil organic carbon in the soils.

The form of the SWRC reflects the underlying distribution of pore sizes. It is possible to approximate a pore-size distribution from the SWRC (see Section 2.6 below). Gao et al. (2016) did this with mollisol soils under ridge tillage and zero tillage from an experiment in China, and showed a reduction in the micropore space in the top 20 cm depth under zero till. Eze et al. (2020) showed increases in porosity, and fine-scale porosity, under CA in Malawi by the same approach. Abu and Abubakar (2013) fitted water retention curves to measurements from samples in experiments with contrasting cultivation methods in the Guinea Savanna of Nigeria and then used these to compute pore space over different intervals and compared these values between pairs of treatments with multiple paired t-tests

Further interpretation of the SWRC parameters can be made in terms of soil physical quality. Dexter (2004) proposes an index, S, based on the slope of the SWRC at its inflexion point (gravimetric water relative to the natural log of water potential). Over a range of soils larger values of S imply a well-defined soil microporous structure (see Section 2.6 below). Aparicio and Costa (2007) found that Dexter's S, CEC and change in soil aggregate mean weight diameter were predictive of the number of years that soil in the Argentinian Pampas had been under cultivation.

The SWRC therefore is a fundamental property of the soil, and the effects of CA on its parameters could give basic insight into potential benefits of CA in particular circumstances. There are two challenges, however. The first is that the statistical methods used to compare SWRC between treatments in the cited studies are limited. Eze et al. (2020), for example, estimated SWRC parameters by a least squares method coded in Excel and then used these to compute available water for each experimental plot. This derived property was then treated as a variable for comparison, but no consideration was given to the uncertainty of the estimate, which is not simple measurement error but depends on the correlated estimation uncertainty of the SWRC parameters. Abu and Abubakar (2013) did a similar analysis after fitting the SWRC parameters by non-linear least squares with the RETC program of van Genuchten et al. (1991). It would be better to be able to make direct inferences about differences of the SWRC between contrasting treatments with some set of parameters allowed to differ between the treatments. Furthermore, when an interpretation is made of some function of the parameter, such as Dexter's (2004) S, the uncertainty of that parameter estimate should be considered, if it is large then the interpretation may have little value.

The second challenge is that measurement of the SWRC requires special equipment, such as pressure vessels (see Section 2.3 below) and trained technical staff both to collect suitable intact soil cores for measurements at the low-tension end of the SWRC and to make the measurements. Measurements are also time consuming. For this reason there are few data on the SWRC made in southern Africa, particularly in recent years. A search on the topic terms {"soil water retention" OR "soil water release" OR "soil water characteristic"}AND{"conservation agriculture" OR "zero till*" OR "min* till*" } on Web of Science (19th May 2025) returned only 56 articles, and just 7 from Africa. Of these only two (plus one conference proceedings from the same project as one of them) reported measurements at multiple points on the SWRC. These are the articles by Abu and Abubakar (2013) and Eze et al. (2020) cited above.

In the project reported here we have attempted to address both challenges, and the results are reported in this paper. First, we propose an approach to estimation and comparison of SWRC models based on the work of Omuto et al. (2006) who first demonstrated that parameters of the SWRC can be estimated in a non-linear mixed effects model (NLME). In this study we use a stochastic method to obtain maximum likelihood estimates of SWRC parameters by expectation maximization within an NLME (Comets et al., 2017), and build these into a workflow to assess the strength of evidence that the parameters differ between treatments and to quantify uncertainty in SWRC parameters. We demonstrate this by using the estimated values of the parameters first to assess soil physical quality using published criteria based on the SWRC and, second, in a version of the Green-Ampt model of soil water infiltration. We then use parametric bootstrap samples of the parameters to assess the uncertainty of the interpretations and the model outcomes which is attributable to parameter uncertainty.

The second challenge was addressed in a project to develop a network of soil physics laboratories at University of Zimbabwe, University of Zambia and Lilongwe University of Agriculture and Natural Resources (Malawi) with capacity to undertake integrated research on soil and groundwater under CA practices (see acknowledgements for project details). This included the establishment (Malawi) or supplementation (Zambia, Zimbabwe) of laboratory capacity to measure soil water retention over the conventional range of tensions, training in the necessary laboratory and field work, and the development and use of the workflow outlined above to analyse water retention measurements from three experiments on CA in Zimbabwe, Zambia and Malawi and to assess the experimental findings. This paper reports the resulting findings, using the NLME modelling

2. Methods

2.1. Field experiments

The locations of the experimental sites, described below, are shown in Fig. 1. Basic information on each experiment is given below, with more detail in supplementary material.

The experiment at the University of Zambia farm (hereafter, we refer to this experiment as 'Liempe Farm') was established in 2017 and has four replicated and randomized complete blocks with a conservation agriculture (CA) treatment with zero tillage and intercropped maize (*Zea mays* L.) and soybeans (*Glycine max*) and a conventional (CV) treatment with inversion tillage and monocrop maize.

The experiment in Zimbabwe was undertaken at the Domboshava Training Centre (hereafter 'Domboshava'). The experiment was established in 2010, with replicates of each of three treatments in complete randomized blocks. For present purposes, we examined two treatments, both with a maize monocrop: a CA treatment (zero tillage and application of crop residues at 5 $\mathrm{t\,ha^{-1}}$) and a CV treatment with inversion tillage and no crop residues applied.

The experiment in Malawi was undertaken at Chitedze Research Station (hereafter 'Chitedze). The experiment was established in 2007 with 8 basic treatments replicated and randomized in four complete blocks. In this study we examined the soils from treatments T1 (monocrop maize planted after cultivation and ridging of the soil by hand-hoe), T3 (monocrop maize planted without cultivation by direct seeding in holes made with a dibble stick, and crop residues retained on the soil surface) and T8 (direct-seeded maize intercropped with velvet bean (*Mucuna pruriens*), crop residues retained on the soil surface).

Note that each of these experiments was analysed individually. This is because of the differences in soil and environmental differences between their locations, the fact that the soil sampling depths differed between the experiments to address local priorities, and that what constitutes a CA treatment is not consistent across all sites, although all included minimum or zero till, retention of residues and (except for Domboshava and T3 at Chitedze) an intercrop.

2.2. Soil sampling for physical properties

In each plot, three locations were selected independently and at random within the rows of maize and between individual plants. Locations that were unrepresentative such as large termite holes and stones were avoided. At each of the selected locations, one undisturbed soil sample was taken using a uniquely-numbered stainless steel sample ring (internal diameter: 50 mm, height 51 mm). Soil samples were collected from the surface of each plot (from 0–5 cm and 5–10 cm depths at Chitedze and Liempe Farm; from 0–10 cm and 10–20 cm at Domboshava). The ring was trimmed to the precise cylindrical volume of the ring, and carefully placed in a pre-labelled sample bag without disturbing the sample further. At the same locations and depths, disturbed soil samples (about 200 g) were collected and placed into pre-labelled sample bags. The within-plot replication of intact and disturbed soil samples collected, per depth, was one sample per plot at Chitedze and three samples per plot at Liempe Farm and Domboshava.

2.3. Measuring points on the soil water retention characteristic

The intact cores were used to measure the soil water retention characteristic (SWRC) at large (less-negative) matric potentials on a large-surface extraction plate (SoilMoisture Equipment Corp., Santa Barbara, CA, USA). The matric potential was controlled by an adjustable Haines-type hanging column of water. A nylon cloth was attached to the underside of the intact core to allow removal from and replacement on the extraction plate in between weighing without losing the hydraulic connection between the soil and extraction plate. The cores were first saturated on the tension plate before the initial mass was recorded. Thereafter a series of decreasing (becoming more-negative) matric potentials from 0 (saturation) to ≤ -30 kPa was set by adjusting the hanging water column and the soil was allowed to equilibrate for a few days with daily recording of the mass for each matric potential. When this process was complete a sample of the material at the smallest tension was oven-dried to determine the water content of the soil at this potential, and the dry soil mass. At smaller (more-negative) matric potentials, we equilibrated subsamples from the disturbed soil samples, held within a shallow retaining ring, on pressure plates within pressure extractor apparatus (SoilMoisture Equipment Corp., Santa Barbara, CA, USA) to obtain equilibrated water contents at matric potentials between ≤ -50 and -1500 kPa. Hereafter we use the absolute (i.e. positive) values to refer to matric potential or tension. All soil samples were oven-dried at 105 °C for 48 h to calculate equilibrated water contents and, for the intact cores, dry bulk density.

2.4. The van Genuchten model

van Genuchten's (1980) model for the soil water retention curve (SWRC) expresses the volumetric water content of the soil at tension h as

$$\theta(h) = \theta_\mathrm{r} + \frac{\theta_\mathrm{s} - \theta_\mathrm{r}}{\left\{1 + (\alpha h)^n\right\}^m}, \tag{1}$$

where θ_s and θ_r are, respectively, the volumetric water content at saturation and the residual water content, α is related to the reciprocal of air-entry tension, and n and m are parameters which describe the shape of the pore size distribution. In this study we did not estimate m as an independent parameter but set it to $1 - n^{-1}$.

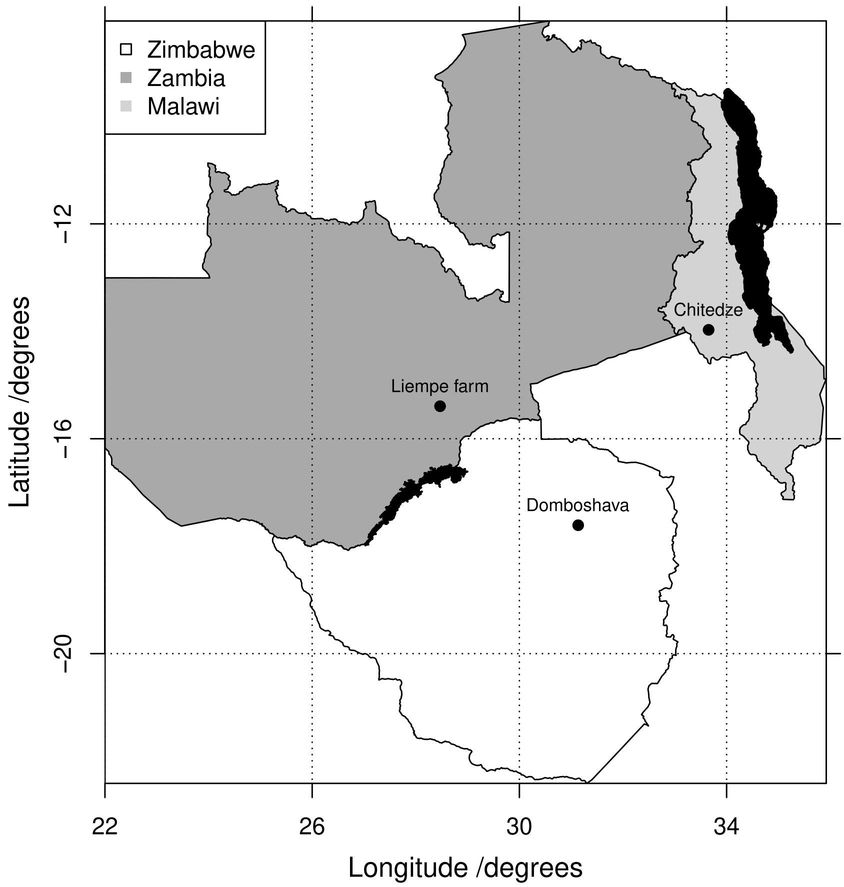

Fig. 1. Map of Zimbabwe, Zambia and Malawi showing location of experimental sites. Large water bodies (Lake Malawi and Lake Kariba) are shown in black.

2.5. Fitting non-linear mixed models by SAEM and inference about treatment effects

Our objective, at each of the three experimental sites was to test the hypothesis that the SWRC differs between soils under contrasting management. The challenge was to estimate parameters for the SWRC under each of the treatments, with a model for the random variation of observations within treatments which allows for a statistical test of a null hypothesis that a common set of parameters applies across the treatments. A natural way to do this is with a non-linear mixed effects model (NLME). A NLME allows one to estimate parameters which have a mechanistic interpretation. Values of the parameters may depend on covariates, or, as in this case, may differ between treatment groups, but are also subject to random variation (e.g., from the random allocation of treatments to plots, and random variation within blocks). In the NLME this random variation enters the model non-linearly, and this complicates the task of estimation (Pinheiro and Bates, 2000).

Omuto et al. (2006) used NLME to estimate parameters of the SWRC, and to relate these to covariates, with a focus on being able to predict SWRC parameters from easier-to-measure data. This same approach can provide an inferential basis for examining experimental effects where the treatment factors are substituted for covariates. We have used a different computational approach, using the Stochastic Approximation Expectation Maximization (SAEM) algorithm. This is one of a number of numerical methods which allow for maximum likelihood estimation without requiring a linearization of the model parameters (Comets et al., 2017). We used the saemixModel function from the saemix library for the R platform (Comets et al., 2017; R Core Team, 2020), and used the importance sampling method for numerical evaluation of the log-likelihood. A form of distribution for each parameter is proposed, either normal, log-normal, probit or logistic. We specified the log-normal distribution for the α and n parameters as the most appropriate for a strictly positive variable without an absolute upper bound, and the logistic distribution for the volumetric water contents as the most appropriate for a variable bounded in the interval $[0, 1]$.

There are exploratory statistics and plots which may be examined to evaluate the fit of the NLME in saemix (Comets et al., 2017). First, the sequence of proposed values of the model parameters (fixed and random effects) can be examined. These should show the algorithm initially exploring a range of values for each parameter and then converging to a solution. The plots which are produced indicate when the algorithm enters a closing phase in which the magnitude of potential changes in the parameter values is damped. Evidence of convergence before this will indicate that a good solution has been found as opposed to a solution which simply represents a point in random exploration of the space ‘frozen’ at initiation of phase 2. For exploratory purposes, Comets et al. (2008) suggest the computation of normalized prediction distribution errors (NPDE), these are generated by simulation of the observed results conditional on the fitted NLME, and decorrelation of the resulting departures from the observations. We used the npde package for R to compute NPDE (Comets et al., 2008), and then examined their distribution with a histogram and box-plot and QQ plot of the observed against the standard normal quantiles to evaluate the plausibility that the errors are normally distributed. We also examined a plot of the NPDE against the fitted volumetric water contents, and against the tensions (Comets et al., 2017) to look for evidence of lack of fit or non-homogeneity of the errors.

Under a ‘null’ model, one may allow all four parameters of the SWRC to be common to observations in all treatments of interest. In an alternative model one or more of those parameters is estimated separately for the treatments. The resulting log-likelihoods of the null model, ℓ_n, and the alternative, ℓ_a, can then be compared by computing the log-likelihood ratio statistic

$$L = 2\{\ell_n - \ell_n\}, \tag{2}$$

which, in the case of an alternative model with q more parameters estimated separately for the groups, has an asymptotic χ^2 distribution with q degrees of freedom if those q parameters do not differ between the groups. This therefore provides a basis for a hypothesis test.

In the case of Domboshava we had two treatments to compare, a CV and a CA treatment, and measurements for the 0–10 and 10–20 cm depth intervals. In each case duplicate samples within the same plot were averaged, that is to say the mean volumetric water content was calculated at each matric potential. We initially fitted a null model in which all the SWRC parameters were common to both treatments. We then fitted an alternative in which the parameter α differed between the treatments and tested the null hypothesis that it was common across the treatments by a log-likelihood ratio test. If the null hypothesis was rejected, then the new null model had different values of α for the treatments, and a new alternative was fitted for comparison with the parameter n also differing between the treatments. If, on the other hand, the first null hypothesis regarding α was accepted, then the alternative model with n differing between the treatments was tested against the original null model with all parameters common. The inclusion of treatment-specific values of θ_s in the model was considered next, following the same procedure. Finally we considered the possibility that θ_r differed between the treatments.

Because this is a multiple testing approach, in which our overall hypothesis of a difference between the SWRC for the two treatments could be supported by rejection of any one of the null hypotheses (or more), we controlled the marginal false discovery rate (mFDR) over the full set at 0.05. The false discovery rate FDR (Benjamini and Hochberg, 1995) is the expected proportion of a set of multiple tests which would falsely reject a true null hypothesis. We followed Foster and Stine (2008) in controlling the mFDR with a method called alpha-investment. In this approach the p-value for each test in the set is compared with a threshold value which depends on the alpha-wealth, a quantity which is depleted when a null hypothesis is accepted and increased when a null hypothesis is rejected. This maintains the control of mFDR, while increasing the power to detect real effects. Lark (2017) provides detail of the method and provides an example from soil science. In this case we applied mFDR control with alpha-investment to the successive tests of differences between treatments for α, n, θ_s and θ_s in that order, retaining terms as distinct between treatments if $p < 0.05$, but only making a final decision as to whether parameters were pooled over treatments or not on the mFDR criterion when all had been considered.

The same approach was used to compare the SWRC for the CV and CA treatments at Liempe Farm (0 – 5 and 5 – 10 cm depth intervals). At Chitedze, with three treatments, we considered evidence for difference in SWRC parameters for two orthogonal comparisons: (1) for a comparison between the check CV plots and pooled observations for the two CA treatments, and, (2) between the two CA treatments.

2.5.1. Parametric bootstrap

To investigate the significance of uncertainty in the fitted parameters of the SWRC parameters we obtained 1000 parametric bootstrap resample sets using the `saemix.bootstrap` function. These parameter sets were retained for use in the Green-Ampt modelling of infiltration.

2.6. van Genuchten parameters, soil porosity and soil physical quality

The SWRC summarizes information about the soil's porous structure over a range of length scales. The pore-size distribution of a soil can be accessed as the slope of the SWRC with respect to the log of the tension, where the 'equivalent pore diameter' (d_e) (in μm) for tension h in kPa is

$$d_e \approx \frac{300}{h}, \tag{3}$$

Table 1
Indices of soil physical quality derived from water retention curve parameters.

1a. Dexter's S, Dexter (2004).	
$S > 0.035$	Good microstructural quality
$0.02 < S \leq 0.035$	Poor microstructural quality
$S \leq 0.02$	Very poor microstructural quality
1b. Macroporosity, Reynolds et al. (2007)	
macroporosity ≤ 0.04	Degraded
macroporosity > 0.04	Undegraded (medium to fine textured soil)
1c. Relative water capacity, RWC suitability for microbial activity (Reynolds et al., 2007)	
RWC ≤ 0.6	Too dry
$0.6 <$ RWC ≤ 0.7	Optimal
$0.7 <$ RWC	Too wet
1d. Plant available water capacity, PAW, Reynolds et al. (2007)	
PAW > 0.2	Ideal
$0.15 <$ PAW ≤ 0.2	Good
$0.1 <$ PAW ≤ 0.15	Limited
PAW ≤ 0.1	Poor
1e. Air capacity, AC, Reynolds et al. (2007)	
AC > 0.15	Aeration likely to be adequate for all soils
$0.10 <$ AC ≤ 0.15	Aeration likely to be adequate except for fine-textured soils
AC ≤ 0.1	Crop-damaging aeration deficit likely

see Reynolds et al. (2007) and Gao et al. (2016). We computed and plotted the pore volume distribution corresponding to each fitted SWRC.

The information on soil porosity can also be used to compute indices of soil physical quality. We consider five such indices for interpretation of water retention curves from the CA experiments. Note that, for those indices where a value of field capacity is required, we specify the water content at a tension of 33 kPa.

2.6.1. Dexter's S

This quantity is the modulus (absolute value) of the gradient of the water retention curve at its inflection point (i.e. where the slope stops increasing with increased tension), interpreted in terms of the microstructure of the soil, which is better-defined, with a wider range of pore sizes, when S is large. Dexter (2004) gives an interpretation of values of S which this function reproduces, and threshold values are presented in Table 1a.

Note that S is defined with respect to the water release curve for *gravimetric* water content, so an adjustment is made to the parameters fitted for volumetric water content.

2.6.2. Macroporosity

The total porosity of the soil is equal to θ_S, i.e. the volumetric water content of the saturated soil. The macroporosity of the soil is the difference between total porosity and porosity at a tension when it is assumed that only micropores are filled (matrix porosity). Reynolds et al. (2007) suggest three values, by default we use the median (4.9 kPa). The interpretation is based on Reynolds et al. (2007), (see Table 1b) if macroporosity is ≤0.04 (volumetric) then the soil is assumed to be degraded by compaction or consolidation. Otherwise, for medium to fine textured soils, it is regarded as undegraded.

2.6.3. Soil relative water capacity (RWC)

RWC is defined as the ratio of the volumetric water content at field capacity to the total porosity. This is interpreted (Table 1c) as optimal for microbial activity in the interval $0.6 <$ RWC ≤ 0.7, too dry below the range and too wet above (Reynolds et al., 2007).

2.6.4. Plant available water capacity (PAW)

This is the difference between the volumetric water content of the soil at field capacity and at the permanent wilting point. Permanent wilting point is a tension of 1471 kPa, it is assumed that the water retained at this tension, or larger, is inaccessible to plants.

PAW is the difference between the water content at field capacity and the permanent wilting point. The values of PAW are interpreted as in Table 1d, following Reynolds et al. (2007).

2.6.5. Air capacity (AC)

AC of the soil measures how well-aerated the soil environment is to allow the growth, development and function of plant roots. The measure of AC based on the water retention curve is the difference between the total porosity and the field capacity. Following Reynolds et al. (2007) these values are interpreted according to threshold values presented in Table 1e.

2.7. Green-Ampt model

The statistical methods outlined above allow us to assess evidence for differences between SWRC parameters for soils under different treatments. The practical significance of these differences is another matter. One approach to assessing the impact of an observed difference in SWRC parameters is to consider their effect on hydraulic processes in the soil. A simple case is given in 2.6.4 above, the difference between the water content at two specified tensions gives a measure of available water. Another approach is to consider a process model, and we do that here.

The model of infiltration due to Green and Ampt (1911) has been developed and extended by various workers and applied for catchment-scale hydrological modelling (Zubelzu et al., 2024) and catchment-scale modelling of transfers of soil water and contaminants (Zhu, 2019). It has been applied to investigate run-off and infiltration by water (e.g. Mallari et al., 2015). Its solutions correspond to those of Richards' equation under certain assumptions (Barry et al., 1993). We acknowledge that Richards' equation is more general, and may therefore be more generally physically realistic. For example, under the Green-Ampt model a sharp wetting front moves down the soil profile during a process of infiltration, the soil above the front is saturated and the soil below is in its initial state of wetness (e.g. Warrick, 2003), wheras Richards' equation does not necessarily have a sharp wetting front. However, the Green-Ampt model, as noted above, is physically based, it is relatively simple and computationally tractable and key parameters can be obtained from the van Genuchten model. For that reason we chose to use it to explore the implications of treatment differences in van Genuchten parameters for important processes in the water cycle.

We used the extension of the Green-Ampt model for soils with contrasting layers and irregular rainfall input as presented by Liu et al. (2008). In this model the soil is considered as N successive layers of thickness $\mathrm{d}z_i, i = 1, 2, \ldots, N$. It is assumed that the water content is uniform in each layer, that the soil above the wetting front is saturated, and that there is a sharp wetting front at which 'piston flow' takes place with a uniform water potential.

The ith layer can accommodate a depth of infiltration of $\mathrm{d}z_i M_i$ where

$$M_i = \theta_{\mathrm{s},i} - \theta_{0,i}, \tag{4}$$

and where $\theta_{\mathrm{s},i}$ and $\theta_{0,i}$ denote, respectively, the saturated and initial volumetric water content of soil in the ith layer.

The second assumption of the Green-Ampt approach is that, over a short time interval, the water flux is uniform in all layers above the wetting front. If the saturated hydraulic conductivity and the matric potential of the ith soil layer are K_i and h_i respectively and the wetting front is at depth l_{i+1} in the $i+1^{\text{th}}$layer then the water flux in the ith layer is

$$q_i = K_i \frac{\mathrm{d}z_i - h_i + h_{i-1}}{\mathrm{d}z_i}, \tag{5}$$

and that in the $i+1^{\text{th}}$ layer is

$$q_{i+1} = K_{i+1} \frac{l_{i+1} + S_{i+1} + h_i}{l_{i+1}}, \tag{6}$$

The term S_{i+1} is the capillary drive, or mean suction in the designated layer. Given the assumption of uniform water flux in all layers, it is then possible (Liu et al., 2008) to obtain the following expression where f_p is the infiltration capacity of the soil when the wetting front is in layer $i+1$.

$$f_p = \frac{\sum_{l=1}^{i} \mathrm{d}z_l + S_{i+1} + \frac{F'_{i+1}}{M_{i+1}}}{\sum_{l=1}^{i} \frac{\mathrm{d}z_l}{K_l} + \frac{F'_{i+1}}{M_{i+1} K_{i+1}}}, \tag{7}$$

where F'_{i+1} is the cumulative infiltration. In this study we obtained a numerical solution, computing f_p with Eq. (7) for successive time steps during a rainfall event, with known water input for each time-step, and calculated runoff (assuming that all water which did not infiltrate in the time step ran off) and the depth of the wetting front for each time-step by distributing the infiltrated water in the profile under the assumption of piston flow with saturated soil above the wetting front.

We followed Morel-Seytoux et al. (1996) and Chen et al. (2015) in obtaining the capillary drive from the van Genuchten parameters α and $m = 1 - 1/n$ as

$$S = \frac{0.046\ \mathrm{m} + 2.07\ \mathrm{m}^2 + 19.5\ \mathrm{m}^3}{\left(1 + 4.7\ \mathrm{m} + 16\ \mathrm{m}^2\right)\alpha}. \tag{8}$$

We followed Guarracino (2007) by inferring the saturated conductivity (cm day^{-1}) as

$$K = 4.65 \times 10^4 \phi \alpha^2, \tag{9}$$

where ϕ denotes the soil porosity.

The model was run with rainfall data recorded at 15 min intervals at the University of Zambia farm, beginning at 10.00 AM Central African Time on 29$^{\text{th}}$ January 2022. The model was run using the sets of van Genuchten parameters estimated for each location, and for separate treatments where significant differences were found. It was assumed that, at the onset of the rainfall event, the soil profile had a uniform soil moisture deficit of 40% of the plant-available water capacity, and these results are reported in detail, but we also assessed the modelled infiltration and depth of the wetting front assuming a range of values of the initial soil water content to check any sensitivity to this assumption.

We also used the bootstrap samples of van Genuchten parameters (Section 2.5.1) and ran the model with each sample set to investigate the implications of the model parameter uncertainty for modelled run-off and infiltration.

3. Results

3.1. Inferences about treatment effects on the SWRC parameters, their interpretation and its uncertainty

Our results showed contrasting effects of the local CA treatment on the SWRC over the different experiments. These are discussed in more detail below but, in summary, there was no evidence for management effects at either depth at Chitedze, but evidence from the NLME model inference for a difference between CA and CV in the shallower soil at Liempe farm and the deeper soil at Domboshava. As seen below, where there are differences they may be interpreted in terms of quality measures and the bootstrap resampling allows us to account for parameter uncertainty in this interpretation

At Liempe farm there was evidence (Fig. 2(a), Table 2) for differences between the CA and CV treatment in the van Genuchten parameters α, θ_{s} and θ_{r} for the 5 – 10 cm depth interval. The convergence plot for the fit of the final models for 0 – 5 cm and 5 – 10 cm are shown in Figs. A1 and A4 respectively of the Supplementary Material. Convergence to a value close to the final solution within phase 1 is seen for all parameters. Exploratory plots of NDPE for the two depths are in Fig. A2, A3 and A5, A6. The distribution of the NPDE is close to normal at both depths although with somewhat heavy tails at 5 – 10 cm (Fig A5). The plots of the NPDE against predicted values, and the measured

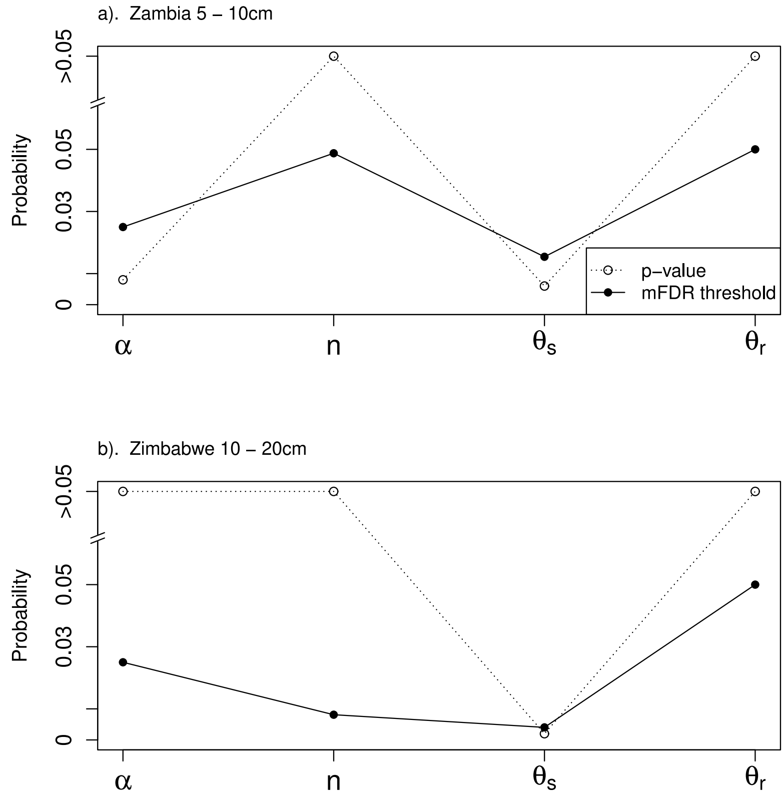

Fig. 2. Successive hypothesis testing on treatment contrasts for van Genuchten parameters of the water retention curve with marginal false discovery rate control and α-investment for (a) Zambian site, Liempe farm, 0–5 cm, (b) Zambian site, Liempe farm, 5–10 cm, (c) Zimbabwean site, Domboshava Training Centre , 10–20 cm.

tensions (A6 and A9) not indicate any lack of fit, the variability of the errors may be more limited in the range of predicted θ between 0.25 and 0.35 than at smaller or larger tensions. There is no evidence for a difference in these plots between the CA treatments (black symbols) or the CV treatments (red symbols).

The saturated water content is larger under the CA treatment as is the α parameter. As can be seen in Fig. 3, the soil at 5 – 10 cm under CA has a somewhat larger modal pore diameter and the pore volume distribution is shifted to larger values. The equivalent pore size distribution was computed from each of the bootstrap-resample sets of SWRC parameters for the soil at 5 – 10 cm, and the plot is shown in Fig. A25 in the Supplementary Material. This shows that, despite the uncertainty in the estimated parameters the distributions for CA and CV soils are quite clearly separated at larger pore sizes (larger than about 60 µm).

At Liempe farm the fitted value of Dexter's S is larger under CA than CV at each 5 – 10 cm (Table 3), but both count as indicating 'good microstructural quality' according to the criterion in Table 1. In fact all the structural quality measures from Dexter (2004) and Reynolds et al. (2007) have the same interpretation for the CA and CV soils at 5 – 10 cm by Table 1. On examining the empirical distribution of the soil quality measures obtained from the bootstrap resamples of the fitted SWRC parameters (Figs. 6 and 7) to account for the uncertainty in parameter estimation, it is seen that the distributions of S for 5 – 10 cm under CA and CV have distinct modes, although they overlap, and all boot-strap resamples fall in the 'good microstructural quality' interval (Fig. 7a). There are clear separations of the distributions for total porosity, macroporosity and air capacity at 5–10 cm (all larger under CA), even though they sit in the same interpretative ranges. The plant-available water capacity is poor under both depths as is the relative water capacity. At 5 – 10 cm at Liempe farm there is no evidence for an effect of management. The boot-strap resampled values of plant-available water capacity fall mainly in the 'limited' category, although about one third fall in the category 'poor'.

Table 2
Inferences and estimates for van Genuchten parameters of the water retention curve for all sites. For Zambia and Zimbabwe the p-value relates to comparisons between the CA and CV treatments for each parameter. For Malawi contrast 1 is a comparison between the check plots (conventional management) and those with zero-tillage, and contrast 2 is between the two zero-tillage treatments (maize monocrop or intercrop with velvet bean). Where no treatment difference was found a pooled parameter value is shown across the two treatment columns.

<table>
<tr><td colspan="7">(a). Zambia, Liempe farm</td></tr>
<tr><td>Parameter</td><td colspan="3">0–5 cm</td><td colspan="3">5–10 cm</td></tr>
<tr><td></td><td>p-value</td><td>CA</td><td>CV</td><td>p-value</td><td>CA</td><td>CV</td></tr>
<tr><td>α</td><td>0.118</td><td colspan="2">0.459</td><td>0.008</td><td>0.384</td><td>0.266</td></tr>
<tr><td>n</td><td>0.396</td><td colspan="2">1.310</td><td>1.0</td><td colspan="2">1.609</td></tr>
<tr><td>θ_s</td><td>0.228</td><td colspan="2">0.424</td><td>0.006</td><td>0.409</td><td>0.380</td></tr>
<tr><td>θ_r</td><td>0.598</td><td colspan="2">0.057</td><td>0.839</td><td colspan="2">0.115</td></tr>
<tr><td colspan="7">(b). Zimbabwe, Domboshava</td></tr>
<tr><td>Parameter</td><td colspan="3">0–10 cm</td><td colspan="3">10–20 cm</td></tr>
<tr><td></td><td>p-value</td><td>CA</td><td>CV</td><td>p-value</td><td>CA</td><td>CV</td></tr>
<tr><td>α</td><td>0.318</td><td colspan="2">0.216</td><td>1.0</td><td colspan="2">0.235</td></tr>
<tr><td>n</td><td>1.0</td><td colspan="2">1.390</td><td>0.184</td><td colspan="2">1.392</td></tr>
<tr><td>θ_s</td><td>0.669</td><td colspan="2">0.308</td><td>0.002</td><td>0.297</td><td>0.331</td></tr>
<tr><td>θ_r</td><td>1.0</td><td colspan="2">0.003</td><td>0.621</td><td colspan="2">0.011</td></tr>
<tr><td colspan="7">(c). Malawi, Chitedze</td></tr>
<tr><td>Parameter</td><td colspan="3">0–5 cm</td><td colspan="3">5–10 cm</td></tr>
<tr><td></td><td>Contrast 1 p-value</td><td>Contrast 2 p-value</td><td>Pooled estimate</td><td>Contrast 1 p-value</td><td>Contrast 2 p-value</td><td>Pooled estimate</td></tr>
<tr><td>α</td><td>0.798</td><td>0.485</td><td>0.042</td><td>0.887</td><td>0.290</td><td>0.042</td></tr>
<tr><td>n</td><td>0.779</td><td>0.784</td><td>2.907</td><td>0.178</td><td>0.709</td><td>2.590</td></tr>
<tr><td>θ_s</td><td>0.227</td><td>0.383</td><td>0.496</td><td>0.746</td><td>0.421</td><td>0.492</td></tr>
<tr><td>θ_r</td><td>0.186</td><td>0.516</td><td>0.157</td><td>0.214</td><td>0.246</td><td>0.166</td></tr>
</table>

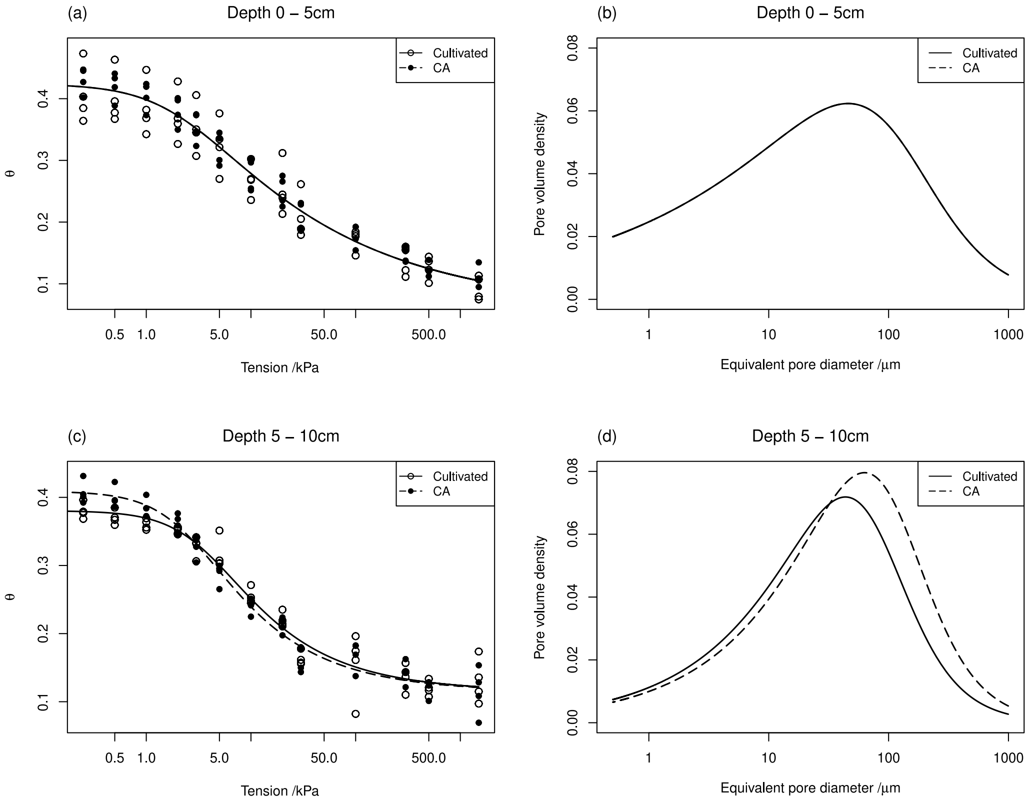

Fig. 3. Zambia, Liempe Farm: (a) Measured points on the water retention curve (0 – 5 cm) with final (pooled) model and (b) corresponding pore volume distribution (c) Measured points on the water retention curve (5 – 10 cm) with models by treatment and (d) corresponding pore volume distributions.

It is interesting to note that the plant-available water capacities for the two treatments at Liempe farm, based on the estimated SWRC parameters, are identical at the 5 – 10 cm depth, despite the evidence for a difference between the curves with respect to two parameters. The difference, as shown in Fig. 3c, are largest at small tensions (i.e. in pores too coarse to retain water against gravity), but the curves are very close at field capacity and the permanent wilting point. This highlights that a real change in the porous structure of the soil, reflected in the SWRC, does not necessarily increase the water-retaining properties of the soil, although there may be other benefits.

The soil at Liempe farm is known to have considerable potential for crop production, but soil structure is the main limitation although micropores are common in the surface soil. Conventional practice has been to till with a ripper cultivator at regular intervals to address this. However, the results here for the soil at 5 – 10 cm indicate that macroporosity (pores >75 µm) is increased under CA relative to CV. This might be due to the effects of roots of the soybean intercrop, and possibly a tendency for macropores to slump under conventional tillage. Longer monitoring of this relatively new trial is needed to show whether the increased macroporosity under CA is sustained, and whether, after longer under CA, there are further changes which affect the plant-available water capacity.

The fitted models for Domboshava are shown in Fig. 4(a,c) and convergence plots and NPDE plots are shown in Figs. A7, A8 and A9 (0 – 10 cm) and A10, A11, A12 (10–20 cm) in the Supplementary Material. These do show the fitted SWRC systematically below the measurements at −20 kPa and over at −100 kPa, most markedly in the shallower soil. At Domboshava there was no evidence for a difference in the SWRC between CA and CV at depths 0 – 10 cm. However, there was evidence for a difference in the θ_s parameter at the 10–20 cm depth (Fig. 2c). In contrast to Liempe farm, however, θ_s was smaller under the CA treatment than under conventional cultivation. The value of S was larger under CV at the lower depth, indicating good microstructural quality, whilst that under CA was poor (Table 3) and Fig. A10a shows that, when we consider the bootstrapped distribution of S to allow for uncertainty in its estimation, the modes are strongly separated for CA and CV falling below and above the threshold for good microstructural quality respectively. Fig. A10c in the Supplementary material shows that the difference in Total Porosity for the two management systems at the lower depth is very marked in the bootstrapped distributions.

Despite the difference in the θ_s parameter for the CA and CV soils at 10–20 cm, the difference in the plant-available water capacity are very small (0.11 and 0.10 for CV and CA respectively) and both are interpreted as ‘poor’. The modes of the bootstrapped distributions for this index do fall either side of the threshold between ‘poor’ and ‘limited’, but are not strongly separated (Fig A2). Again, on examining the fitted SWRC (Fig. 4c) it is clear that the main difference between the SWRC for the two management systems is at the smaller tensions, where water is not retained against gravity.

The soil at Domboshava has the largest proportion of sand in the mineral fraction of the soils in this study and the smallest baseline organic carbon content (Table A1 in the Supplementary Material). The larger porosity of the soil (10–20 cm) under the CV treatment may indicate that tillage is needed to avoid soil compaction, although the CA treatment may be beneficial for other aspects of soil quality. This would be consistent with studies on other sites with coarse-textured soils in Zimbabwe (66%–75% sand) where runoff from soils under CA was greater than from conventionally cultivated soils (Baudron et al., 2012).

The fitted models for Chitedze are shown in Fig. 5(a,c) and convergence plots and NPDE plots are shown in Figs. A13, A14 and A15 (0 – 5 cm) and A16, A17 and A18 (5 – 10 cm) in the Supplementary Material. The NPDE plots do suggest some lack of fit and Fig. 5(a) shows most observations above the function for the drier soils at 0 – 5 cm, and poor fit at tensions of −20 and -50 kPa which bound the steepest portions of the curve for soils at 5–10 cm.

There was no evidence for differences between the SWRC for the CA and CV plots at Chitedze, for either 0 –5 cm or 5 – 10 cm (Table

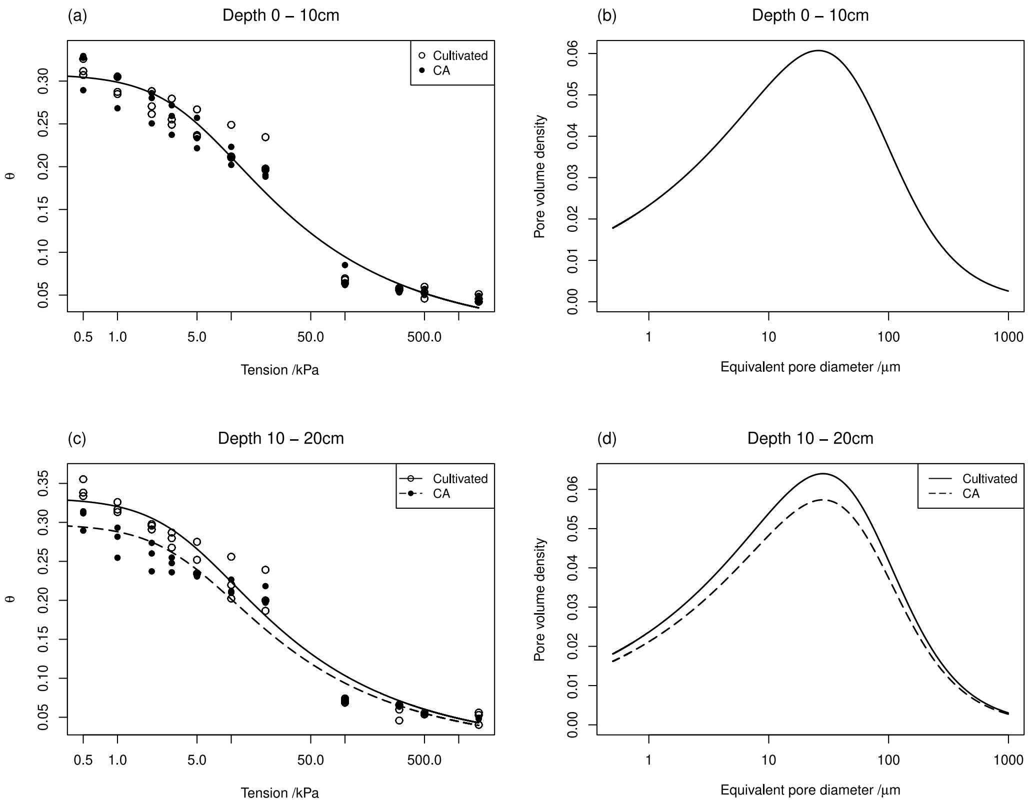

Fig. 4. Zimbabwe, Domboshava: (a) Measured points on the water retention curve (0–10 cm) with final (pooled) model and (b) corresponding pore volume distribution (c) Measured points on the water retention curve (10–20 cm) with models by treatment and (d) corresponding pore volume distributions.

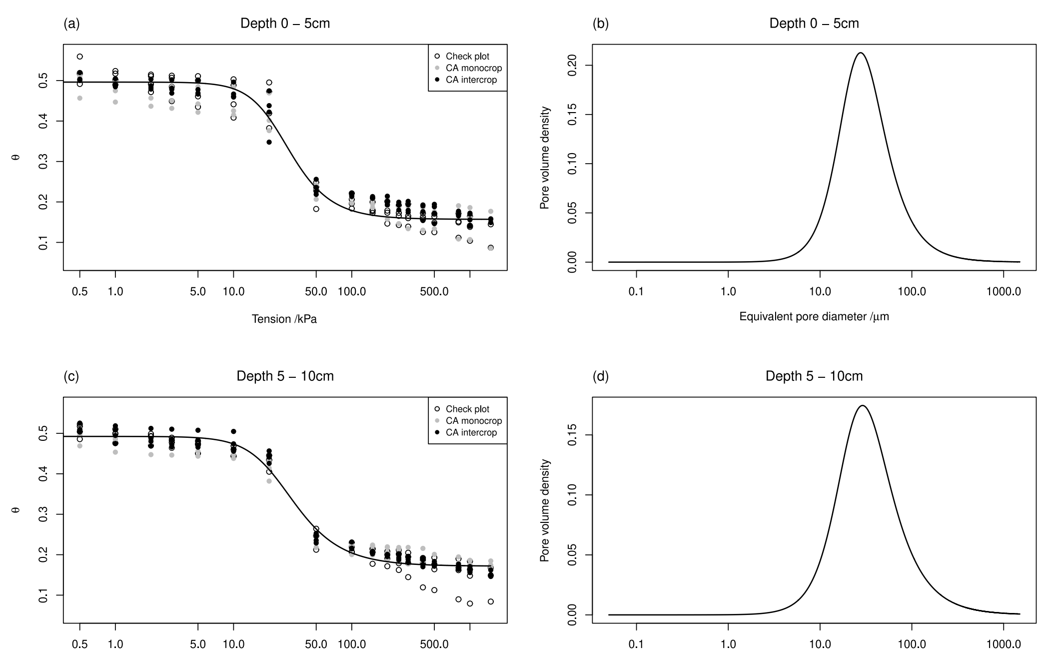

Fig. 5. Malawi, Chitedze: (a) Measured points on the water retention curve (0 – 5 cm) with final (pooled) model and (b) corresponding pore volume distribution (c) Measured points on the water retention curve (5 – 10 cm) with final (pooled) model and (d) corresponding pore volume distribution.

Table 3
Soil quality measures computed from the fitted water retention curves following Dexter (2004) and Reynolds et al. (2007).

(a). Zambia, Liempe farm						
Variable	0–5 cm		5–10 cm			
	Joint model		CA		CV	
	Value	Category	Value	Category	Value	Category
Dexter's S	0.041	Good μsq	0.051	Good μsq	0.04	Good μsq
Total porosity	0.42		0.41		0.38	
Macroporosity	0.1	Undegraded[b]	0.12	Undegraded[b]	0.08	Undegraded[b]
Relative water capacity[c]	0.5	Suboptimal	0.40	Suboptimal	0.50	Suboptimal
Available water capacity[c]	0.11	Limited	0.06	Poor	0.06	Poor
Air capacity[c]	0.21	Adequate[d]	0.23	Adequate[d]	0.20	Adequate[d]
(b). Zimbabwe, Domboshava						
Variable	0–10 cm		10–20 cm			
	Joint model		CA		CV	
	Value	Category	Value	Category	Value	Category
Dexter's S	0.033	Poor μsq	0.031	Poor μsq	0.036	Good μsq
Total porosity	0.31		0.30		0.33	
Macroporosity	0.06	Undegraded[b]	0.06	Undegraded[b]	0.06	Undegraded[b]
Relative water capacity	0.50	Suboptimal	0.50	Suboptimal	0.50	Suboptimal
Available water capacity[c]	0.11	Limited	0.10	Poor	0.11	Poor
Air capacity[c]	0.17	Adequate[d]	0.16	Adequate[d]	0.18	Adequate[d]
(c). Malawi, Chitedze						
Variable	0–5 cm		5–10 cm			
	Joint model		Joint model			
	Value	Category	Value	Category		
Dexter's S	0.16	Good μsq	0.031	Poor μsq		
Total porosity	0.50		0.30			
Macroporosity	0.06	Undegraded[b]	<0.01	Degraded		
Relative water capacity	0.60	Suboptimal	0.50	Optimal		
Available water capacity[c]	0.15	Limited	0.10	Limited		
Air capacity[c]	0.17	Adequate[d]	0.16	Adequate[d]		

[a] Microstructural quality.
[b] For medium to fine-textured soils.
[c] Assuming that field capacity is equivalent to −33 kPa.
[d] For all soils.

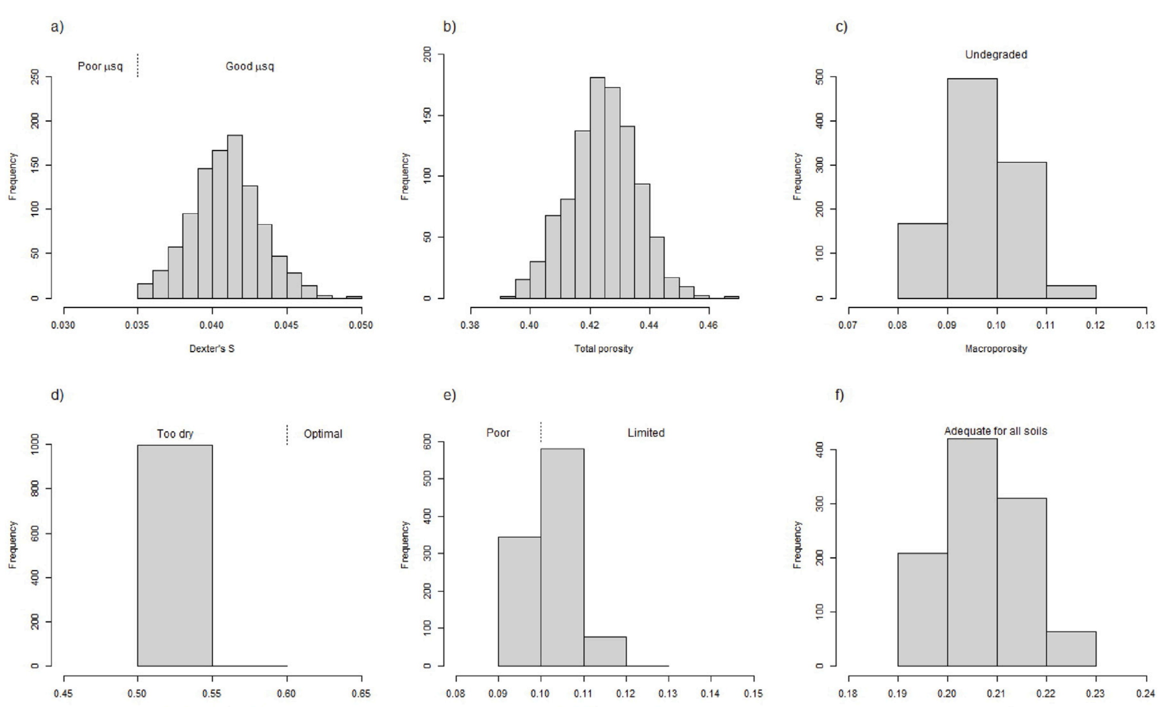

Fig. 6. Histograms of soil quality measures evaluated on bootstrap sample from the water retention curves from Zambia, Liempe farm, under contrasting treatments, depth 0 – 5 cm.

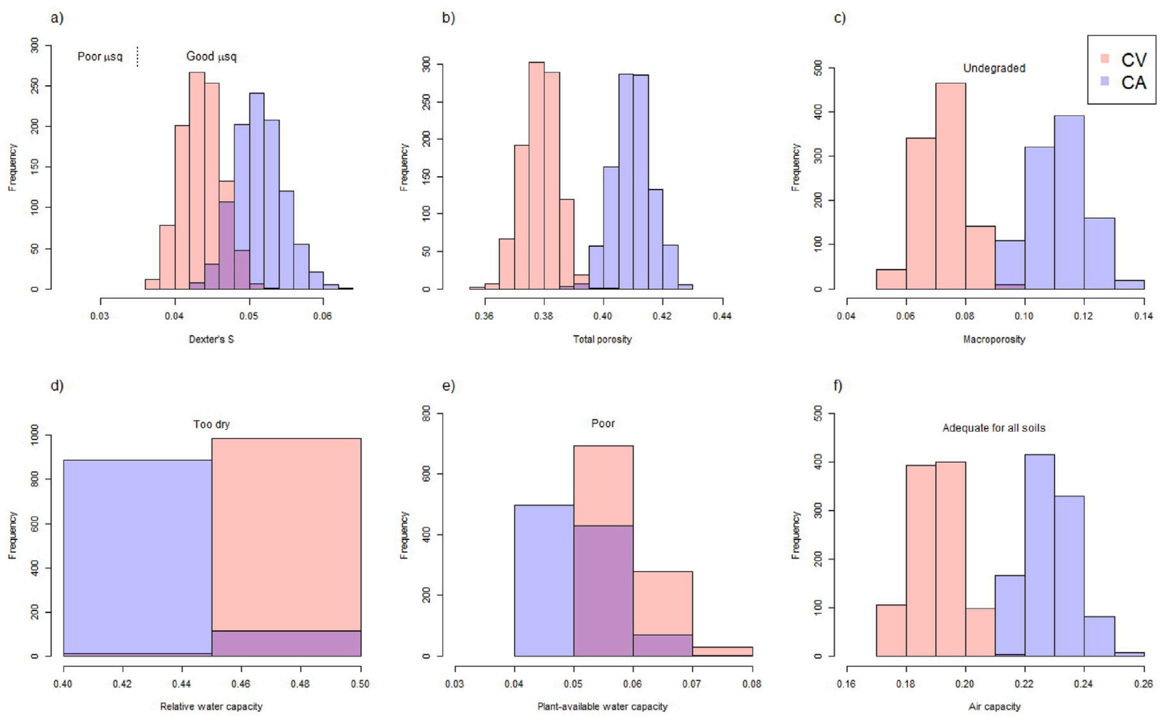

Fig. 7. Histograms of soil quality measures evaluated on bootstrap sample from the water retention curves from Zambia, Liempe farm, under contrasting treatments, depth 5 – 10 cm.

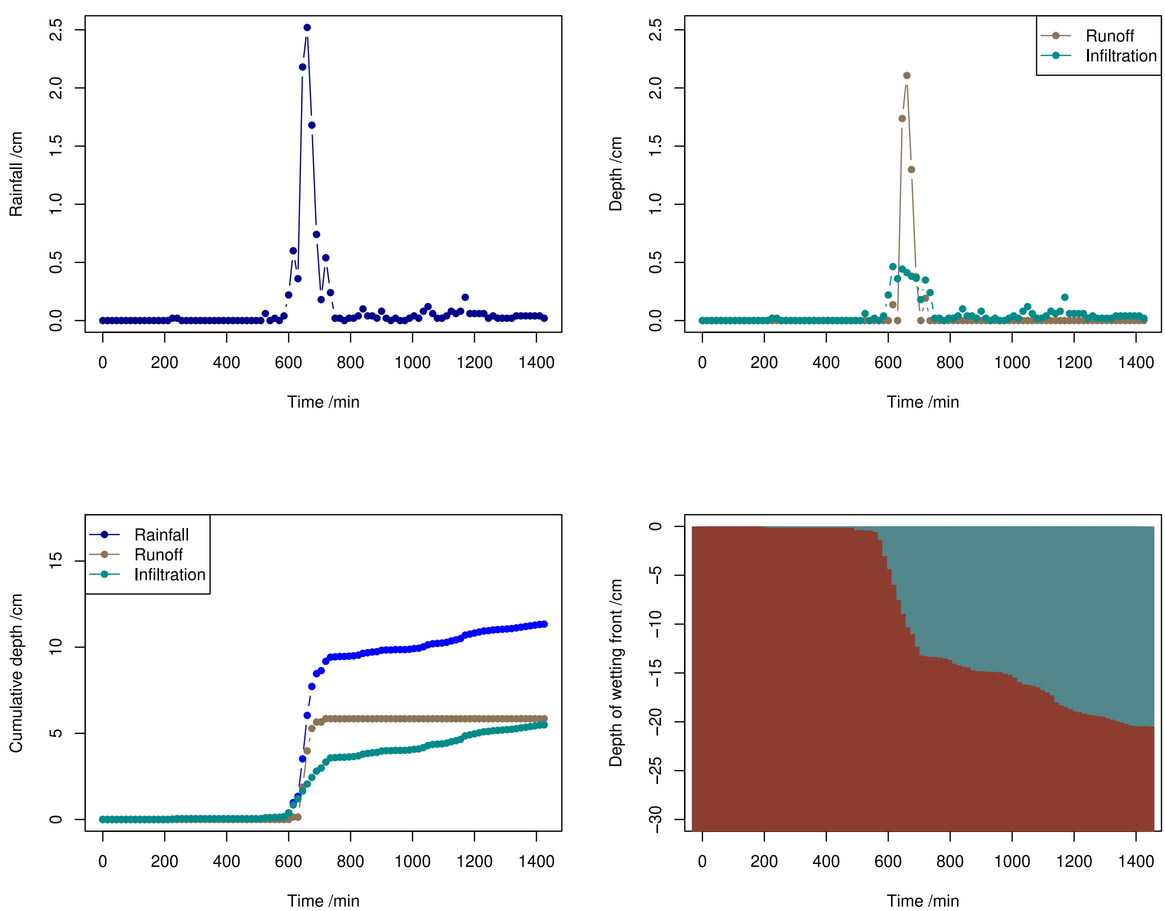

Fig. 8. Green-Ampt simulation for 24-h rainfall event with van Genuchten parameters for conventionally cultivated soil, Zambia, Liempe Farm.

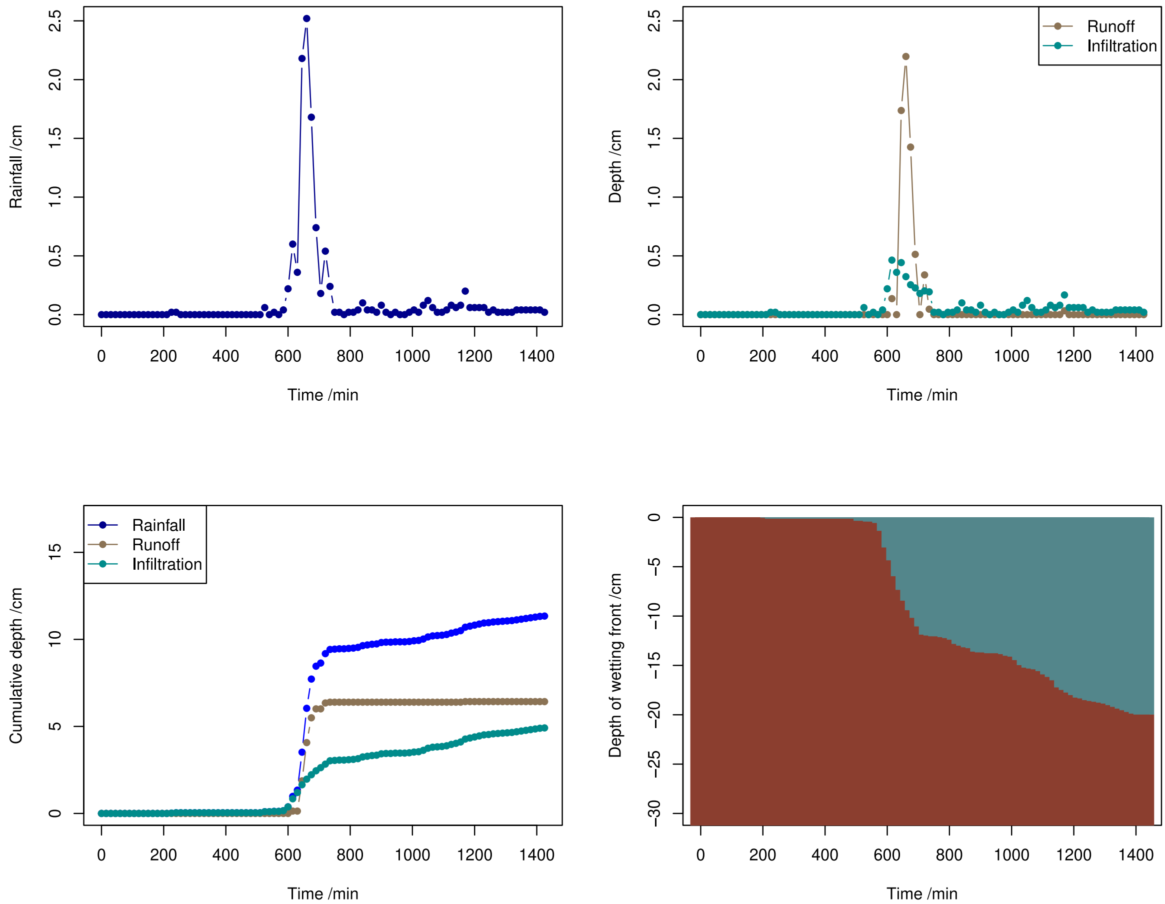

Fig. 9. Green-Ampt simulation for 24-h rainfall event with van Genuchten parameters for soil under conservation tillage, Zambia, Liempe Farm.

3). Fig. 5 shows that, at both depths the pore volume distributions are much narrower than at either Liempe farm or Domboshava. The 0 – 5 cm depth interval shows good microstructure with undegraded macroporosity and adequate air capacity. However, the plant-available water capacity is limited, and the relative water capacity is suboptimal (too small). At the 5 – 10 cm depth the microstructure is poor and the macroporosity is degraded. As in the shallower interval, the relative and plant-available water capacities are suboptimal and limited respectively and the air capacity is adequate. For physical properties other than macroporosity and air capacity the conditions are better at Chitedze than at the other sites, although indistinguishable between the CA and CV treatments. This may reflect the larger clay content and larger baseline organic carbon content in the soils at the Chitedze experiment.

3.2. *Green-Ampt simulation of infiltration with inferred parameters*

The outputs of the Green-Ampt model, for a common rainfall event, differ markedly between the sites. The largest effect of CA versus CV is seen with the SWRC parameters for Liempe farm, with more infiltration expected under CA. At Domboshava the overall infiltration is less than at Liempe, and there is no treatment effect. Infiltration is smallest at Chitedze, which has markedly more heavy-textured soil. Again, the bootstrap resampling allows us to quantify and assess the effects of uncertainty on the model outputs.

The results of the Green-Ampt simulation of water infiltration over a 24-h period under the two treatments are shown in Figs. 8 and 9. As might be expected from the greater macroporosity of the soil under CA, the infiltration is greater under this treatment, very nearly equal to runoff over the 24-h period, whereas under CV, runoff exceeds infiltration. Accounting for the effect of uncertainty in the estimated parameters of the SWRC by running the model with 1000 bootstrap resamples of the parameters produces distinct distributions for total runoff (Fig. 10), overlapping but with interquartile ranges separated.

Fig. A21 in the Supplementary Material shows the results for the Green-Ampt simulation using the CA parameter set for Domboshava. In fact, the results for CA and CV are indistinguishable. The figure shows that the wetting front only just reaches 10 cm in the period of the simulated response to the rainfall events, and so the infiltration all takes place in the depth interval where no difference was found between the SWRC. There is less infiltration than in the simulation for the Liempe farm site.

The Green-Ampt simulation with the SWRC parameters estimated for the Chitedze experiment (Fig. A24) shows very limited infiltration (the wetting front only goes to just over 1 cm depth) and most of the precipitation runs off.

Fig. A26 in the supplementary material shows the effect of the initial water content on the simulated cumulative infiltration and final depth to the wetting front for each of the three sites, differentiating the treatments at Liempe farm. The effect on cumulative infiltration was very small, with a slight reduction with increasing water content for Liempe farm, more pronounced for the CV treatment. There is an effect of initial water content on the final depth of the simulated wetting front for the Liempe and Domboshava sites, with deeper wetting with larger initial water content. This is consistent with the ‘plug flow’ model, with the infiltration displacing water down the profile.

4. Discussion and conclusions

This study has shown how the linear mixed model, estimated by the SAEM algorithm, can be used to assess evidence for differences between the SWRC of soils under different management systems. The method

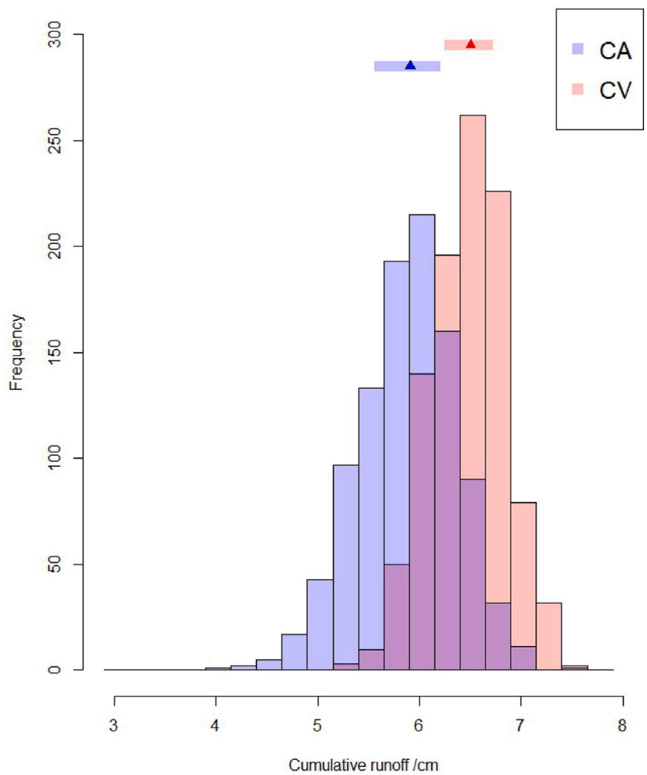

Fig. 10. Histograms showing cumulative runoff in the Green-Ampt model for 24-h rainfall event with bootstrap samples of the van Genuchten parameters for soil under (a) conventional cultivation and (b) conservation tillage, Liempe Farm, Zambia. On each histogram the solid coloured symbol shows the median of the simulated values (5.9 and 6.5 cm for CA and CV respectively) and the shaded coloured bars show the inter-quartile ranges.

has been applied to data from three experiments to examine evidence for differences in parameters of the SWRC under local CA and CV management systems. This is an advance over previous work to evaluate treatment effects on water retention which treat estimated parameters or predicted water content at specified tensions as observations in an analysis separate from the estimation of the SWRC parameters (e.g. Eze et al., 2020; Abu and Abubakar, 2013). The same approach could be used to compare the SWRC of unmanaged soils, for example when considering the impact of soil variation on information requirements to model water dynamics at catchment scale.

The SWRC parameters are estimated with uncertainty because of the variation of the soil within management systems, or soil classes of interest. This will arise from short range variation in soil texture and organic carbon content, and in processes such as root development or the activity of mesofauna which affect the soil macroporosity. In the face of this variation the LMM approach allows us to evaluate the evidence for differences in the SWRC attributable to management or to paedogenetic differences between soil classes. The SAEM algorithm also allows us to generate samples from the joint distribution of the SWRC parameters which can be used to evaluate the uncertainty of soil quality indices inferred from the SWRC, and, as demonstrated in this paper, to examine how this uncertainty propagates through non-linear process models to evaluate the uncertainty in predicted outcomes, here the runoff computed by the Green-Ampt model for a soil with heterogeneous layers.

In some cases at Chitedze and Domboshava we noted some poorer fits of the Van Genuchten SWRC function at tensions near the gap between those measured (wet end) on intact soil cores and those measured (dry end) on disaggregated soil in pressure vessels. This might reflect some inconsistency between the results from the two methods, which could be a matter for further investigation.

Having estimated SWRC parameters, and identified differences which can be detected between soil management practices, we have shown how the fitted SWRC functions can be used to compute pore size distributions and soil physical quality indices to interpret those differences. The bootstrap resampling of the SWRC parameters can be used to find distributions of the soil quality indices which shows how uncertainty in the SWRC estimation affects our conclusions. Similarly, the Green-Ampt model for water infiltration into layered soil can be used to explore the implications of differences in the SWRC for practically important effects, and again the implications of the uncertainty in the parameter estimates can be assessed.

The second objective of this paper was to examine differences between the SWRC under CA and CV treatments at the three experiments. We found evidence for differences in the SWRC between CA and CV in some conditions at Liempe Farm (5–10 cm) and Domboshava (10–20 cm) but not at Chitedze.

This lack of consistency between the sites is not surprising. First, there are differences between the baseline soil conditions at the three sites (the soil texture at Domboshava is sandier than at the others, for example, and the organic content of the soil at Chitedze is larger (See Table A1 in the Supplementary material). Furthermore, the treatments at each site, and the depths at which soil samples were collected for SWRC measurements, were selected to address local questions rather than for consistency between sites.

Considering each experiment in turn, the following observations can be made. First, although the Liempe experiment was the most recent, it was there that we saw the biggest differences in the SWRC between CA and CV, and so in the pore-size distributions and modelled rainfall infiltration. It is interesting to note that the soil at this site was known to be particularly subject to structural limitations, and interesting that effects of the CA treatment could be seen over a relatively short period. The modelling provided evidence that these effects could be expected to have some effect on water infiltration into the soil. However, the plant-available water capacity was more or less the same under both treatments because the differences in the SWRC curve were seen at tensions where water is not retained against gravity. This should be a warning against simple generalizations that a treatment, be it CA or any other regenerative practice, 'improves' soil physical quality. There may be different effects (and conceivably contradictory effects) over different pore-size intervals, and in the Liempe case infiltration was improved but water retention was not. This shows the importance of estimating key soil physical properties from measurements, such as parameters of the SWRC. These are more informative than measurements of properties such as the volumetric or gravimetric water content of the soil at an unknown and arbitrary matric potential. There are also potentially useful for process modelling.

Second, at Domboshava a difference was seen in the water retention at 10–20 cm, but this was in the opposite direction to the effect at Liempe farm (porosity was larger under CV than CA). The Domboshava site has the lightest-textured soils (sandy loam) with 74% sand and just 0.6% organic carbon Table A1). The scope to build soil organic carbon on these soils is limited, even with large inputs of crop residues, so structural development is unlikely. It is, perhaps, not surprising that greater macroporosity occurs in the conventionally cultivated soils, given that scope to develop more stable macroporosity around root channels or other biopores is probably limited in such low-carbon soils.

At Chitedze, although the CA practices have been in use for longer than at either of the other two sites, there was no evidence for a difference in the SWRC at either depth (and some physical properties such as plant-available water capacity) are poor under both treatments regardless of the long period of CA practice. This underlies the importance of not making generalizations about the impact of CA without considering local conditions.

CRediT authorship contribution statement

I. Sandram: Writing – review & editing, Writing – original draft, Investigation, Data curation. **W. Namaona:** Writing – review & editing, Writing – original draft, Investigation, Data curation. **N. Magwero:** Writing – review & editing, Writing – original draft, Investigation, Data curation. **V. Mbanyele:** Data curation, Writing – review & editing, Writing – original draft, Investigation. **C. Miti:** Writing – review & editing, Writing – original draft, Software, Investigation, Data curation, Conceptualization. **M. Moombe:** Investigation, Data curation, Conceptualization, Writing – review & editing, Writing – original draft. **T. Mtangadura:** Writing – review & editing, Writing – original draft, Investigation, Data curation. **P. Lubinga:** Writing – review & editing, Writing – original draft, Investigation, Data curation. **C.B. Chisanga:** Writing – review & editing, Writing – original draft, Investigation, Data curation. **I. Nyagumbo:** Writing – review & editing, Investigation. **K. Njira:** Writing – review & editing, Investigation. **I.S. Ligowe:** Writing – review & editing, Investigation. **J. Banda:** Writing – review & editing, Investigation. **W.R. Whalley:** Writing – review & editing, Investigation, Funding acquisition, Conceptualization. **G. Sakala:** Writing – review & editing, Investigation, Funding acquisition, Conceptualization. **E. Phiri:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization. **P.C. Nalivata:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization. **H. Nezomba:** Supervision, Project administration, Investigation, Conceptualization, Writing – review & editing. **P. Mapfumo:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **F. Mtambanengwe:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization. **R.M. Lark:** Writing – original draft, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **A.S. Gregory:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Conceptualization. **J.G. Chimungu:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.geoderma.2025.117431.

Data availability

The data shown in this paper will be provided on reasonable request. The data from the Domboshava, Liempe and Chitedze sites are held, respectively, by University of Zimbabwe, University of Zambia and Lilongwe University of Agriculture and Natural Resources, and requests should be made, respectively to Dr H. Nezomba (hnezomba@agric.uz.ac.zw), Prof. E. Phiri (ephiri@unza.zm) and Dr. J.G. Chimungu (jchimungu@luanar.ac.mw).

The code used for these analyses is available from the following link along with a demonstration R script which uses data on the SWRC of two soil classes (Solonetz and Nitosols according to World Reference Base (1998) measured in Kenya. The data were obtained from the WOSIS data base (Batjes et al., 2016) and had been published with a CC-BY-NC licence. https://github.com/rmlark/Soil_Water_Retention.

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