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Modelling SOC in Switzerland's mineral agricultural soils using RothC: Sensitivity analysis

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Table of Contents

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Summary

Changes in soil organic carbon (SOC) stocks in Switzerland's mineral agricultural soils are simulated using RothC, the results of which are used for national GHG reporting. A sensitivity analysis of these simulations and of the system used to upscale these simulations to the national scale is described in this report. The main aim of the analysis was to understand which input or model parameters need to be estimated more precisely or accurately in the future and thus where resources need to be prioritised. A Monte Carlo approach was used, varying all parameters simultaneously. The input and model parameters were set to vary i. by a fixed amount and ii. according to their uncertainty or the variation they are expected to vary by in reality. The latter allowed the importance of parameters to be judged, as both model sensitivity and extent of variation of the parameters are considered. The change in SOC stocks over 28 years was used as the response variable. Changes in SOC stocks in cropland, in year-round managed grassland and in summer pasture areas were investigated separately. Although the results for these three land use types differ, a common set of parameters important for all of them was identified (the carbon use efficiency scaling factor, the decay rate constants of the humified organic matter and resistant plant matter C pools, initial SOC, temperature and precipitation). The variation of the two latter parameters is mainly due to the sometimes large regions that are used for the upscaling of simulations to the national scale, rather than uncertainty in the parameter estimates themselves. A move to simulating smaller regions, for example raster-based modelling, would therefore improve the simulation of SOC changes greatly. The estimate of the former three parameters (all model parameters) will on the other hand not be improved with simulations at higher spatial resolution and should be prioritised for future research. Lastly, we show that a model parameter associated with topsoil moisture deficit becomes more important in years with hot and dry summers; this parameter is likely to be very important for countries with frequent drought and will become more important for Switzerland in the future. Though the analysis pertains to the Swiss inventory system, it aims to provide information that can be used in other countries or regions, or for the improvement of the RothC model in general.

1 Introduction

Soils store more than twice the amount of carbon (C) as the atmosphere and about four times as much as global aboveground vegetation (Batjes, 1996; Sanderman et al., 2017). These stocks are dynamic. C is lost from the soil predominantly as CO_2, meaning changes in soil organic carbon (SOC) are relevant for greenhouse gas (GHG) budgets. In agricultural soils, where SOC stocks have often decreased in the past, there is large potential for C-sequestration (Paustian et al., 2019), meaning monitoring and reporting changes in SOC stocks in these soils is needed (Smith et al., 2020). Although simulating SOC stocks or stock changes cannot be a substitute for their measurement, it can offer a cost-efficient method – especially for large regions – to estimate SOC changes, also in response to changes in management. Additionally, modelling SOC offers the potential to predict future SOC stocks or dynamics, considering different management measures and climate, useful for planning or estimating sequestration potentials (Lee et al., 2021; Wiesmeier et al., 2014).

In Switzerland, SOC changes in mineral agricultural soils are simulated using RothC and results based on this are used for its annual GHG inventory (FOEN, 2020). An inventory system was developed for this purpose (Wüst-Galley et al., 2020). Components of this inventory system include the SOC modelling itself, as well as the upscaling of model outputs to the national level, the latter made more challenging by the wide range of management systems and the large topographic and climatic variation in the country. A sensitivity analysis of this whole inventory system is described in the present report.

1.1 Modelling SOC changes in Swiss soils

SOC stock changes in the topsoil (0-30 cm) are simulated for cropland (arable land including leys, ca. 398,000 ha[1]), for year-round managed pastures and meadows (ca. 606,000 ha[1], excluding leys) and for pastures and meadows in the summer pasture area ('SPA', ca. 466,000 ha, Herzog et al., 2014). Though most of the Swiss agricultural surface is grassland, cropland is also important.

Cropland is concentrated in flatter regions, mostly in the lowlands. For those crops receiving organic amendments (OrgAm), inputs as calculated in the inventory system are generally high (1.3 to 2.6 t C ha^{-1} a^{-1}) and cover crops are – in accordance with the ecological requirements for farm subsidies[2] – assumed to be used in the rotation if fields would otherwise be bare over the winter. Year-round managed grassland occurs also in the flatter lowlands, as well as in hilly and lower mountainous regions. A wide range of management intensity occurs, corresponding to a large range of OrgAm inputs (from no inputs to an estimated 1.5 t C ha^{-1} to a^{-1}, excluding leys). The SPA occurs in mountainous parts of the country, bounded at higher elevation by unproductive vegetation / land cover. At lower elevation it is separated from year-round managed land by specified boundaries and therefore occurs in regions (and with climates) distinct from the rest of agriculture. The land is grazed only in the summer months and receives little OrgAm only during this period. To incorporate this diversity of management in the inventory system, SOC stocks are simulated for 19 crops and 6 different grassland types (one of which refers to the grasslands in the SPA, the other five of which encompass year-round managed grassland of varying intensity, Wüst-Galley et al., 2020: pp. 36-40).

The inventory system uses the RothC model (Coleman et al., 1997; Jenkinson et al., 1990), which simulates the dynamics of four soil C pools in response to user-given C inputs from plants and OrgAm (in the inventory system, comprising manure and inputs from anaerobic digestion). These C pools decompose at their own rates, using climate- and / or clay content dependent first-order kinetics to simulate SOC mineralisation. The model uses a monthly time step.

To upscale the results of the RothC simulations, the country is partitioned into regions (hereafter 'strata') which have similar climatic and topographic conditions, and clay content (Wüst-Galley et al., 2020: pp. 29-31). Additionally, 25 different management systems (the different grassland types and individual crops, Wüst-Galley et al., 2020: pp. 29-31) are considered. The simulations are carried out for all combinations of the regions and management, and the simulation outputs are weighted according to the occurrence of the strata-management combination, to obtain national level results (Wüst-Galley et al., 2020: pp. 67-68). Though these strata capture some variation in climate and topography, their sometimes large size (e.g. one stratum contains 255,000 ha of cropland and another, in the

[1] Federal Statistics Office, https://www.pxweb.bfs.admin.ch/pxweb/de/, accessed 17th February 2021; in German only.
[2] Verordnung über die Direktzahlungen an die Landwirtschaft (Direktzahlungsverordnung, DZV); SR 910.13: https://www.admin.ch/opc/de/classified-compilation/20130216/index.html; in German, French and Italian.

SPA, contains 146,000 ha of grassland) combined with the steep environmental gradients mean there is considerable variation within some of them. Likewise, though SOC is simulated for many different management systems, there is also variation within these that is not captured by the inventory system. Simulations are run from 1975 to present and results reported for the period 1990 to present.

1.2 Types of sensitivity analysis

The type of sensitivity analysis carried out is determined in part by the aim of the sensitivity analysis and the complexity of the model. Two important aspects are as follows.

The first aspect concerns whether the parameters are set to vary by a fixed amount (e.g. by ±10 %), or by varying amounts. The first option allows a direct comparison of the **sensitivity** of the model to the parameters and can help understand the behaviour of a model in a general context. This method has disadvantages, including the fact that non-linear effects of the parameter value on the model outcome can only be determined by varying the input parameter's value around a number of different starting points (Wallach et al., 2019). The second option is that model and input parameters can be set to vary depending on the amount of variation or uncertainty encountered in the real world (or an estimate thereof). Contrary to the first option, this method allows non-linear relationships between input parameter and model outcome to be revealed. Additionally, this method is important if the aim of the sensitivity analysis is to understand the **importance** of parameters for the model, enabling future resources to be prioritised to improve the quality of the inputs and thus the inventory system. This is because the importance of different parameters depends on i. their influence on the model outcome *per se*, i.e. the sensitivity, as well as ii. the magnitude of their uncertainty or variation (

Figure 1). For example, if an input parameter is known to vary considerably but alters the outcome of the simulation relatively little (i.e. the model is relatively insensitive to that parameter), expending large amounts of resources on that parameter makes little sense; improving its estimate will not improve the outcome of the simulation substantially. Conversely, it makes sense to improve the estimate of an input parameter to which the model is very sensitive, especially if that parameter is known to vary a lot or if the estimate of it is uncertain. The second option indeed combines both these aspects.

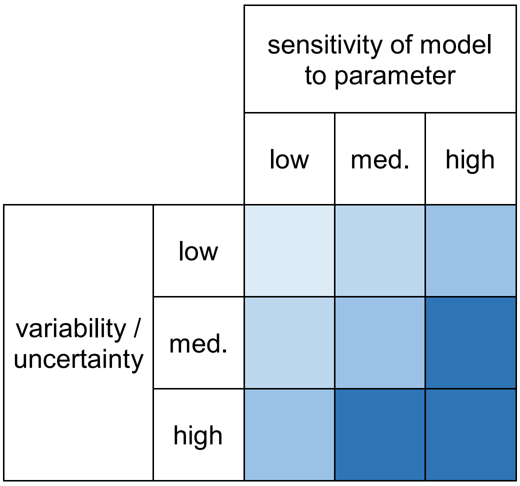


Figure 1 The importance of an input or model parameter (paler blue = least important, darker blue = most important) depends on it the extent of its variation or uncertainty, as well as the sensitivity of the model to that parameter.

The second aspect concerns whether or not parameters are varied one at a time, or simultaneously. The first option increases the direct comparability of results as only the parameter of interest is varied; interpretation of the results is thus much simpler. For example, if a 10 % increase in the value of parameter one causes a 4 % change in the outcome or a model and a 10 % increase in the value of parameter two causes an 8 % change in the outcome of the same model, it can be stated that the model is twice as sensitive to parameter two as it is to parameter one. A disadvantage of this method however is that interactions between input or model parameters are not accounted for. The second option involves varying multiple (or generally, all) parameters simultaneously, meaning the multi-dimensional parameter space is investigated. The main advantage to this method is that interactions between input or model parameters can be accounted for and can be quantified (Wallach et al., 2019). Disadvantages include the more complicated interpretation of results, especially if a large number of parameters is tested.

Within the RothC model, there are interactions between variables as well as non-linear relationships between input parameters and the model outcome (Jenkinson et al., 1990). It was therefore decided to carry out a sensitivity analysis in which all parameters are varied simultaneously. Furthermore, parameters were allowed to vary by the whole range of their expected variation, allowing the importance of parameters to be compared. As the entirety of the parameter space is investigated, this method is termed a 'global' sensitivity analysis (Wallach et al., 2019). An MC approach was used to do carry out the analysis, whereby a number of replicates were run, each replicate representing one run of the inventory system (i.e. simulations and upscaling). For each replicate, model and input parameter values are randomly picked from pre-determined parameter distributions, rather than being fixed values (as would otherwise be the case in a model run).

1.3 Sources of variation

The variation associated with a parameter may have two sources. Firstly, the 'true' value of a parameter might be uncertain, either if there is measurement uncertainty or for example if a database from which data for the model are obtained includes only a sample of a population. Secondly, variation occurs because (single) simulations represent entire regions or management systems, although there might be (or almost certainly is) variation within a management system or across a region. For example, for a given region, the mean monthly temperature is represented by a single value, although in reality, temperature will vary across the region. This is particularly relevant for the inventory system investigated here, as simulations represent sometimes large regions and Switzerland has very variable topography.

Both sources of variation are important for a sensitivity analysis and therefore both were considered. Where several sources of variation could be identified, the largest one was accounted for.

1.4 Aims and Scope

A sensitivity analysis forms part of good practice for model application and is especially important if a model is used outside of the conditions for which it was originally developed (Smith and Smith, 2007). The general question of a sensitivity analysis is what is the sensitivity of the outcome of the simulations (e.g. SOC stock changes) to changes in the inputs? The main aim of the sensitivity analysis described here was to identify those inputs most important for the Swiss inventory system and thus those that need to be estimated with more precision, or whose accuracy needs to be ascertained. Understanding this in turn helps to prioritise resources for future work. Though the analysis pertains to the Swiss inventory system, it is aimed to provide information that can be used for simulating SOC for other countries or regions, or for the improvement of the RothC model in general.

2 Methods

2.1 Overview

An MC approach was used to estimate the sensitivity of the inventory system to the input and model parameters. Both model and input parameters were varied according to the amount of variation associated with them (either due to uncertainty in the parameter estimate or due to spatial variation not represented in the model), meaning that secondly, the importance of the parameters could also be determined. Within RothC, SOC mineralisation rates are influenced by several parameters (so-called decomposition rate constants and rate modifying factors), some of which interact with one another. For this reason, all parameters were varied simultaneously.

2.2 Parameters

Three groups of parameters were varied in the sensitivity analysis, namely i) dynamic input parameters that vary over time e.g. meteorological information, plant C inputs; ii) static input parameters that are defined only once e.g. initial SOC; and iii) model parameters e.g. decay rate constants. The list of parameters included is given in Table 1.

Table 1 List of input and model parameters included in the sensitivity analysis; parameters are classified as either static or dynamic (i.e. changing each month) input parameters, or as model parameters (always static); all parameters used in main Monte Carlo analysis, unless otherwise stated (see section 2.5 for details); CUE = carbon use efficiency.

Parameter	Abbreviation	Parameter type	Brief description
Temperature		Dynamic input	Monthly average temperature of each stratum (°C)
Precipitation		Dynamic input	Monthly summed precipitation of each stratum (mm)
Evapotranspiration		Dynamic input	Monthly summed evapotranspiration of each stratum (mm)
Plant-C inputs	PlantC	Dynamic input	The quantity of plant-C inputs including above- and below-ground inputs, as well as root exudates (t C ha^{-1} a^{-1})
Organic amendments inputs	OrgAm	Dynamic input	The quantity of C from organic amendments (OrgAms) that is applied to agricultural surfaces (t C ha^{-1} a^{-1}); calculated for five OrgAm types: Stacked manure, slurry, poultry waste, deep litter and fresh manure
Herd sizes		Dynamic input	Number of animals; used to estimate the parameter 'OrgAm' *
OrgAm-C excretion rates		Dynamic input	Rate of C excretion of animals (t C $animal^{-1}$ a^{-1}); used to estimate the parameter 'OrgAm' *
Straw production		Dynamic input	Production rate of straw (t C ha^{-1} a^{-1}); used to estimate the parameter 'OrgAm' *
OrgAm-C loss during storage		Static input	Loss of OrgAm-C due to storage (%); used to estimate the parameter 'OrgAm' *
Duration of OrgAm storage		Static input	Typical duration of OrgAm storage (years); used to estimate the parameter 'OrgAm-C loss during storage' *
Rate of OrgAm-C loss		Static input	Rate of C loss as a function of time (t C a^{-1}); used to estimate the parameter 'OrgAm-C loss during storage' *
Initial SOC stocks	Initial TOC	Static input	Total organic C (TOC) stocks (t C ha^{-1} a^{-1}) at start of simulation (1975)
Clay content		Static input	Soil clay content (%)
Timing of C inputs		Static input	Timing of C inputs from OrgAm and plants (month of C inputs)
Initial HUM pool	HUM pool	Model	Relative size of the humified organic matter (HUM) pool at start of simulation (1975)
Initial IOM pool	IOM pool	Model	Relative size of the inert organic matter (IOM) pool at start of simulation (1975)
Initial RPM pool	RPM pool	Model	Relative size of the resistant plant material (RPM) pool at start of simulation (1975)
BIO decay rate constant	kBIO	Model	Decomposition rate constant of the microbial biomass (BIO) pool (a^{-1})
DPM decay rate constant	kDPM	Model	Decomposition rate constant of the decomposable plant material (DPM) pool (a^{-1})
HUM decay rate constant	kHUM	Model	Decomposition rate constant of the HUM pool (a^{-1})
RPM decay rate constant	kRPM	Model	Decomposition rate constant of the RPM pool (a^{-1})
DPM / RPM ratio	DPM/RPM	Model	Proportion of incoming plant matter going to the DPM versus RPM pool
Minimum beta value	TSMD-b	Model	Minimum value that the beta value can take (under conditions of topsoil moisture deficit, TSMD)
CUE scaling factor	CUE	Model	A scaling factor that relates clay content to the CO_2 / (BIO+HUM) ratio
HUM pool proportion of OrgAm inputs	OrgAm-HUM	Model	Proportion of incoming OrgAm-C going to the HUM pool

* Not used in main MC analysis

2.3 Extent of variation

The amount of variation associated with each input or model parameter was estimated, based either on data or from literature sources. The sources are listed in the following text and the parameters relevant for establishing the probability distribution functions (PDFs, typically the mean and coefficient of variation, CV [%]) are given in Table 2. Details on the resulting parameter distributions given in Appendix A.

The meteorological data sets used in this project are MeteoSwiss Grid-data products, based on networks of meteorological stations (temperature and precipitation) or satellite information (surface incoming shortwave radiation, for calculation of evapotranspiration). The three data sets are described in more detail in MeteoSwiss (2013); MeteoSwiss (2017); MeteoSwiss (2018) and their implementation in the Swiss inventory system in Wüst-Galley et al. (2020, pg. 32). For **temperature** and **evapotranspiration**, the basic data are considered high quality. For **precipitation** there is systematic under-estimation in rain gauge measurements, but this affects times of the year and / or regions for which an underestimate of precipitation would alter the outcome of the simulation very little, if at all (Wüst-Galley et al., 2020, pg. 75). Uncertainty from the basic data sets was therefore not considered in the sensitivity analysis. A much greater source of variation however is that due to the use of strata for the simulations: Although the strata were established to be representative of regions of similar meteorological conditions, they are nonetheless sometimes large and cover large topographical gradients. The variation of the three meteorological parameters was estimated by inspecting the gridded data for the relevant strata, for the years 1990, 2000 and 2010. For each year, stratum and land use type, the CV of each parameter was calculated. Per land use type, variation was similar between the strata and between the three years, meaning constant CVs could be used. For temperature, the low temperatures in the winter led to extremely high CV values, although variation in the winter months is, in absolute terms, similar to that in the summer months; the standard deviation was therefore used.

Plant C inputs are calculated as a function of yield, C allocation within the plant and the proportion of the plant that remains in the field (both above- and below-ground). Estimates of the variation for each of these parameters could not be obtained. We expect variation in crop yields across the country to be one of the major sources of uncertainty in plant C inputs in general, because regions for which yield estimates exist – individual cantons – cover large topographic and climatic gradients across the country. The variation in yields was therefore used to represent the variation in *total* plant inputs. Crop yields for 13 crops in the main 10 to 14 crop-producing cantons in Switzerland were inspected, for the years 1991, 1995, 2000, 2005, 2010 and 2015 (data from the Agristat reports of the SFU[3]). For each year and crop, the CV of yields across the cantons was calculated. With the exception of summer crops in 2015 – an unusually dry and hot summer – and of silage corn (high variation across the years), yield variation was stable for each crop across the years considered. The mean CV of each crop was used to determine the variation in total plant C inputs, per crop.

The variation in the quantity of C inputs through organic amendments (**OrgAm**) incorporated uncertainty in herd size, OrgAm-C excretion rate, straw production and OrgAm-C loss during storage. It was calculated for five OrgAm types (Table 1), estimated using an MC analysis. Uncertainty in **herd sizes** was estimated by Bretscher and Leifeld (2008) and includes uncertainty in the counts themselves as well as seasonal variation (counts are given annually, but the herd size varies throughout the year). Uncertainty in **OrgAm-C excretion rate** was estimated by Bretscher and Leifeld (2008), based on Minonzio et al. (1998). Uncertainty in **straw production** was based on the average yield variation of small-grain cereals, calculated using regional (cantonal) yield data from 1991, 1995, 2000, 2005, 2010 and 2015 (Agristat annual reports[3] from the Swiss Farmers' Union). The variation in **OrgAm-C loss due to storage** (for each type of OrgAm) was itself estimated using an MC analysis, incorporating variation in the rate of OrgAm-C loss and in the duration of OrgAm storage. Information regarding the variation in the **duration of OrgAm storage**, for all manure types of OrgAm except fresh manure, was estimated using guidelines of crop fertilisation and OrgAm storage (Aeby et al., 1995; Flisch et al., 2009; Kupper et al., 2013; Sägesser and Weber, 1992), assuming OrgAm is produced at a constant rate throughout the year. For fresh manure, the duration of time during which CO_2 was emitted from dung patches was obtained from Pecenka and Lundgren (2018) and Penttilä et al. (2013). Variation in the **rate of OrgAm-C loss** during storage was obtained from published experiments in the temperate zone, where OrgAm-C

[3] Annual reports available from: https://www.sbv-usp.ch/de/services/agristat-statistik-der-schweizer-landwirtschaft/statistische-erhebungen-und-schaetzungen-ses/; in German and French.

content had been measured prior to and following OrgAm storage (Wüst-Galley et al., 2020, pg. 43, see references therein). The results from these studies were combined, allowing – for each OrgAm-C type – a statistical model describing OrgAm-C loss as a function of storage duration to be built. The standard error of each of the two coefficients (intercept and the multiplier) was used to determine the variation in the relationship between OrgAm-C loss and storage duration, for each OrgAm-C type.

Initial TOC was calculated as a function of stone content, soil depth and C concentration, the latter of which is a function of clay content and, for grassland, also elevation (Leifeld et al., 2005). The uncertainty of the calculation of initial TOC is higher than the spatial variation associated with this parameter, therefore the former was considered in this analysis. The standard errors of the parameter estimates from the statistical models were used to quantify the uncertainty.

The importance of **clay content** for the inventory system was estimated by comparing SOC stock changes for simulations run for three clay classes. For cropland and year-round managed grassland, these were 10, 20 and 35 %. Ca. 90 % of cropland and ca. 80 % of year-round managed grassland occurs on soils within this clay content range (calculated from FSO 2000 and the Swiss land use statistics[4]). For the SPA, the clay classes considered were 5, 10 and 27 %. Ca. 75 % of grassland in the SPA is estimated to occur in this clay content range.

Variation in the **timing of C inputs** (both OrgAm and plant inputs) was set to between one month prior to or later than the month used in the main analysis.

In the inventory system, the initial pool sizes are determined by SOC stocks and clay content (Wüst-Galley et al., 2020: pp.59-61). The variation in the proportion of the initial C in the **HUM**, **RPM** and **IOM** pools (see Table 1 for meaning of these terms) was determined by inspecting the variation in these three pools across all strata and clay classes. The variation considered is therefore representative of variation throughout the country, but does not include possible variation due to error in their estimate. The **BIO** pool was assumed not to vary meaning the model's sensitivity to it was not tested. This is consistent with other sensitivity analyses (Janik et al., 2002) and with the fact that the BIO pool has little influence on the model outcome. The initial **DPM** pool was assumed to be zero, as is carried out in the main analysis (Wüst-Galley et al., 2020).

The estimates of variation (CV) for the decay rate constants **kDPM**, **kBIO**, **kRPM** and **kHUM** (see Table 1) were adopted from Janik et al. (2002), as no further information was found.

Little information was found regarding the variation of the allocation of OrgAm-C and plant C inputs to the DPM and RPM pools (**DPM / RPM ratio**). The default DPM / RPM ratio for improved grasslands is 1.44 (Jenkinson et al., 1991). For unimproved grasslands and savannas a DPM / RPM ratio of 0.67 is recommended (Coleman and Jenkinson, 2014). It was assumed that this is the minimum DPM / RPM ratio for plant C inputs in the Swiss agricultural system, representing a 0.01 percentile.

The **TSMD-b** value in RothC – relevant under periods of topsoil moisture deficit – is 0.2, meaning that under strong topsoil moisture deficit, C mineralisation is reduced to 20 %. Variation around this value was derived from Paul et al. (2003), using relative N mineralisation rates as a proxy for relative C mineralisation rates (Falloon et al., 2011).

In RothC, the relationship between clay and C-use efficiency (CUE) is altered by the **CUE scaling factor**. The default scaling factor is 1.67, corresponding to a CUE (C going to the HUM and BIO pools divided by C going to HUM and BIO pools and CO_2) in Rothamsted of ca. 22 %. Expected variation in the CUE scaling factor was obtained from Sinsabaugh et al. (2013) and Sinsabaugh et al. (2017), considering grassland and cropland sites with similar mean annual temperature and precipitation as Switzerland, yielding a CUE range of circa 10 % to 45 %. Assuming this range represents the 95 % of variation, these values were used to construct the PDF of the CUE scaling factor corresponding to these CUE values.

The default proportion of OrgAm going to the HUM pool (**OrgAm-HUM**) is 2 %. The dominant OrgAm considered in the inventory system of Swiss SOC is farmyard manure (> 96 % for the period 2015 to 2019, with other inputs being from anaerobic digestion). OrgAm-HUM values for farmyard manure (only) were obtained from Peltre et al. (2012) and used to set the limits of the PDF. A log normal distribution was used, to ensure the median value of the PDF corresponds to the default value of 2 %.

[4] https://www.bfs.admin.ch/bfs/de/home/statistiken/raum-umwelt/nomenklaturen/arealstatistik.html; in German and French.

Table 2 The properties of the probability distribution functions (PDFs) used to describe the variation of parameters, namely the mean and the coefficient of variance (CV, in %) and the type of PDF used; units of the mean are the same as the units of the parameter; 'v' indicates that the value varies (either per crop / grassland category, per stratum or per month) and absolute values are therefore not given; parameter names, where abbreviated, are given in Table 1.

Parameter	mean	CV (%)	Distribution of PDF	Comment
Temperature (°C)				
Cropland	v	1.4	Truncated normal	Values given are standard deviations, not CV (see text for details).
Year-round grassland	v	1.7	Truncated normal	
Grassland in the SPA	v	2.9	Truncated normal	
Precipitation (mm)				
Cropland	v	26	Truncated normal	
Year-round grassland	v	24	Truncated normal	
Grassland in the SPA	v	43	Truncated normal	
Evapotranspiration (mm)				
Cropland	v	8.3	Truncated normal	
Year-round grassland	v	7.3	Truncated normal	
Grassland in the SPA	v	9.8	Truncated normal	
Plant-C inputs (t C ha^{-1})				
Cropland	v	8.4	Truncated normal	CV values here are averages of different crops or grassland categories. See Appendix A for individual values.
Year-round grassland	v	8.3	Truncated normal	
Grassland in the SPA	v	8.3	Truncated normal	
OrgAm-C inputs (t C ha^{-1})				
Cropland	v	8.6	Truncated normal	CV values are averages of different crops or grassland categories. See Appendix A for individual values.
Year-round grassland	v	9.2	Truncated normal	
Grassland in the SPA	v	9.3	Truncated normal	
Herd sizes	v	6.0	Normal	For cattle
	v	6.5	Normal	For other animal groups
C excretion rates (t C animal^{-1} a^{-1})	v	-16 to +12	Normal	
Straw production (t C a^{-1})	v	6.7	Normal	
OrgAm-C loss during storage (%)				Includes the variation of the duration of OrgAm storage (below) and rate of OrgAm-C loss (not shown in table)
Stacked manure	27.5	44.6	Truncated normal	
Slurry	10.6	51.4	Truncated normal	
Poultry waste	30.5	42.9	Truncated normal	
Deep litter	30.5	45.4	Truncated normal	
Fresh	21.5	45.9	Truncated normal	
Duration of OrgAm storage (years)				
Stacked manure	n/a	n/a	Trapezoid	min = 0, mode 1 = 0.04, mode 2 = 0.25, max = 0.33
Slurry	0.076	25	Log normal	Median is given instead of the mean; CV refers to the CV of the log distribution

Parameter	mean	CV (%)	Distribution of PDF	Comment
Poultry waste	n/a	n/a	Trapezoid	min = 0, mode 1 = 0.08, mode 2 = 0.25, max = 0.33
Deep litter	n/a	n/a	Trapezoid	min = 0, mode 1 = 0.04, mode 2 = 0.25, max = 0.33
Fresh	1.3	11	Normal	
Initial TOC (t C ha^{-1}, 0-30 cm)				
Cropland	49.1	13.4	Truncated normal	The mean values are averages across different strata. See Appendix A for individual values.
Year-round grassland	61.5	22.4	Truncated normal	
SPA	49.5	22.4	Truncated normal	
Clay content (%)	n/a	n/a	n/a	Discrete values were used; for cropland and year-round managed grassland: 10, 20 and 35 %; for SPA: 5, 10 and 27 %
Timing of C inputs	n/a	n/a	n/a	C inputs (from plants or OrgAms) were added either 1) one month earlier than, or 2) at the same time as, or 3) one month later than the month the C inputs are typically applied.
HUM pool (proportion)	0.767	1.1	Normal	
IOM pool (proportion)	0.085	3.2	Normal	
RPM pool (proportion)	0.131	8.0	Normal	
kBIO (a^{-1})	0.66	20	Truncated normal	
kDPM (a^{-1})	10.02	20	Truncated normal	
kHUM (a^{-1})	0.02	30	Truncated normal	
kRPM (a^{-1})	0.3	30	Truncated normal	
DPM / RPM ratio	1.44	21	Normal	
TSMD-b	0.425	17.6	Normal	
CUE scaling factor	1.67	19.4	Normal	
OrgAm-HUM (proportion)	0.02	24.4	Log normal	Median is given instead of the mean; CV refers to the CV of the log distribution

n/a = not applicable, see comments

2.4 Extent of analysis

The SOC inventory system as implemented for the Swiss GHG inventory is extensive, including 24 strata, 19 crops and 6 grassland types and 10 clay classes, resulting in a total of 6,000 combinations and covering over 99 % of agricultural land in the country. For the sensitivity analysis, only the most important strata / crop or grassland / clay combinations were considered, as shown in Table 3.

Table 3 The strata / crop or grassland / clay class combinations considered in the sensitivity analysis; meanings of the two-letter abbreviations of the crop and grassland types are given in Appendix B.

Land use	Region	Clay content	Crops or grassland types considered	Number of combinations	% of that land use surface represented
Cropland	The Swiss central plateau (stratum A1_F2*)	10, 20 and 35 %	10 out of 20 (BA, GM, MA, PO, RA, SB, SB, SC, TR, VE, WH)	30	46
Grassland: year-round management	The central plateau and hilly regions in the Jura and pre-Alps (strata A1_F2, A3_F3 and A3_F1*)	10, 20 and 35 %	5 out of 5 (EM, EP, IM, IP, LM)	45	41
Grassland: Summer pasture area (SPA)	SPA in the drier and wetter Alps (strata A4_F4_C and A4_F4_W*)	5, 10 and 27 %	1 out of 1 (SU)	6	40

* Codes refer to strata as defined in Wüst-Galley et al. (2020: pp. 28-31)

2.5 MC analysis

Three MC analyses were used. In each MC analysis, each of the (relevant) parameters was varied simultaneously. The first analysis estimated the uncertainty associated with OrgAm-C loss during storage. This was calculated as a function of the storage duration, as described in Wüst-Galley et al. (2020, pg. 43), using a separate function for each of the OrgAm types (stacked manure, slurry, poultry waste, deep litter and fresh manure). The output of this MC analysis (five PDFs of OrgAm-C storage loss, one for each OrgAm type) was used as one of several input parameters for the second MC analysis, where the uncertainty associated with OrgAm-C application (t C ha^{-1} a^{-1}) was calculated. The third (main) MC analysis estimated the uncertainty of annual SOC stock changes based on RothC simulations, using the output of the second MC analysis as one of several input parameters. Each analysis was run for 3,000 replicates. The second analysis was carried out in Excel. The first and third analyses were carried out in R (R Core Team, 2014) and simulations were run from 1975 to 2017.

2.6 Calculation of SOC stock changes

The output of the inventory system was the SOC stock change between 1990 and 2017. This was calculated as the SOC stock (= average over 12 months) of 2017 minus the SOC stock of 1990, resulting in an SOC change over 28 years. The base year 1990 was chosen because it corresponds to the base year of the calculations as submitted for the GHG inventory (FOEN, 2020) and because the quality of some of the input data is lower for years prior to 1990 (Wüst-Galley et al., 2020).

2.7 Reported statistics

Three assessments were calculated to summarise the results.

Firstly, the range in SOC stock changes associated with a ±10 % change in each input or model parameter was calculated, based on a linear or additive model. The range in SOC changes was calculated as the maximum predicted SOC stock change minus minimum predicted SOC stock change. This index indicates the **sensitivity** of the inventory system to each parameter and is independent of the total (expected) variation or uncertainty in parameters.

Secondly, the range in SOC changes was calculated, as above, but this time considering SOC changes associated with the total variation of each input or model parameter. This index indicates the **importance** of each parameter for the inventory system, as it combines the sensitivity of the inventory system to change in each parameter, accounting for the amount of variation or uncertainty associated with each parameter. For parameters whose distributions were assumed to follow a truncated normal distribution, the full extent of the variation in that parameter was used for calculations of the change in SOC. For parameters whose distributions were assumed to follow a normal or log normal distribution, 95 % of the variation was used for calculations.

Lastly, the r^2 of a linear (or where a better fit was obtained, additive) model relating the SOC change to each model parameter was calculated. In addition the Pearson correlation coefficient was calculated for parameters linearly related to the SOC change.

3 Results

Results of the main MC analysis are shown for cropland (Table 4 and Figure 2), for year-round managed grassland (Table 5 and Figure 3) and for the SPA (Table 6 and Figure 4) in this section, as summary statistics; dot plots showing the results of individual replicates are given in the appendices (section 8, cropland; section 9, year-round managed grassland and section 10, SPA). All results pertain to SOC stock changes from 1990 to 2017. Unless otherwise stated, the parameter variation refers to the *total* parameter variation (not the ±10 % fixed variation).

The tornado plots indicate the change in SOC stocks associated with an increase (= SOC change associated with maximum parameter value minus SOC change associated with median parameter value) and with a decrease of each parameter (= SOC change associated with median parameter value minus SOC change associated with minimum parameter value), separately. Where the SOC change is linearly related to variation in a parameter, the bars are symmetrical and the total change in SOC associated with variation in that parameter equals their sum. In the case of a non-linear relationship between a parameter and SOC change, the changes in SOC do not necessarily sum to the total SOC change; total SOC changes associated with all parameters are however given in Table 4 to Table 6. SOC changes in the tornado plots are always displayed as positive and are not indicative of direction of SOC change; whether an increase in a parameter leads to an increase or decrease in SOC stocks can be seen in the appendices (section 8, cropland; section 9, year-round managed grassland and section 10, SPA) and – for parameters that have a linear relationship with SOC change – in Table 4 to Table 6, as the sign of the correlation coefficient.

For each land use type, parameters vary greatly in their importance for the simulation of SOC changes. This variation is most pronounced in the SPA, where variation in the most important parameter caused a change in SOC of >20 t C ha^{-1} a^{-1} and variation in the least important parameters, almost no change in SOC.

There is a set of important parameters common to all three land use types (Table 7). More specifically, the CUE scaling factor, kHUM, kRPM, precipitation, temperature and initial TOC, are the six most important parameters in year-round managed grassland and SPA, and are among the seven most important parameters for cropland. Likewise, there is a set of parameters that is consistently unimportant: The initial pool distribution of the IOM, HUM and RPM pools, and the timing of C inputs (Table 7).

A comparison was made between the SOC changes assuming the total variation in each parameter (~importance) and the SOC changes assuming only 10 % variation in each parameter (~sensitivity). For cropland (Figure 5) there is general congruence between these two indices, though there are three parameters, the CUE scaling factor, evapotranspiration and initial TOC, with lower importance than expected based on the sensitivity index, as well as one parameter, kHUM, that is more important than would be expected. There is also general congruence between the two indices for year-round managed grassland (Figure 6), again except for three parameters, plantC, temperature and initial TOC, that have lower importance than expected based on the sensitivity index, as well as one parameter, kHUM, that is more important than would be expected. For SPA (Figure 7) there are two parameters, initial TOC and plantC, that have a lower importance than would be expected based on the sensitivity index and one parameter, precipitation, that is more important than expected.

The parameter TSMD-b was of low importance for SOC changes across the 28 years (Table 7 and Figure 8a). Inspection of individual year-pairs however indicate that although this is generally true, for year-pairs in which one year was particularly hot and dry (e.g. 2017-2018, with 2018 being hot and dry), the parameter is important (Figure 8c). The range in annual SOC changes (2017-2018) for the drier replicates was 0.47 t C $ha^{-1}a^{-1}$.

Table 4 Result metrics for cropland; Corr = Pearson correlation coefficient; r^2 = adjusted r^2 from linear or additive model, 'Range ΔSOC' = the range of SOC stock changes over 27 years predicted using a general linear or additive model (see main text), considering the whole variation in that parameter, and 'Range ΔSOC 10 %' = as for 'Range ΔSOC', but considering a constant (±10 %) variation in each parameter.

Parameter	Corr	r^2	Range ΔSOC (t C ha^{-1})	Range ΔSOC (t C ha^{-1}) 10 %
Temperature	-0.359	0.129	6.050	1.386
Precipitation	*	0.067	4.422	1.137
Evapotranspiration	0.091	0.008	1.527	1.385
Plant-C inputs	0.096	0.009	1.628	1.111
OrgAm-C inputs	0.056	0.003	0.955	0.787
Initial TOC	-0.284	0.081	4.882	1.950
Clay content	**	**	1.604	0.681
Timing of C inputs	**	**	0.172	0.172
Initial HUM pool size	0.023	<0.001	0.370	0.688
Initial IOM pool size	0.014	<0.001	0.230	0.301
Initial RPM pool size	-0.026	<0.001	0.419	0.362
kBIO	0.005	<0.001	0.094	0.509
kDPM	-0.003	<0.001	0.047	0.142
kHUM	-0.612	0.374	11.440	1.663
kRPM	*	0.007	1.780	0.493
DPM/RPM ratio	-0.030	<0.001	0.470	0.149
TSMD-b	-0.082	0.007	1.321	0.237
CUE scaling factor	*	0.268	7.905	2.042
OrgAm-HUM	0.187	0.035	2.965	-0.502

*Non-linear relationship between parameter and SOC stock change therefore index not calculated

**Parameter takes discrete values therefore index not calculated

Table 5 Result metrics for year-round managed grassland; Corr = Pearson correlation coefficient; r^2 = adjusted r^2 from linear or additive model, 'Range ΔSOC' = the range of SOC stock changes over 27 years predicted using a general linear or additive model (see main text), considering the whole variation in that parameter, and 'Range ΔSOC 10 %' = as for 'Range ΔSOC', but considering a constant (±10 %) variation in each parameter.

Parameter	Corr	r^2	Range SOC (t C ha^{-1})	Range SOC (t C ha^{-1}) 10 %
Temperature	-0.410	0.168	7.605	2.018
Precipitation	**	0.013	2.838	0.650
Evapotranspiration	0.026	<0.001	0.492	0.284
Plant-C inputs	0.110	0.012	2.086	1.375
OrgAm-C inputs	0.021	<0.001	0.406	0.201
Initial TOC	-0.505	0.255	9.655	2.490
Clay content	*	*	0.623	0.184
Timing of C inputs	*	*	0.524	0.524
Initial HUM pool size	0.022	<0.001	0.378	0.738
Initial IOM pool size	-0.006	<0.001	0.101	0.343
Initial RPM pool size	-0.020	<0.001	0.347	0.000
kBIO	0.032	<0.001	0.651	0.940
kDPM	0.009	<0.001	0.192	0.459
kHUM	-0.564	0.318	11.731	1.807
kRPM	**	0.011	3.561	0.379
DPM/RPM ratio	-0.033	0.001	0.587	0.703
TSMD-b	-0.040	0.002	0.720	0.487
CUE scaling factor	-0.395	0.156	6.937	1.113
OrgAm-HUM	0.091	0.008	1.603	0.584

*Non-linear relationship between parameter and SOC stock change therefore index not calculated

**Parameter takes discrete values therefore index not calculated

Table 6 Result metrics for grassland in the SPA; Corr = Pearson correlation coefficient; r^2 = adjusted r^2 from linear or additive model, 'Range ΔSOC' = the range of SOC stock changes over 27 years predicted using a general linear or additive model (see main text), considering the whole variation in that parameter, and 'Range ΔSOC 10 %' = as for 'Range ΔSOC', but considering a constant (±10 %) variation in each parameter.

Parameter	Corr	r^2	Range ΔSOC (t C ha^{-1})	Range ΔSOC (t C ha^{-1}) 10 %
Temperature	**	0.618	20.179	2.573
Precipitation	**	0.084	8.749	0.277
Evapotranspiration	0.029	<0.001	0.751	0.772
Plant-C inputs	0.162	0.026	4.256	3.006
OrgAm-C inputs	0.010	<0.001	0.273	0.652
Initial TOC	-0.205	0.042	5.443	2.826
Clay content	*	*	3.786	1.452
Timing of C inputs	*	*	0.426	0.426
Initial HUM pool size	0.011	<0.001	0.274	0.536
Initial IOM pool size	0.004	<0.001	0.098	0.029
Initial RPM pool size	-0.013	<0.001	0.309	0.000
kBIO	-0.001	<0.001	0.037	1.186
kDPM	0.008	<0.001	0.191	0.463
kHUM	-0.176	0.031	5.070	0.544
kRPM	**	0.059	7.757	1.511
DPM/RPM ratio	-0.089	0.008	2.180	0.526
TSMD-b	-0.044	0.002	1.102	0.231
CUE scaling factor	-0.201	0.040	4.904	0.786
OrgAm-HUM	-0.016	<0.001	0.401	0.288

*Non-linear relationship between parameter and SOC stock change therefore index not calculated

**Parameter takes discrete values therefore index not calculated

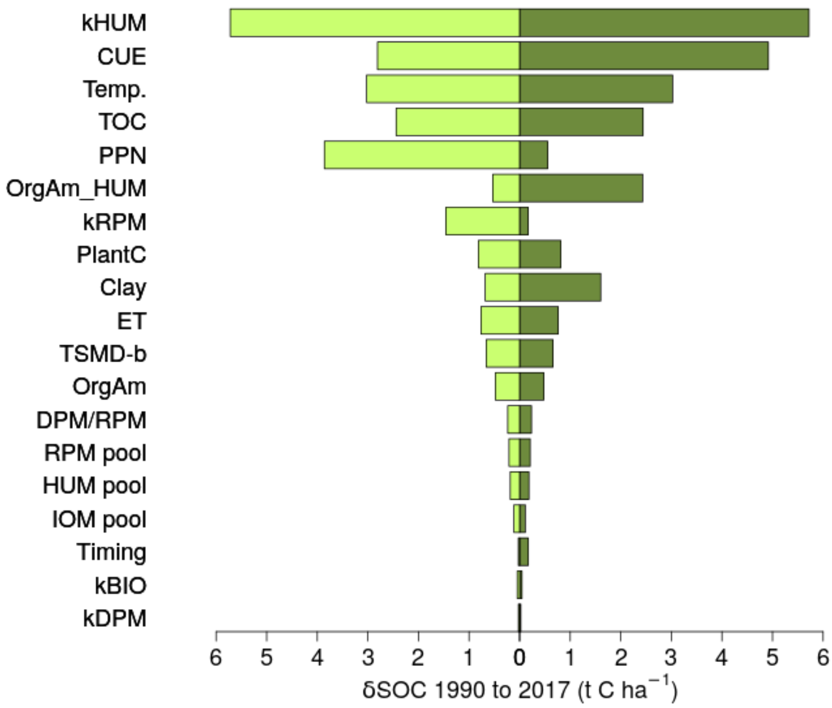


Figure 2 Tornado plot for cropland, showing the range of SOC stock changes resulting from an increase (dark green bars, right-hand side) or decrease (pale green, left-hand side) in each parameter; sign of SOC change is not indicative of direction of SOC change (see main text); CUE = CUE scaling factor; Temp. = temperature: ppN = precipitation, ET = evapotranspiration, TOC = initial TOC; see Table 1 for meaning of other abbreviated parameter names.

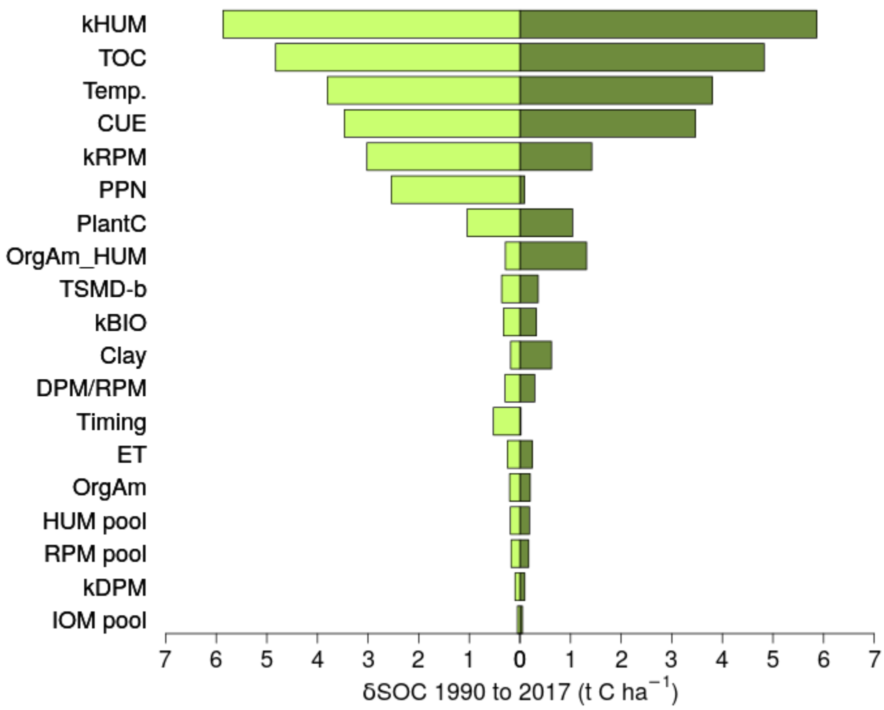


Figure 3 Tornado plot for year-round managed grassland, showing the range of SOC stock changes resulting from an increase (dark green bars, right-hand side) or decrease (pale green, left-hand side) in each parameter; sign of SOC change is not indicative of direction of SOC change (see main text); CUE = CUE scaling factor; Temp. = temperature: ppN = precipitation, ET = evapotranspiration, TOC = initial TOC; see Table 1 for meaning of other abbreviated parameter name; see Table 1 for meaning of abbreviated parameter names.

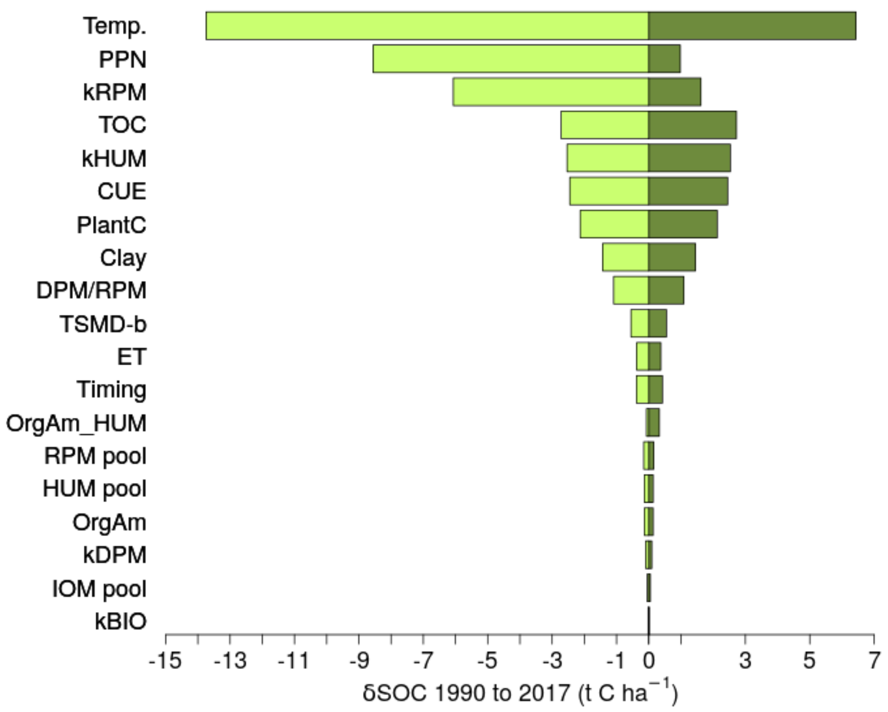


Figure 4 Tornado plot for grassland in the SPA, showing the range of SOC stock changes resulting from an increase (dark green bars, right-hand side) or decrease (pale green, left-hand side) in each parameter; sign of SOC change is not indicative of direction of SOC change (see main text); CUE = CUE scaling factor; Temp. = temperature: ppN = precipitation, ET = evapotranspiration, TOC = initial TOC; see Table 1 for meaning of other abbreviated parameter names.

Table 7 The importance ranking of the parameters for each land use type, based on the range of SOC stock changes associated with each parameter; rank = 1 indicates the most important parameter and rank = 19 indicates the least important parameter; grey shading = the set of most important parameters as described in text.

	Importance ranking		
Parameter	**Cropland**	**Year-round managed grassland**	**Grassland in the SPA**
Temperature	3	3	1
Precipitation	5	6	2
Evapotranspiration	10	14	11
Plant-C inputs	8	7	7
OrgAm-C inputs	12	15	16
Initial TOC	4	2	4
Clay content	9	11	8
Timing of C inputs	17	13	12
Initial HUM pool size	15	16	15
Initial IOM pool size	16	19	18
Initial RPM pool size	14	17	14
kBIO	18	10	19
kDPM	19	18	17
kHUM	1	1	5
kRPM	7	5	3
DPM/RPM ratio	13	12	9
TSMD-b	11	9	10
CUE scaling factor	2	4	6
OrgAm-HUM	6	8	13

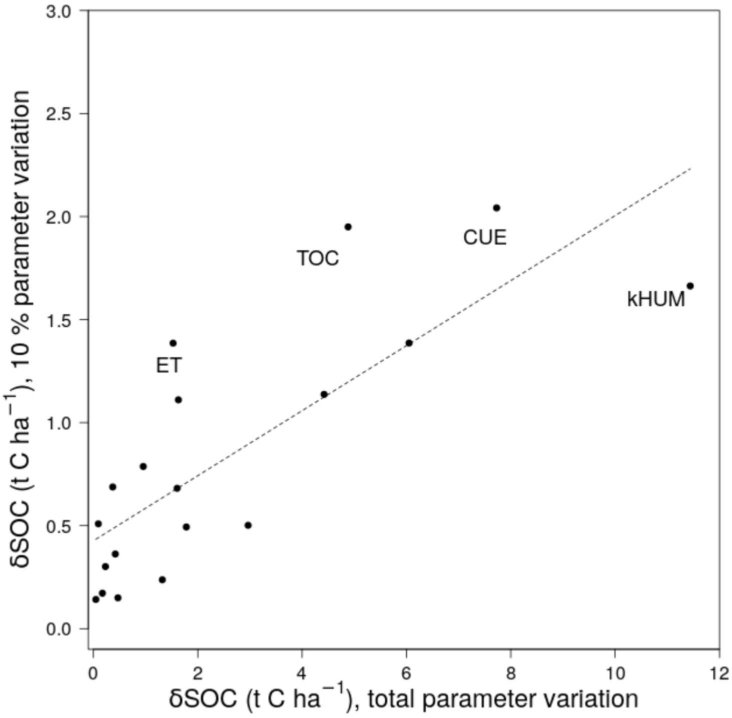


Figure 5 Comparison of sensitivity and importance for cropland; sensitivity represented by the range of SOC changes associated with a standard (±10 %) change in each parameter (y-axis) and importance represented by the range of SOC changes associated with total change in each parameter (x-axis); labelled parameters are discussed in the main text; ET = evapotranspiration, TOC = initial TOC, CUE = CUE scaling factor, kHUM = decay rate constant of the HUM pool.

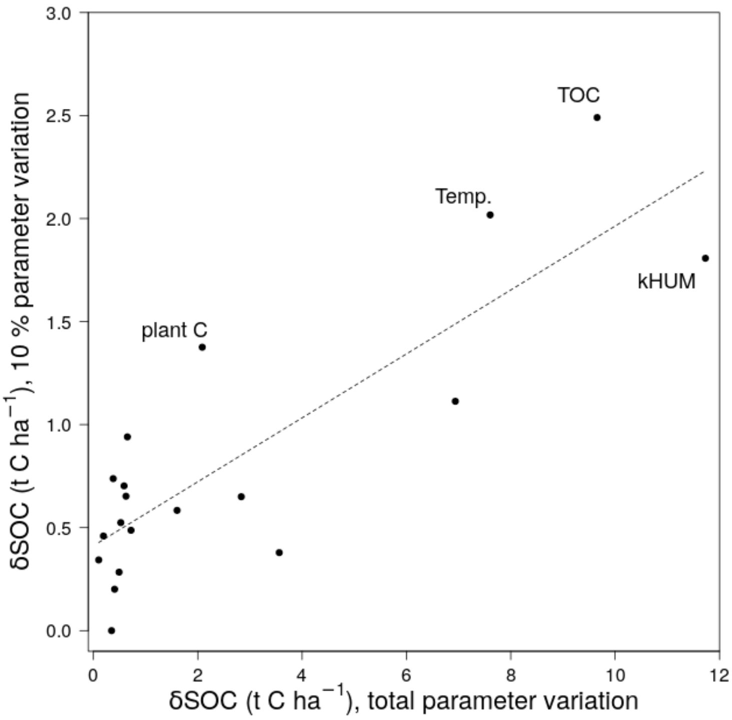


Figure 6 Comparison of sensitivity and importance for year-round managed grassland; sensitivity represented by the range of SOC changes associated with a standard (±10 %) change in each parameter (y-axis) and importance represented by the range of SOC changes associated with total change in each parameter (x-axis); labelled parameters are discussed in the main text; plantC = plant C inputs, Temp. = temperature, TOC = initial TOC, kHUM = decay rate constant of the HUM pool.

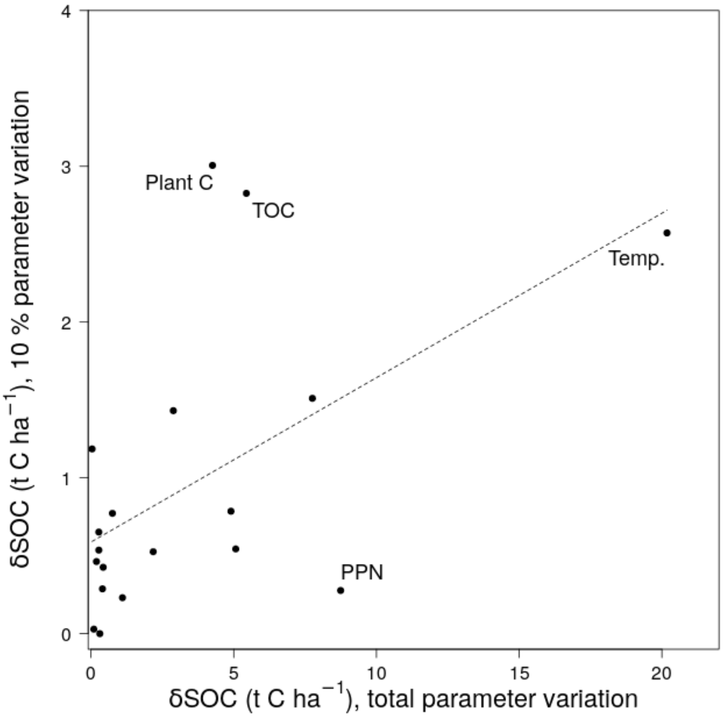
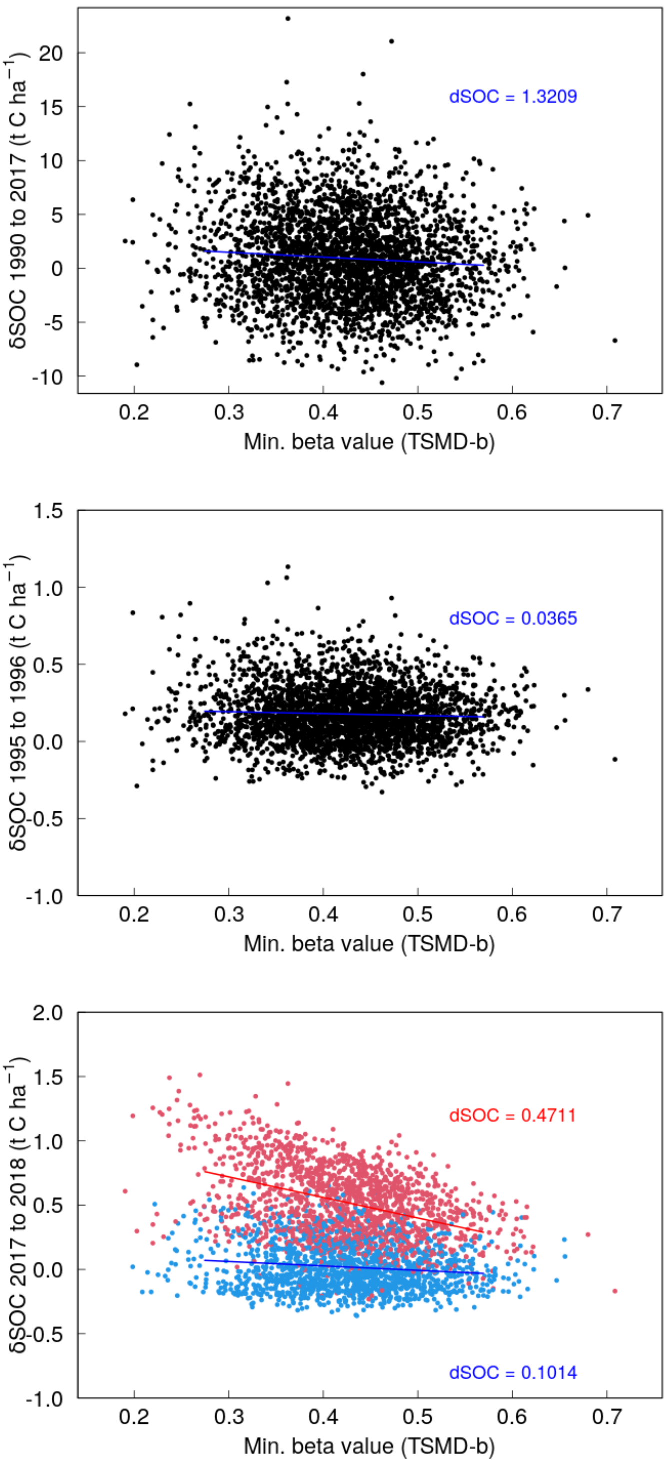


Figure 7 Comparison of sensitivity and importance for grassland in the SPA; sensitivity represented by the range of SOC changes associated with a standard (±10 %) change in each parameter (y-axis) and importance represented by the range of SOC changes associated with total change in each parameter (x-axis); labelled parameters are discussed in the main text; plantC = plant-C inputs, TOC = initial TOC: ppN = precipitation, Temp. = temperature.



(a)

(b)

(c)

Figure 8 The range of SOC stock change associated with variation in the TSMD-b parameter (which becomes relevant under conditions of topsoil moisture deficit) for the whole period (a), and the year-pairs (b) 1995 to 1996 (neither particularly dry or warm years) and (c) 2017 to 2018 (2018 had a hot and dry summer) for cropland, where the colour refers to replicates that were drier (red) or wetter (blue) than average, i.e. that had lower or higher than average precipitation, respectively; dSOC = range of change in SOC stocks – over the respective period – associated with the variation in the TSMD-b parameter as predicted by a linear model; points = individual replicates; lines = predicted lines, based on linear model.

4 Discussion

4.1 Sensitivity and importance

The aim of this work was to provide information enabling research needs and resources to be prioritised, to improve the simulation of SOC stock changes with RothC; in particular, the simulation of SOC stock changes in Switzerland's agricultural soils, for national GHG reporting and the estimation of SOC sequestration potentials. This was carried out by identifying parameters most or least important for the simulation of SOC changes. The importance of a parameter involves two factors: Firstly, how sensitive the model is to the variation in each parameter, and secondly, the extent of the variation or uncertainty that is expected for that parameter. The range of SOC changes associated with the total variation in each parameter incorporates both factors and was therefore considered an indicator of importance. The advantage of this index is that it is applicable to parameters that have a linear or non-linear relationship with SOC change. The disadvantage of this index is that it cannot be used to partition the variation in SOC change between the parameters, however this was not of primary interest in this study.

The amount that the parameters were set to vary by was decisive for outcome of this study. As the expected variation in some parameters is unknown or uncertain (e.g. was not data-driven, or was based on a small data set), it is possible that the expected variation was under- or overestimated. For this reason, and additional index was calculated, namely the range in SOC changes associated with a *fixed* (here, 10 %) change in each parameter. This indicated the sensitivity of the inventory system to each parameter. A comparison of the sensitivity and importance indices of the parameters was carried out to identify parameters that might have been misidentified as unimportant or important, due to an under-estimation or over-estimation of their variation, respectively.

To check for the first possibility, we identified parameters that had a high sensitivity score but particularly low importance score. This could be important, because *if* the variation or uncertainty associated with such parameters was underestimated in this study, there is the risk that a potentially important parameter has been missed (i.e. we consider it to have low importance because we underestimated its variation). In SPA and to a lesser extent in cropland and year-round managed grassland, such parameters were identified. In the SPA, two parameters, plantC and initial TOC, had a lower importance than would be expected based on the sensitivity of the model to these parameters and indeed, the model is more sensitive to these parameters than it was to the most important parameter, temperature. In cropland, three parameters, evapotranspiration, initial TOC and the CUE scaling factor, had a lower importance than would be expected based on the sensitivity of the model to these parameters, though the effect here is less pronounced. A similar effect was seen for year-round managed grassland for the parameters, plantC, temperature and initial TOC. The variation or uncertainty attributed to these five parameters (CUE scaling factor, plantC, evapotranspiration, temperature and initial TOC) was data-driven. We consider the variation in the latter four parameters to have been well estimated and there is thus no indication that their importance was underestimated. For the parameter CUE scaling factor, it is possible that we underestimated its variation, as Qiao et al. (2019) indicated larger ranges of CUE than were applied in this analysis. It is therefore possible that the importance of this parameter has been underestimated.

To check for the second possibility, we identified parameters that had a particularly high importance score compared to their sensitivity score. One such parameter, precipitation, was identified in the SPA. The variation attributed to this parameter was however data-driven and well estimated, and there is thus no indication that its importance has been overestimated. Reducing its variation would be an effective way of decreasing uncertainty in the SOC simulations.

A final consideration is the duration over which the SOC changes are simulated, as this might affect the type of parameters deemed important. This study simulated SOC stocks for almost three decades. It is possible that if a much shorter period had been considered, parameters related primarily to initial conditions (e.g. initial C pool distributions) might have been deemed more important and parameters related to dynamics, less so.

4.2 Implications for future resource / research priorities

Two sets of parameters were identified that are i. consistently important or ii. consistently unimportant for simulating SOC stock changes in the three land use types. This is in spite of differences between them in terms of management and climate, and enables research and resource priorities to be set.

Three of the most important parameters are **initial TOC**, **precipitation** and **temperature**. The sensitivity of the simulations to the latter two variables is not particularly high, and their importance is dominated by their variation. The cause of variation in all three parameters is to a large extent the large regions – the strata – for which simulations are carried out, rather than uncertainty in their estimates per se (initial TOC is an exception as both sources of variation play a role, see below). This suggests much of their variation is an artefact of our method of up-scaling, an effect amplified also by Switzerland's very variable topography and the fact that farming is carried out across this variable landscape. This implies that a move towards higher spatial resolution of simulations (e.g. raster-based simulations) would substantially improve the estimate of SOC changes for Switzerland. This should be a priority in the development of the inventory system. Such a move would also improve the estimates of evapotranspiration and clay content, two parameters of moderate importance. The estimate in **initial TOC** would however be improved only to a certain extent by a higher spatial resolution of the simulations and an improved estimate of this parameter is otherwise needed. This is being addressed in a current research project[5], where soil parameters including SOC and soil texture are being estimated using digital soil mapping. Outputs from that project can be used to improve the estimate of the parameters initial TOC and clay content.

The other three most important parameters, the **CUE scaling factor**, **kHUM and kRPM**, are model parameters. This implies firstly, that improvement of the inventory system needs to consider model as well as input parameters and secondly, that if the model is to be improved or calibrated to a region, these parameters should be prioritised. A possibility to improve estimates of the kHUM and kPRM parameters is the use of incubation experiments for their calibration (e.g. Mondini et al. 2017; Nicolardot et al. 1994), ideally incorporating the most common soil types in the study region. Such work forms part of the European Joint Programme 'Soil' subproject, CarboSeq[6]. Additionally, Zimmerman et al. (2007) demonstrated that soil organic matter fractions can be related to the pools used in RothC.

The parameters **OrgAm** and **OrgAm-HUM** are of low (SPA) to moderate (cropland and year-round managed grassland) importance. For the SPA, this result can be explained by the very low amounts of OrgAm this grassland system receives. For cropland and year-round managed grassland, this result, as well as the fact that the OrgAm parameter is less important than the plantC parameter, is unexpected. It can be possibly explained by two reasons. The first is that C inputs from OrgAm are generally much lower than C inputs from plants; with the exception of cereals and silage corn (where few residues tend to remain on the field), plant C inputs – as calculated in the inventory system, including inputs from cover crops – are 1.6 to 6 times the amount of the OrgAm-C inputs. It is possible that for a given field receiving OrgAms, the inventory system has underestimated the inputs: The inventory system assumes OrgAms are spread evenly across all surfaces of a given crop or grassland, whereas in reality some will receive much more and some none. A corollary of this is that on the other hand, the inventory system probably *overestimates* the surfaces of a particular crop or grassland type receiving OrgAm inputs; it assumes all surfaces of a given crop or grassland type receive OrgAm inputs whereas in reality only some do. It is unclear how these two opposing biases might alter simulated SOC changes. A second possible reason why the OrgAm and Org-HUM parameters are only moderately important might be that the variation for Org-HUM was underestimated in this study, for the following reason: The default parameter value in RothC is 0.02 (2 % of OrgAm goes to the HUM pool). Peltre et al. (2012) indicated that OrgAm-HUM could be as high as 0.2 and this value was therefore used as an upper value for the PDF in this study. An initial sensitivity analysis assuming a uniform PDF of OrgAm-HUM (min = 0, max = 0.2) however caused biased estimates of SOC changes, with SOC gains being overestimated (data not shown). In order to avoid such a bias, a PDF with a median of 0.02 (i.e. the same as the RothC default) was used[7]. A corollary of this is that in the MC analysis, an OrgAm-HUM value of between 0 and 0.02 was as likely to be picked as a value of between 0.02 and 0.20, probably leading to an under-estimation of the variation in this parameter. Improving the estimate of how OrgAms are represented in RothC is however not as simple as improving the OrgAm-HUM parameter alone. It is known that different OrgAms have different decomposability; representing these adequately in RothC therefore requires different OrgAm-HUM parameter estimates (see Mondini et al., 2017 and references therein). Such an approach would however require information on the quantity of different OrgAm types added (i.e. an improvement of the parameter **OrgAm**), for individual farms and on an annual basis, which would be challenging to obtain.

[5] Two projects financed by the Federal Office for the Environment being carried out at the Swiss soil competence centre: Nationwide digital mapping of C stocks in soils for Switzerland's GHG inventory ("Landesweite digitale Kartierung von Kohlenstoffvorräten in Böden für das Treibhausgasinventar Schweiz "); Technical and methodological basis for the digital mapping of soil properties ("Technische und methodische Grundlagen für die digitale Kartierung von Bodeneigenschaften").

[6] https://projects.au.dk/ejpsoil/research-projects/carboseq/

[7] The log normal PDF meant the wide range of variation in this parameter indicated by Peltre et al. (2012) could nonetheless be captured.

However, there is an indication that improving their estimates is worthwhile: In the initial sensitivity analysis in which OrgAm-HUM values were on average higher (see above), the importance of the parameters OrgAm-HUM *and* OrgAm was higher (data not shown).

The least important variables are the initial C pool distributions (of the **HUM**, **IOM** and **RPM pools**), as well as the **kDPM** and to a lesser extent **kBIO**. We suggest these parameters should not be a research priority.

The response of SOC to changes in soil moisture is critical for simulating SOC cycling. There is however uncertainty in the soil moisture-respiration function of SOC models, including RothC (Falloon et al., 2011). In RothC, the soil moisture-respiration function is determined in part by the minimum beta parameter (**TSMD-b**), which determines the relative reduction of SOC mineralisation during periods of topsoil moisture deficit (Jenkinson et al., 1990). This study indicates that TSMD-b is not particularly important for SOC simulations. This interpretation requires prudence however, as it is based on SOC changes over almost three decades, meaning the effect of a parameter was integrated over a long period. Inspection of annual SOC change (calculation carried out for cropland only) showed that the TSMD-b parameter was important under certain conditions: For year-pairs where neither year was particularly dry or warm (e.g. 1995 to 1996 and 2004 to 2005), TSMD-b had little effect of SOC changes; on the other hand, for the year-pair 2017 to 2018 (in 2018 the summer was especially warm and dry), TSMD-b was more important, and especially so for replicates where the precipitation was low. The range in SOC changes of the most important parameter for cropland (kHUM) is 11.4 t C $ha^{-1}a^{-1}$, corresponding to an average *annual* SOC change of 0.39 t C $ha^{-1}a^{-1}$. This is comparable to the range in annual SOC changes for the TSMD-b parameter (0.47 t C $ha^{-1}a^{-1}$) and suggests that in years with prolonged drought, the TSMB-b parameter becomes one of the most important parameters for cropland (and presumably for grassland in lowland regions). Such drought conditions have not occurred frequently in Switzerland in the past, but will probably do so in the future, especially given that temperatures in Switzerland are rising faster than the global average (CH2018). It can therefore be expected that TSMD-b parameter will become more important for SOC simulations if the drought effects cannot be mitigated by irrigation. These results also predict that for countries where drought conditions occur regularly and are not mitigated by irrigation, this parameter is more important.

This study indicates that the amount of **plant C inputs** is moderately important. For Switzerland, the importance of this parameter might increase if the inventory system moves to raster-based simulation. This is because the estimate of plant C inputs – or rather, the estimates of yield, from which many of the plant C inputs are derived – are currently not spatially-explicit; due to a lack of spatially-explicit yield data, national yield averages are used. The full benefit of simulations at a higher spatial resolution will not be realised if spatially-explicit yields are not obtained. This applies also to the parameter OrgAm.

4.3 Concluding remarks

A sensitivity analysis was carried out to contribute to prioritising research needs for the simulation of SOC stock changes in agricultural soils, in particular Switzerland's inventory system. The importance of parameters varied massively; some have a very large influence on the SOC simulations whereas for others, the SOC changes varied little when they were varied. This highlights that such a sensitivity analysis is an efficient way of highlighting research or resource priorities, as there is clear distinction between those parameters whose estimates warrant much research or many resources, and those parameters that do not. The outcome of this sensitivity analysis strongly supports the reduction of the spatial scale of simulations, especially for regions with high topographic, climatic or pedological heterogeneity. There remain however further important (model) parameters that will not be improved with this change in the inventory system, and these should be a priority for research efforts and resources. Additionally, the advantage of simulations carried out at a higher spatial resolution can only be realised if spatially-explicit data become available for those parameters that vary at the farm level. Likewise, certain parameters are linked, meaning the improvement in the estimate of one of these parameters only makes sense if the estimate of the other parameter is also improved (e.g. OrgAm-HUM and the addition of different OrgAm types). Lastly, the study carried out separate sensitivity analyses for three different agricultural systems: cropland, year-round managed grassland and grassland in the SPA. Although a common set of parameters was identified that are most important to the three land use types, there were differences between the results, most notably between the SPA and the other two agricultural systems. This highlights the importance of carrying out these analyses separately for different agricultural systems that differ in management and location.

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6 Appendix A – Parameter distributions

Table 8 The properties of the probability density functions (PDFs) created for the sensitivity analysis using parameters information given in Table 2; stratum refers to regions as detailed in Wüst-Galley et al. (2020: pp. 28-31); two-initial abbreviations of crops and grassland types given in Appendix B; 'variable' indicates that the absolute values vary over time and are therefore not given.

Parameter name	Stratum	Land use or OrgAm type or animal	CV (%)	shape of PDF	Percentiles of PDF				
					1 %	2.5 %	50 %	97.5 %	99 %
Temperature (°C)	all	cropland	1.4 *	truncated normal			variable		
	all	year-round managed grassland	1.7 *	truncated normal			variable		
	all	grassland, SPA	2.9 *	truncated normal			variable		
Precipitation (mm)	all	cropland	26	truncated normal			variable		
	all	year-round managed grassland	24	truncated normal			variable		
	all	grassland, SPA	43	truncated normal			variable		
Evapotranspiration (mm)	all	cropland	8.3	truncated normal			variable		
	all	year-round managed grassland	7.3	truncated normal			variable		
	all	grassland, SPA	9.8	truncated normal			variable		
Plant C inputs (t C ha^{-1} a^{-1})	all	BA	6.6	truncated normal			variable		
	all	EM	8.3	truncated normal			variable		
	all	EP	8.3	truncated normal			variable		
	all	GM	8.3	truncated normal			variable		
	all	IM	8.3	truncated normal			variable		
	all	IP	8.3	truncated normal			variable		
	all	LM	8.3	truncated normal			variable		
	all	MA	7.2	truncated normal			variable		
	all	PO	11.1	truncated normal			variable		
	all	RA	7.1	truncated normal			variable		
	all	SB	10.8	truncated normal			variable		
	all	SC	20.1	truncated normal			variable		
	all	SU	8.3	truncated normal			variable		

Parameter name	Stratum	Land use or OrgAm type or animal	CV (%)	shape of PDF	Percentiles of PDF				
					1 %	2.5 %	50 %	97.5 %	99 %
	all	TR	8.35	truncated normal			variable		
	all	VE	8.3	truncated normal			variable		
	all	WH	5.97	truncated normal			variable		
OrgAm inputs (t C ha^{-1} a^{-1})	all	BA	7.8	truncated normal			variable		
	all	EM	receives no OrgAm	n/a			n/a		
	all	EP	9.7	truncated normal			variable		
	all	GM	6.8	truncated normal			variable		
	all	IM	6.7	truncated normal			variable		
	all	IP	9.7	truncated normal			variable		
	all	LM	10.7	truncated normal			variable		
	all	MA	9.6	truncated normal			variable		
	all	PO	9.7	truncated normal			variable		
	all	RA	9.7	truncated normal			variable		
	all	SB	9.7	truncated normal			variable		
	all	SC	9.6	truncated normal			variable		
	all	SU	9.3	truncated normal			variable		
	all	TR	7.8	truncated normal			variable		
	all	VE	receives no OrgAm	n/a			n/a		
	all	WH	7.8	truncated normal			variable		
Herd sizes	all	cattle	6	normal			variable		
	all	non-cattle	6.5	normal			variable		
OrgAm-C excretion rates	all	all	-16 to +12	weakly right-skewed			variable		
Straw production (t C a^{-1})	all	all	6.7						
OrgAm-C loss during storage (%)	all	stacked manure	44.6	left-skewed	1.1	2.4	22.0	32.6	32.9
	all	slurry	51.1	left-skewed	0.4	0.7	7.9	12.7	12.8
	all	poultry waste	42.9	left-skewed	1.1	2.2	14.1	19.9	20.1
	all	deep litter	45.4	left-skewed	1.1	2.6	24.0	35.4	35.8
	all	fresh manure	50.1	normal	1.6	3.7	20.9	41.1	45.5

Parameter name	Stratum	Land use or OrgAm type or animal	CV (%)	shape of PDF	Percentiles of PDF				
					1 %	2.5 %	50 %	97.5 %	99 %
Duration of OrgAm storage (years)	all	stacked manure	n/a	trapezoid	0.015	0.024	0.156	0.297	0.310
	all	slurry	25 #	log normal	0.016	0.021	0.076	0.269	0.342
	all	poultry waste	n/a	trapezoid	0.021	0.032	0.169	0.301	0.313
	all	deep litter	n/a	trapezoid	0.015	0.024	0.156	0.297	0.310
	all	fresh manure	11.0	normal	0.079	0.084	0.107	0.130	0.134
Initial TOC (t C ha^{-1})	A1_F2	cropland	13.4	truncated normal	37.0	38.8	49.1	59.3	61.2
	A1_F2	year-round managed grassland	22.4		36.2	39.9	61.5	82.8	87.0
	A3_F1		22.4		33.0	36.5	56.1	75.6	79.4
	A3_F3		22.4		39.7	43.8	67.4	90.9	95.4
	A4_F4_C	grassland, SPA	22.4		30.4	33.5	51.6	69.5	73.0
	A4_F4_W		22.4		29.1	32.2	49.5	66.7	70.1
Clay content (%)	all	cropland	n/a	n/a	10 +		20 +		35 +
	all	year-round managed grassland	n/a	n/a	10 +		20 +		35 +
	all	grassland, SPA	n/a	n/a	5 +		10 +		27 +
Initial RPM pool (size)	all	cropland	14.5	normal	4.5 σ	4.8 σ	6.9 σ	10.2 σ	10.6 σ
	all	year-round managed grassland	21.9	normal	4.6 σ	5.0 σ	8.6 σ	13.1 σ	13.9 σ
	all	SPA	21.9	normal	3.0 σ	3.3 σ	6.8 σ	13.6 σ	14.5 σ
Initial HUM pool (size)	all	cropland	12.4	normal	28.0 σ	29.1 σ	40.2 σ	58.1 σ	60.0 σ
	all	year-round managed grassland	20.7	normal	27.9 σ	29.9 σ	50.7 σ	75.8 σ	79.0 σ
	all	SPA	20.7	normal	17.9 σ	19.8 σ	39.8 σ	79.1 σ	83.5 σ
Initial IOM pool (size)	all	cropland	12.8	normal	3.0 σ	3.1 σ	4.4 σ	6.3 σ	6.6 σ
	all	year-round managed grassland	21.1	normal	3.1 σ	3.4 σ	5.7 σ	8.6 σ	9.0 σ
	all	SPA	21.1	normal	2.0 σ	2.2 σ	4.5 σ	9.0 σ	9.5 σ
DPM decay rate (a^{-1})	all	all	20	truncated normal	6.3	7.1	10.1	12.9	13.6
BIO decay rate (a^{-1})	all	all	20	truncated normal	0.4	0.5	0.7	0.9	0.9
RPM decay rate (a^{-1})	all	all	30	truncated normal	0.1	0.2	0.3	0.4	0.5

Parameter name	Stratum	Land use or OrgAm type or animal	CV (%)	shape of PDF	Percentiles of PDF				
					1 %	2.5 %	50 %	97.5 %	99 %
HUM decay rate (a^{-1})	all	all	30	truncated normal	0.009	0.011	0.02	0.028	0.031
DPM / RPM ratio of plant C inputs	all	all	21	normal	0.7	1	1.5	1.9	2.1
TSMD-b	all	all	17.6	normal	0.2	0.3	0.4	0.5	0.6
CUE scaling factor	all	all	19.8	normal	0.9	1.1	1.7	2.2	2.4
OrgAm-HUM (proportion)	all	all	24.4 #	log normal	0.002	0.004	0.019	0.095	0.158

* refers to standard deviation, not CV; # refers to the CV of the log-transformed distribution; + actual (tested) values given; σ average across clay classes and strata

7 Appendix B – Crop and grassland abbreviations

Table 9 Abbreviations of crops and grassland categories used throughout this report; see Wüst-Galley et al. (2020: pp. 36-40, 55) for details; SPA = summer pasture area

Abbreviation	Land use	Crop name / grassland type
BA	Cropland	Barley
GM		Ley (clover-grass)
MA		Grain maize
PO		Potato
RA		Rape seed (cooking oil)
SB		Sugar beet
SC		Silage and green corn
TR		Triticale
VE		Vegetables
WH		Wheat
EM	Grassland, year-round management	Extensive meadow
EP		Extensive pasture
IM		Intensive meadow
IP		Intensive pasture
LM		Less intensive meadow
SU	Grassland in the SPA	Summer pastures and meadows

8 Appendix C – Results of cropland

In the following section the SOC stock changes resulting from the main MC analysis are shown. These dotplots display the change in SOC stocks of the individual replicates (total replicates = 3000), plotted against the value of each parameter. For all plots, “corr” refers to the pearson correlation coefficient, “r2” refers to the goodness of fit of the linear model or generalised additive model and “dSOC” refers to the range (maximum – minimum) in SOC stock changes across the range of the parameter in question, as predicted by the model and as indicated by the blue line. For parameters for which a truncated distribution was applied (see Table 2), the calculation of dSOC was carried out for the whole range of the parameter values. For all other parameters, the calculation of dSOC was carried out for 95 % of the values of that parameter. The index dSOC portrays the importance of parameters. Unless otherwise stated, SOC stock changes were modelled with a linear model.

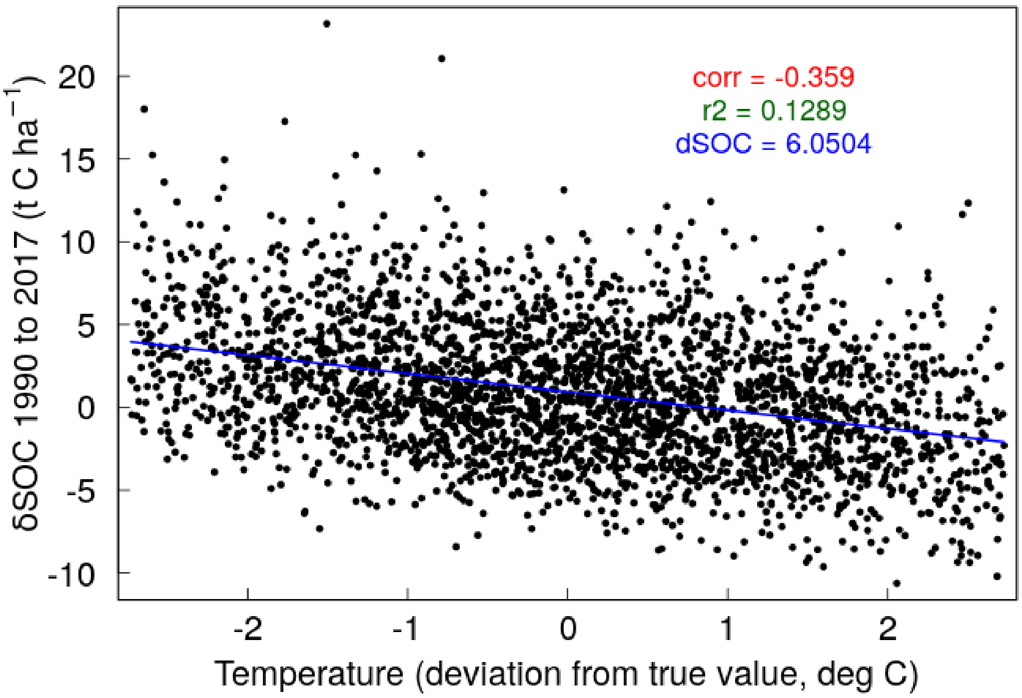

Figure A - 1 The relationship between temperature and SOC stock changes

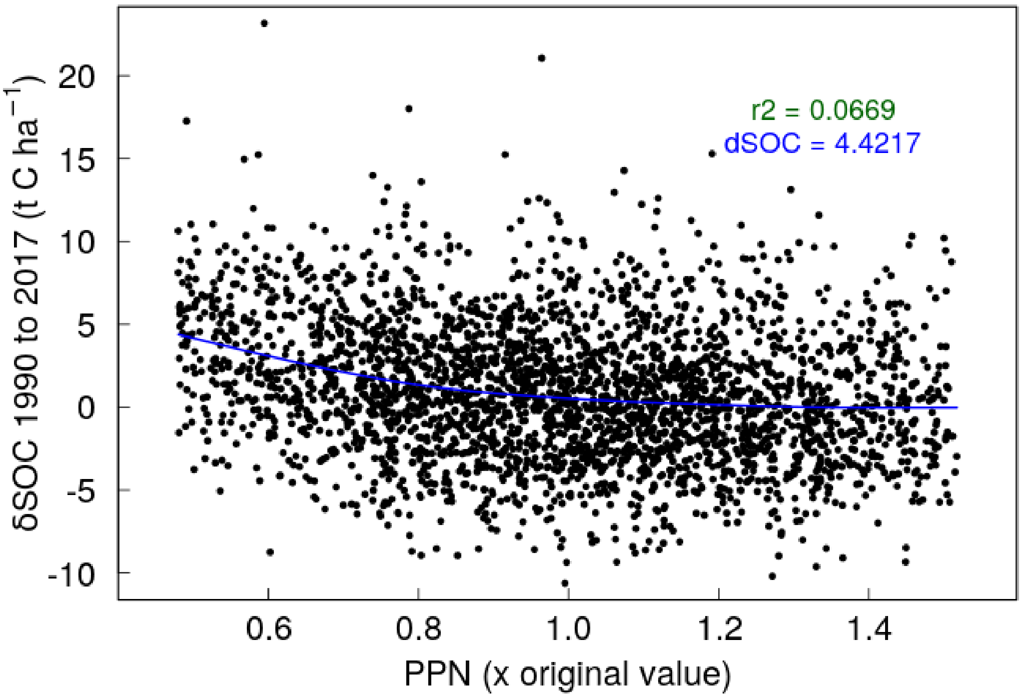

Figure A - 2 The relationship between precipitation (PPN) and SOC stock changes, modelled with an additive model

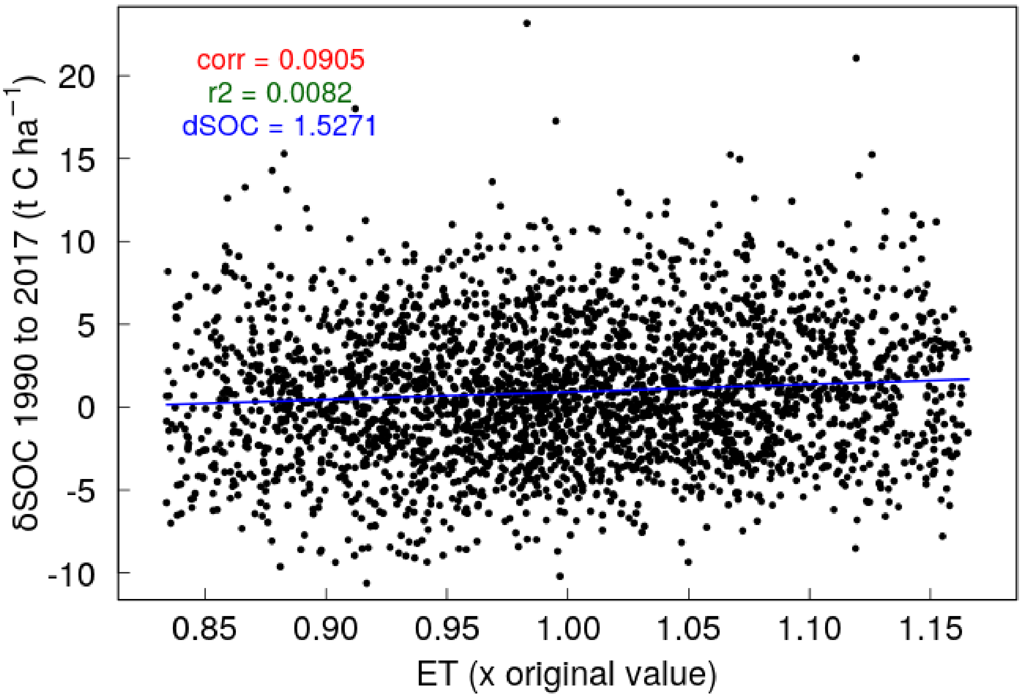

Figure A - 3 The relationship between evapotranspiration (ET) and SOC stock changes

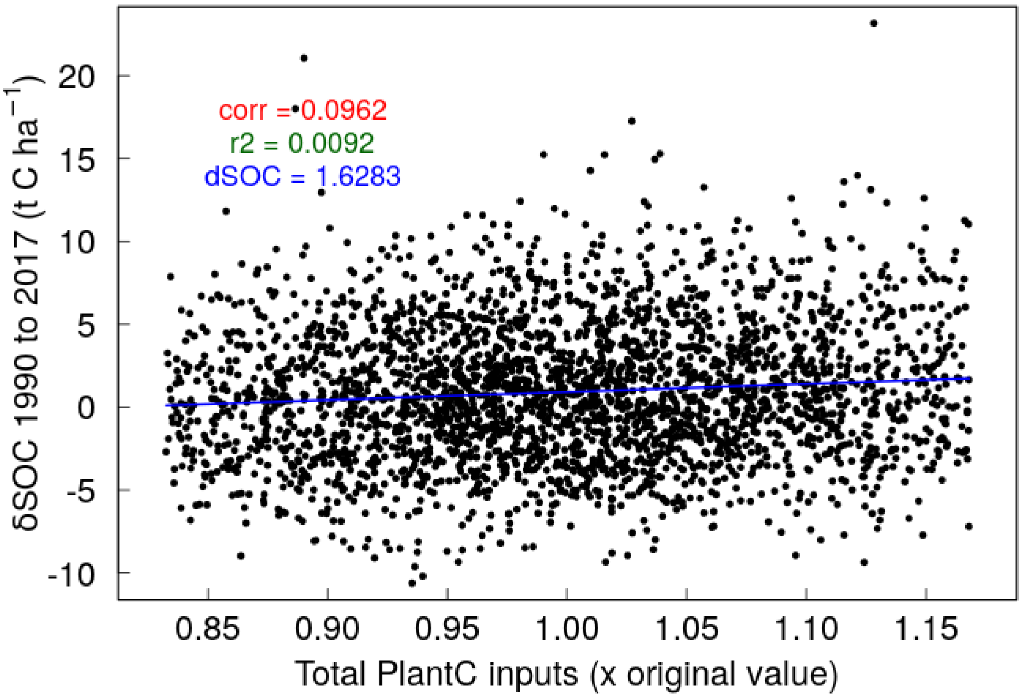

Figure A - 4 The relationship between plant C inputs and SOC stock changes

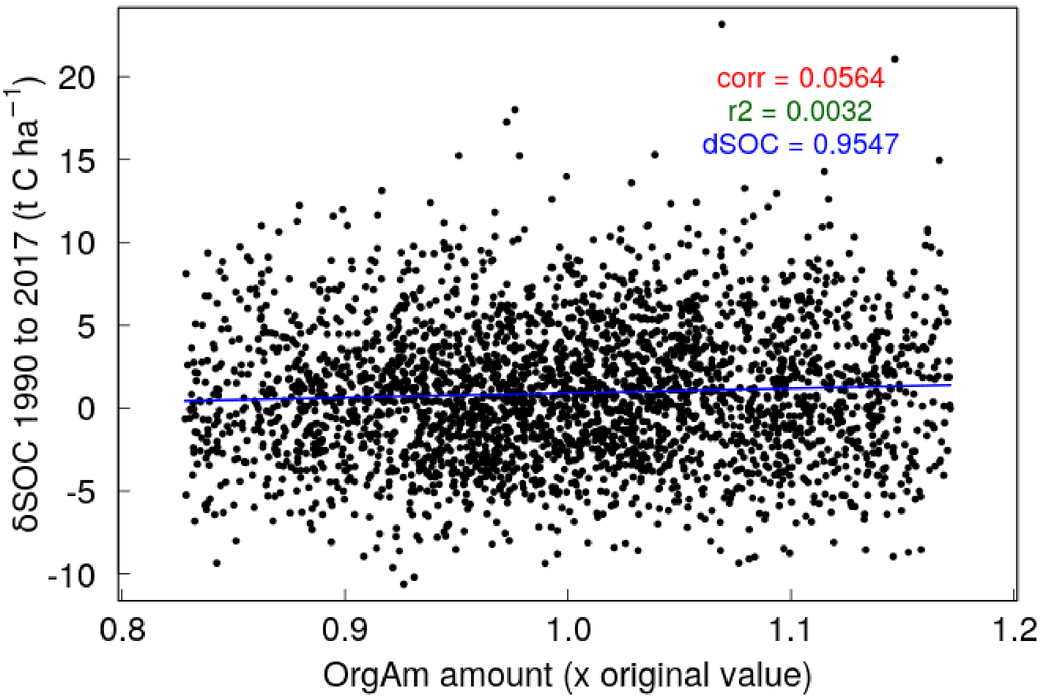

Figure A - 5 The relationship between the amount of OrgAm-C inputs and SOC stock changes

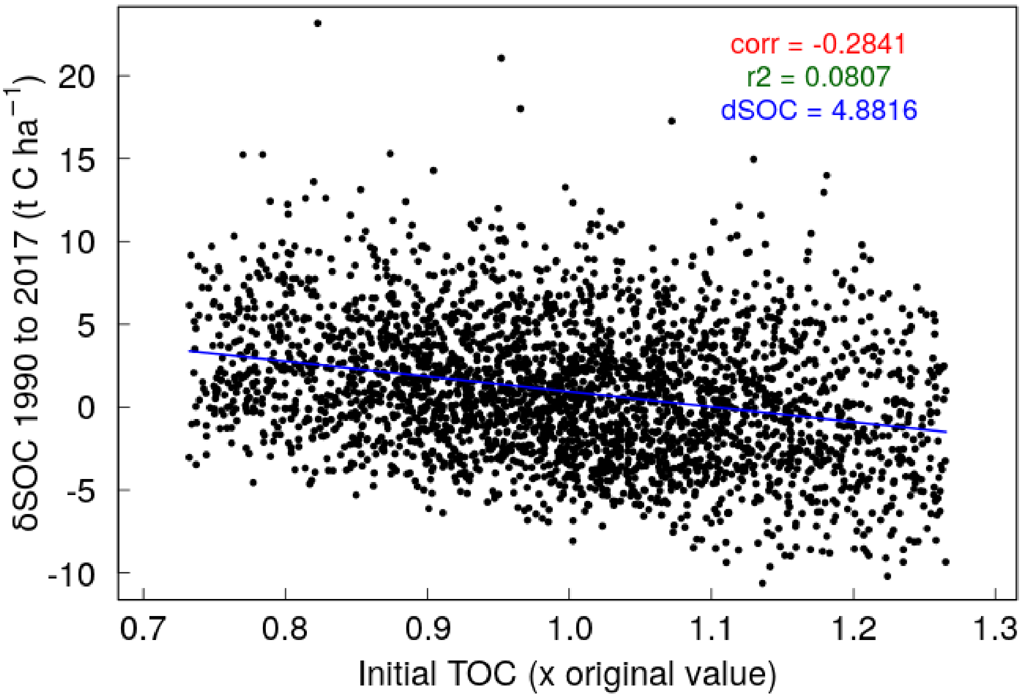

Figure A - 6 The relationship between the initial SOC stocks and SOC stock changes

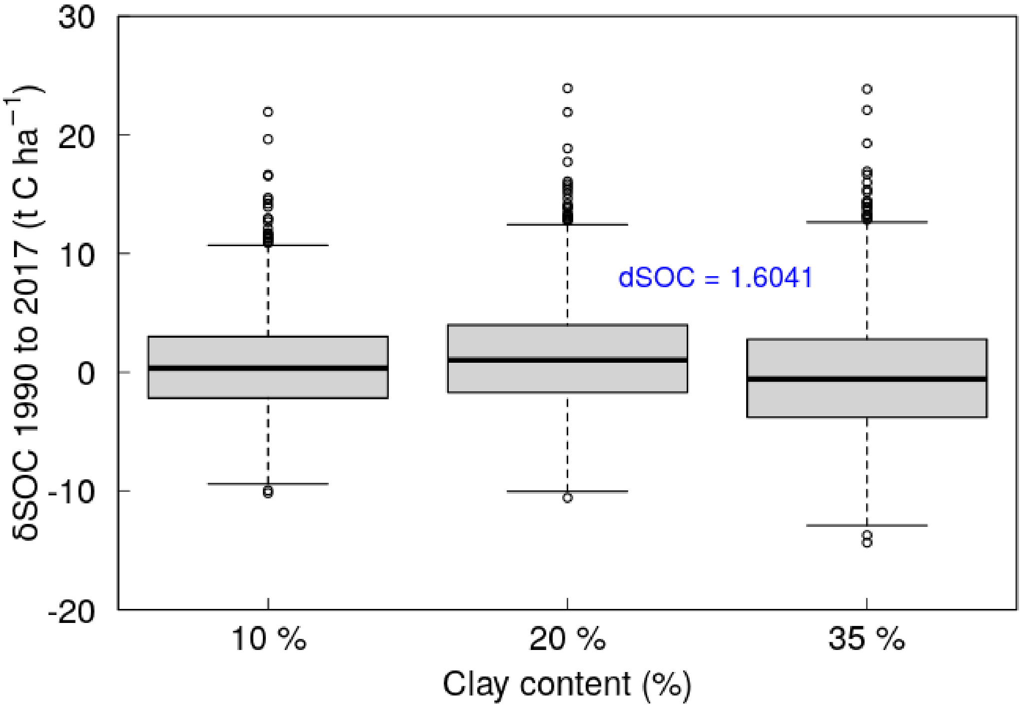

Figure A - 7 The relationship between the clay content of the soil and SOC stock changes; dSOC refers to the largest difference between the three mean dSOC values of the clay content classes

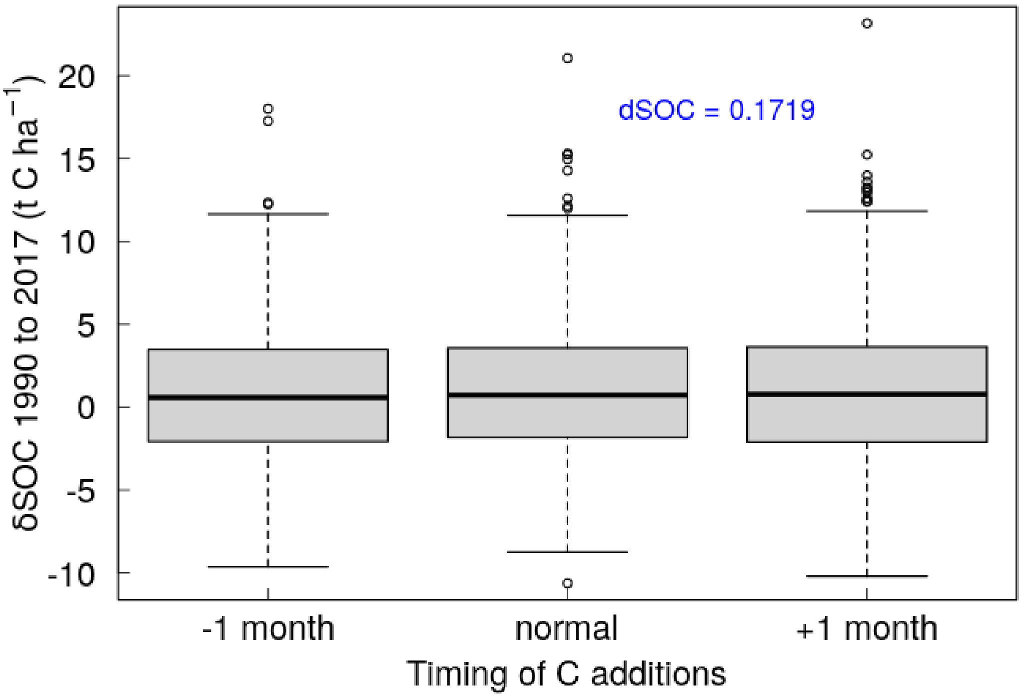

Figure A - 8 The relationship between the timing of C additions and SOC stock changes; dSOC refers to the largest difference between the three mean dSOC values

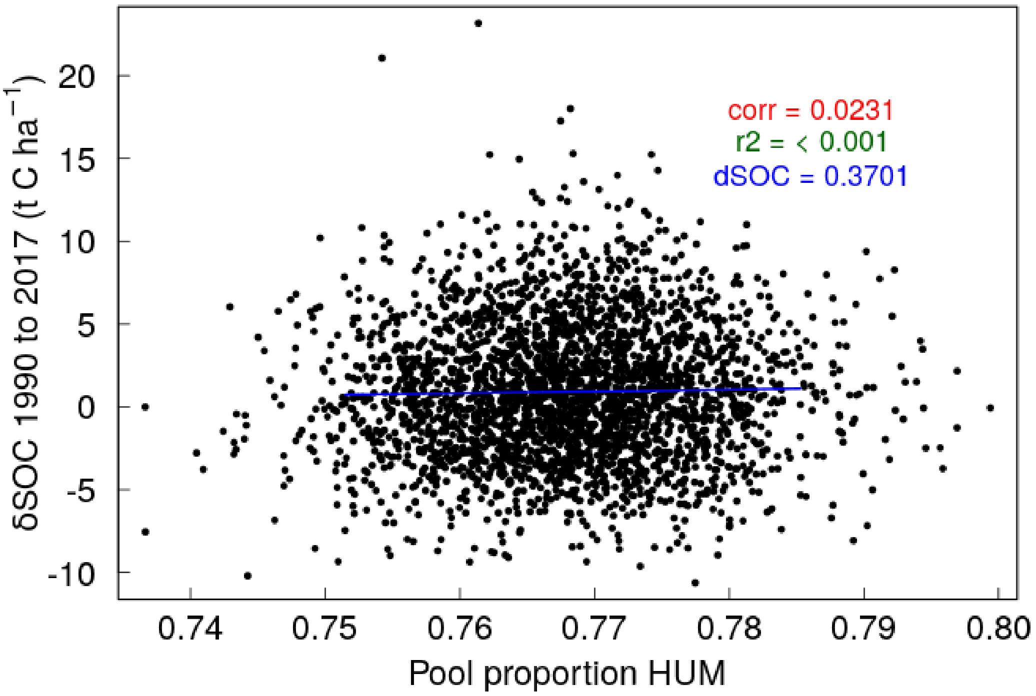

Figure A - 9 The relationship between the initial HUM pool size and SOC stock changes

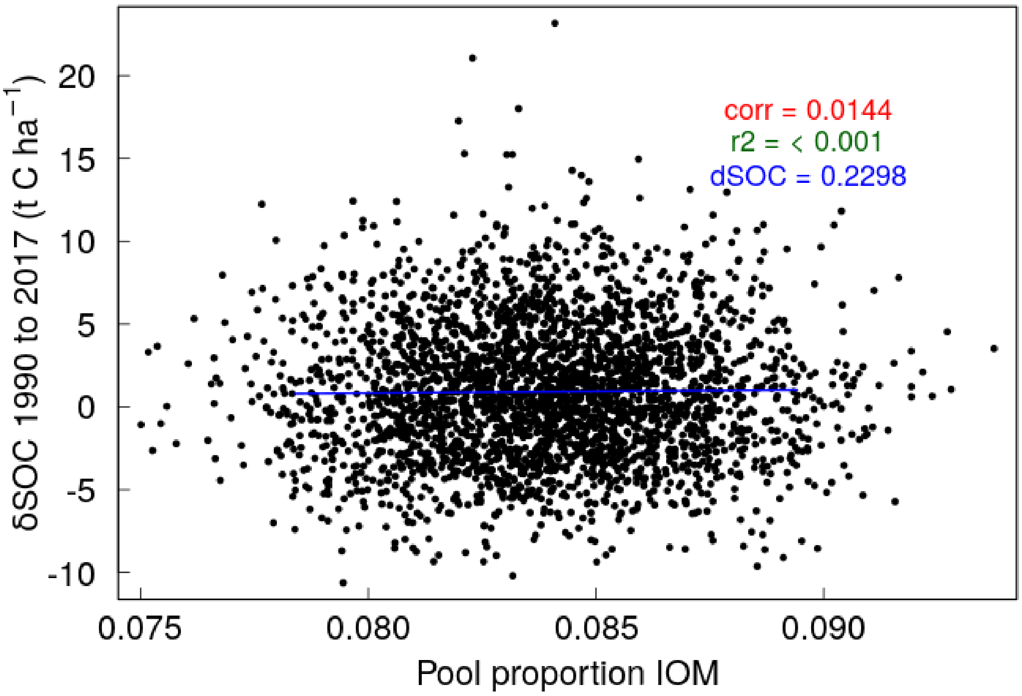

Figure A - 10 The relationship between the initial IOM pool size and SOC stock changes

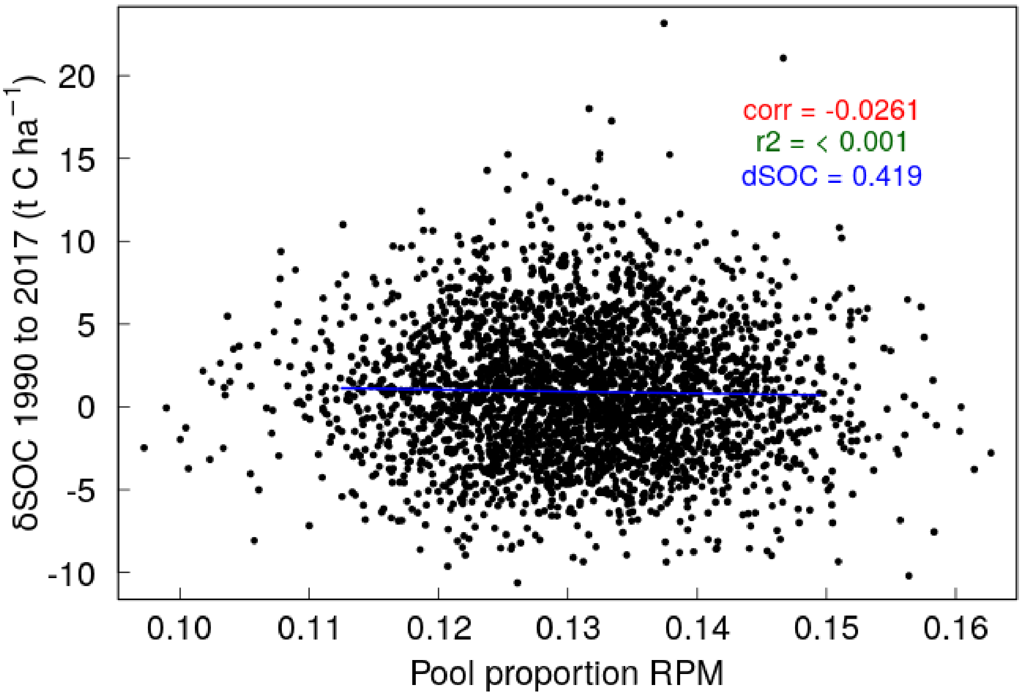

Figure A - 11 The relationship between the initial RPM pool size and SOC stock changes

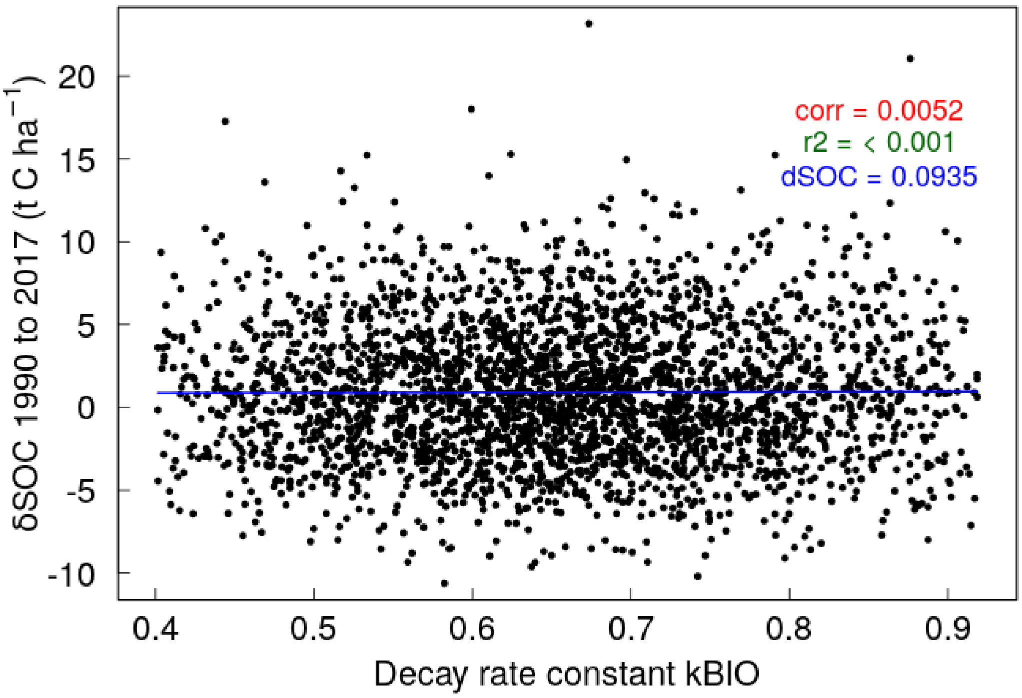

Figure A - 12 The relationship between the BIO pool decay rate constant and SOC stock changes

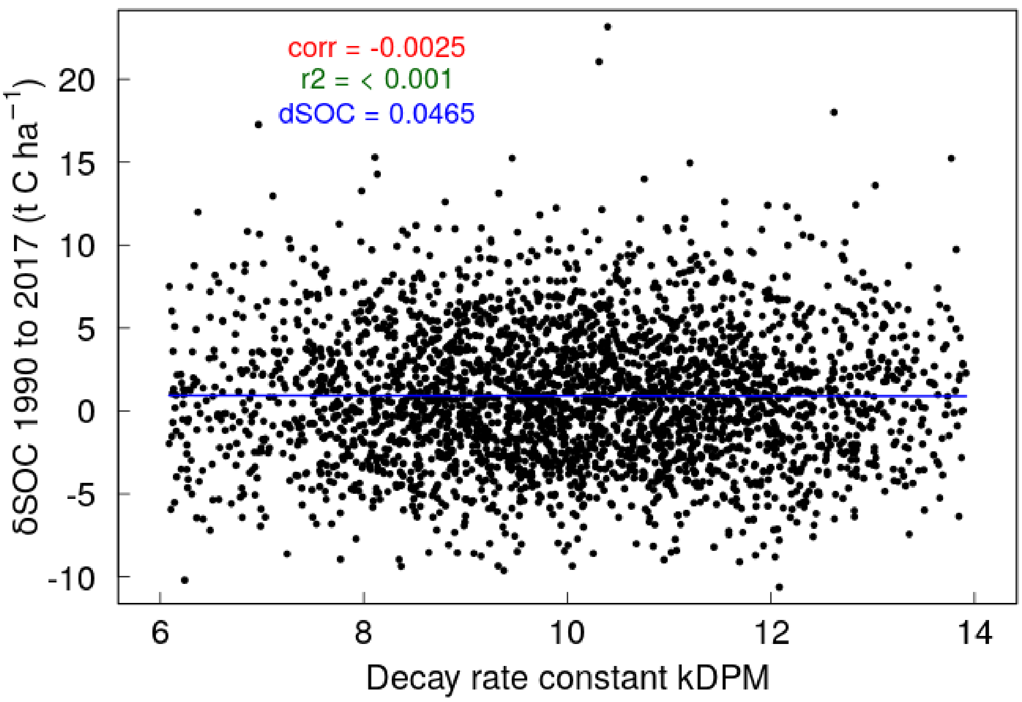

Figure A - 13 The relationship between the DPM pool decay rate constant and SOC stock changes

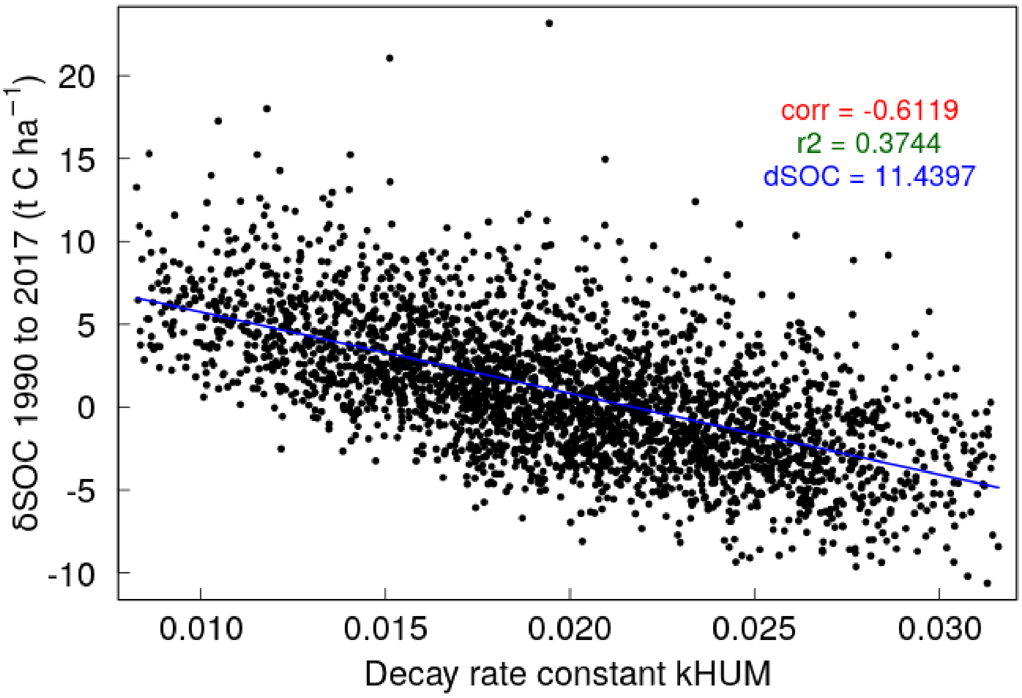

Figure A - 14 The relationship between the HUM pool decay rate constant and SOC stock changes

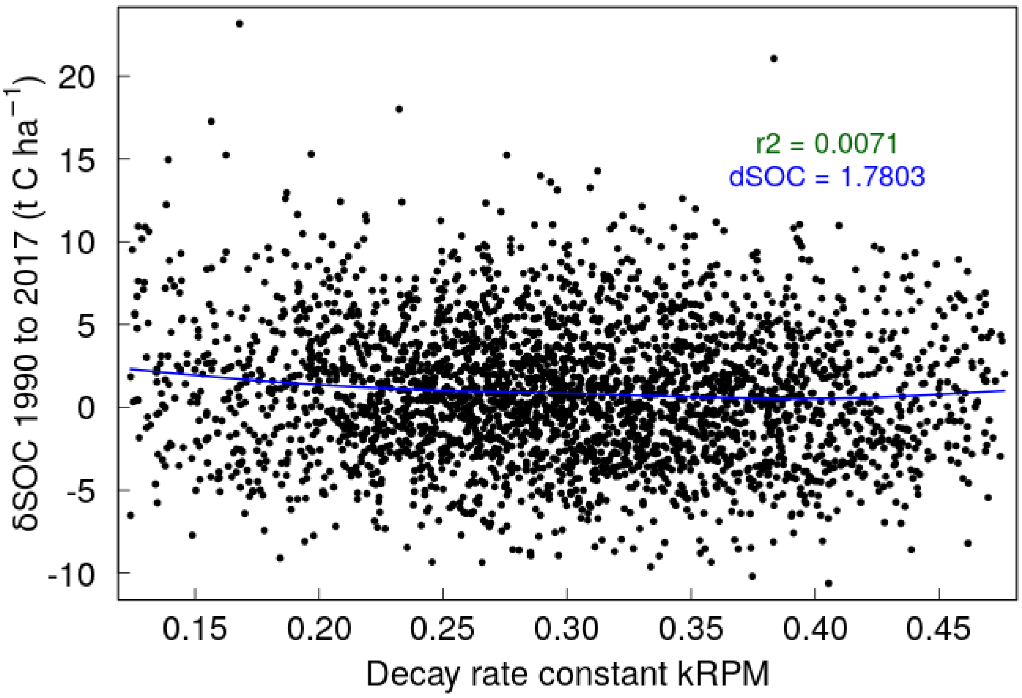

Figure A - 15 The relationship between the RPM pool decay rate constant and SOC stock changes, modelled with an additive model

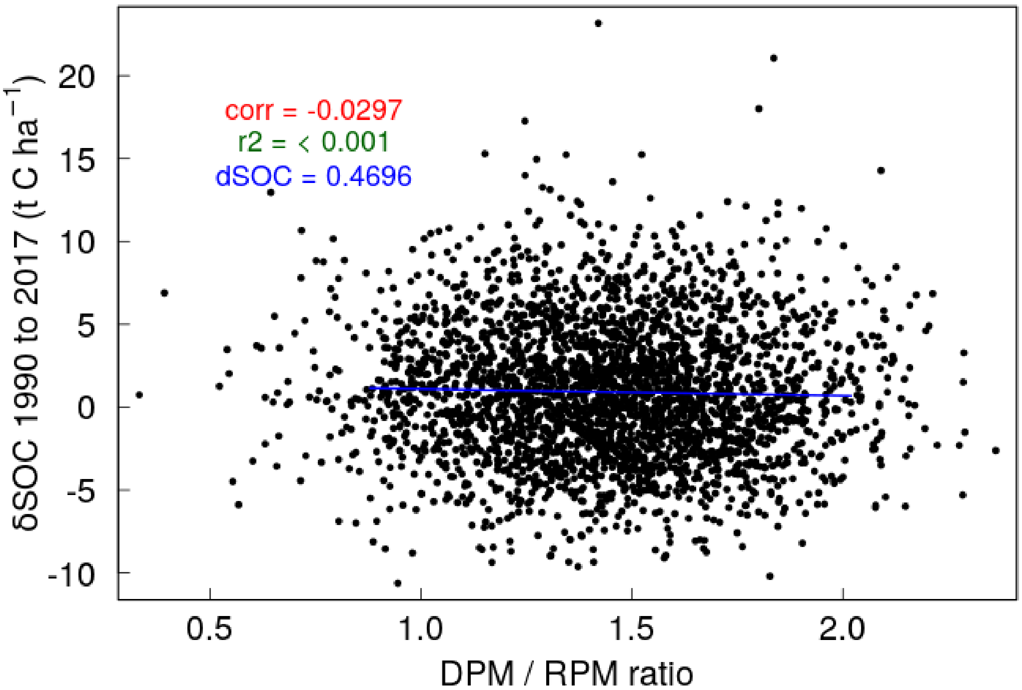

Figure A - 16 The relationship between the DPM / RPM ratio and SOC stock changes

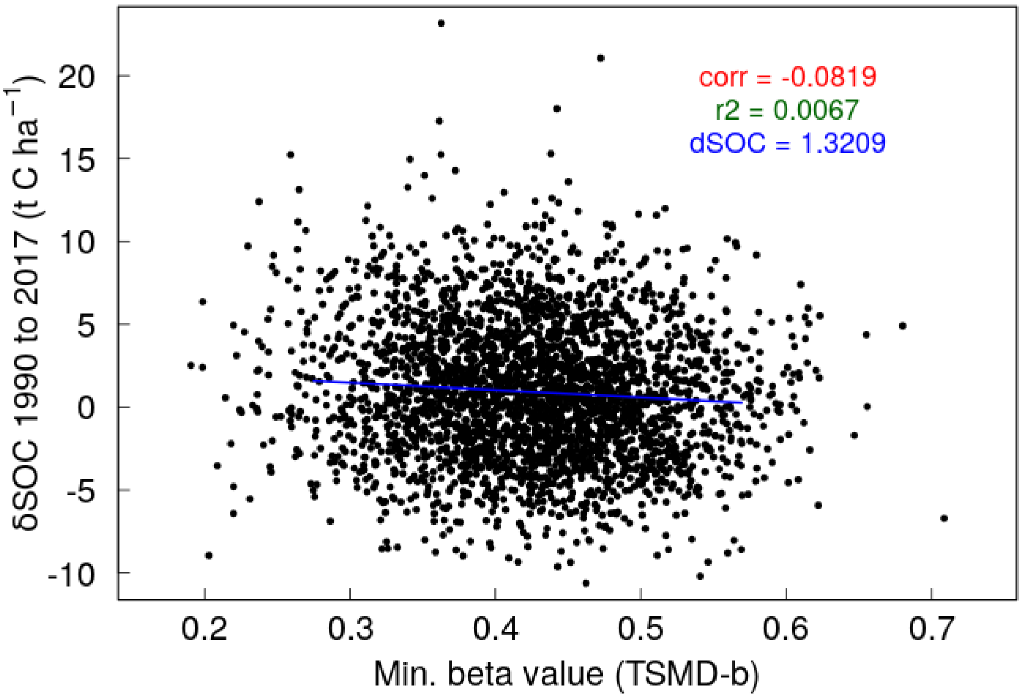

Figure A - 17 The relationship between the TSMD-b parameter (applied by RothC during periods of strong topsoil moisture deficit) and SOC stock changes

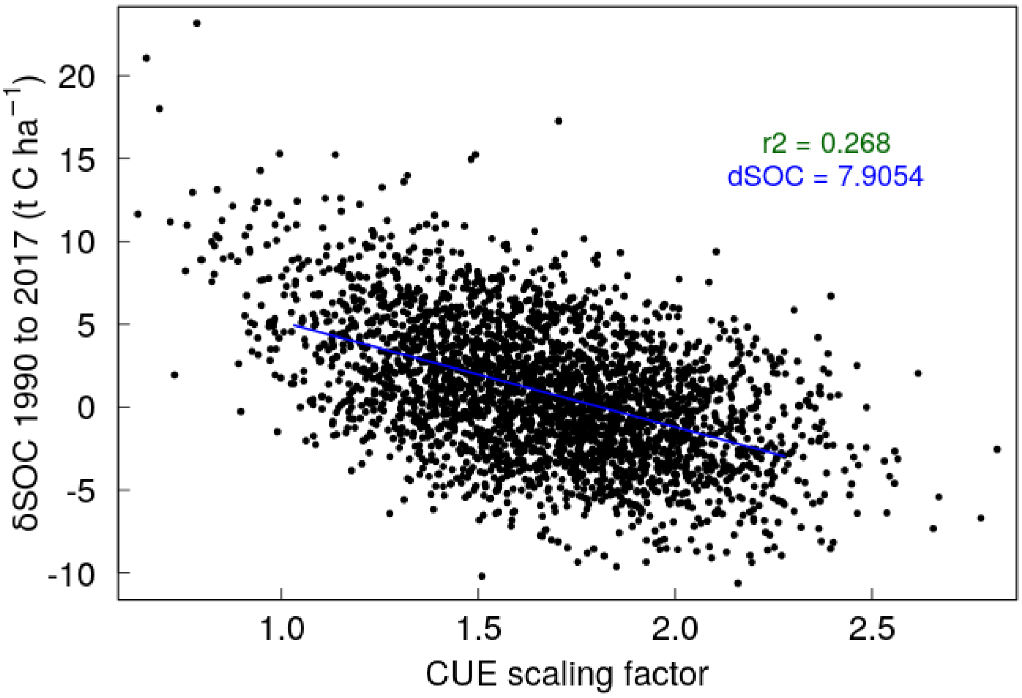

Figure A - 18 The relationship between the CUE scaling factor and SOC stock changes, modelled with an additive model

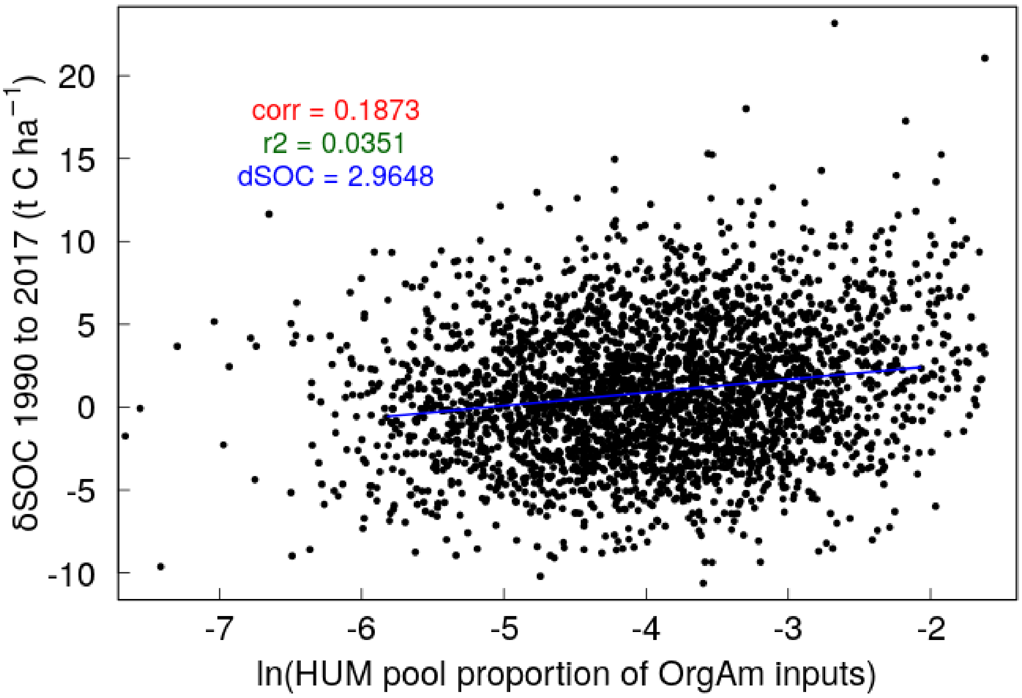

Figure A - 19 The relationship between the proportion of OrgAm inputs going to the HUM pool and SOC stock changes; note the natural log x-axis

9 Appendix D – Results of year-round managed grassland

In the following section the SOC stock changes of the individual replicates (total replicates = 3000) are plotted against the variation in each parameter. For all plots, “corr” refers to the pearson correlation coefficient, “r2” refers to the goodness of fit of the linear model or generalised additive model and “dSOC” refers to the range (maximum – minimum) in SOC stock changes across the range of the parameter in question, as predicted by the model and as indicated by the blue line. For parameters for which a truncated distribution was applied (Table 2), the calculation of dSOC was carried out for the whole range of the parameter values. For all other parameters, the calculation of dSOC was carried out for 95 % of the values of that parameter. Unless otherwise stated, SOC stock changes were modelled with a linear model.

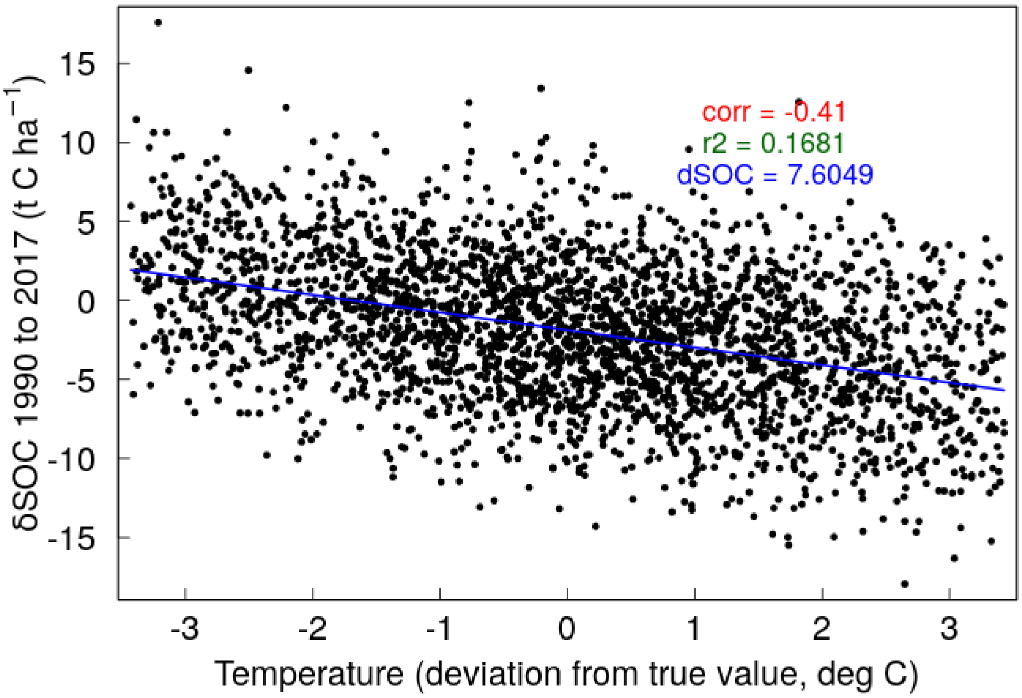

Figure A - 20 The relationship between temperature and SOC stock changes

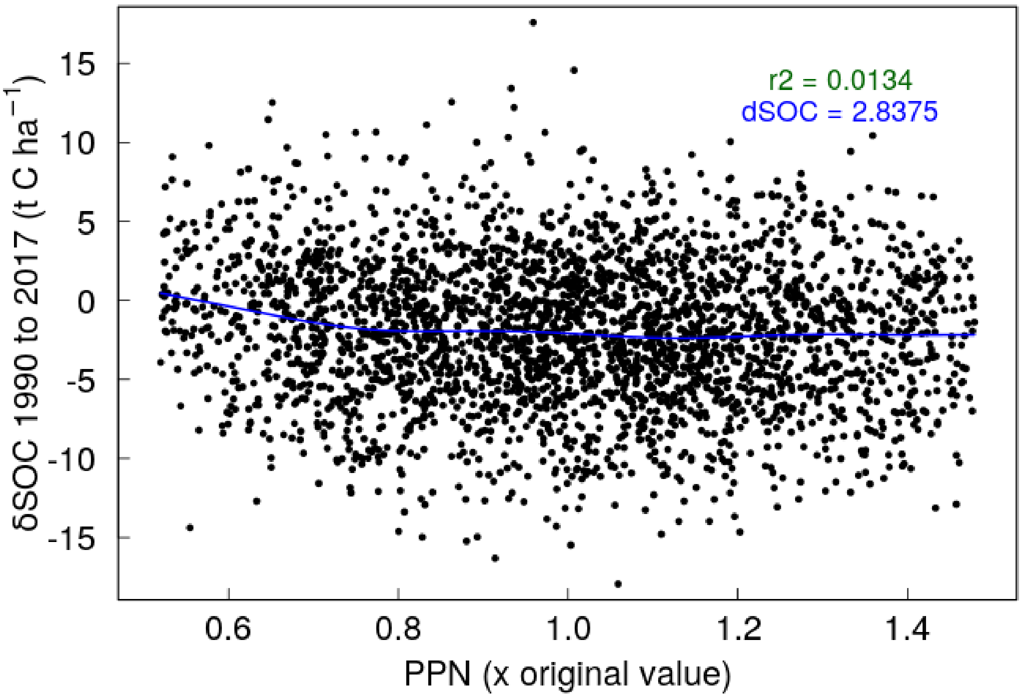

Figure A - 21 The relationship between precipitation (PPN) and SOC stock changes, modelled with an additive model

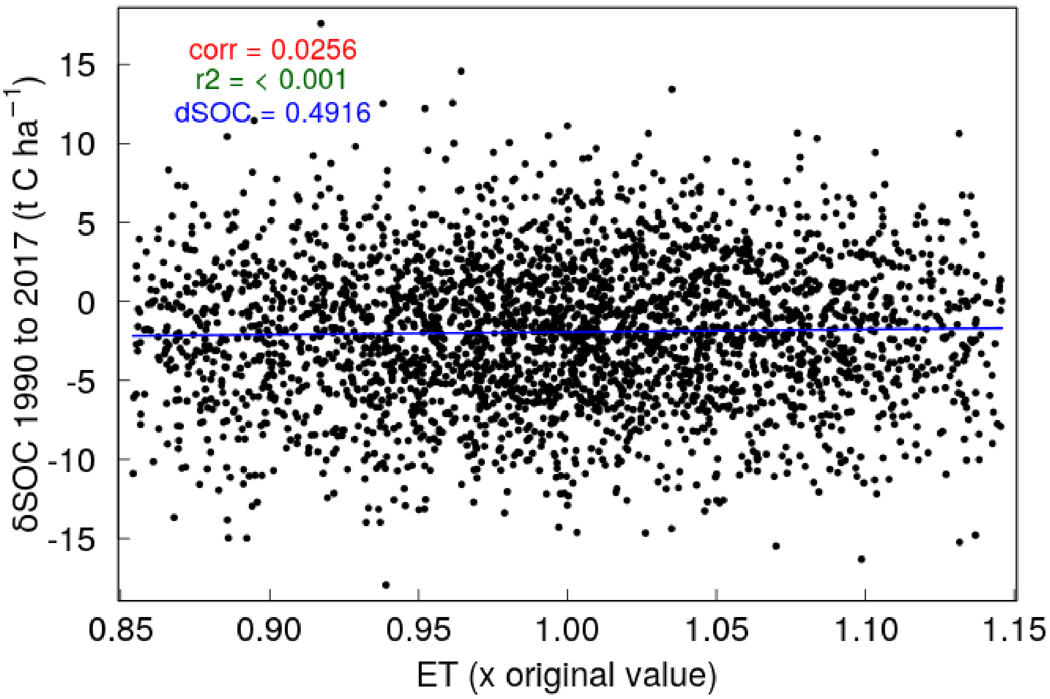

Figure A - 22 The relationship between evapotranspiration (ET) and SOC stock changes

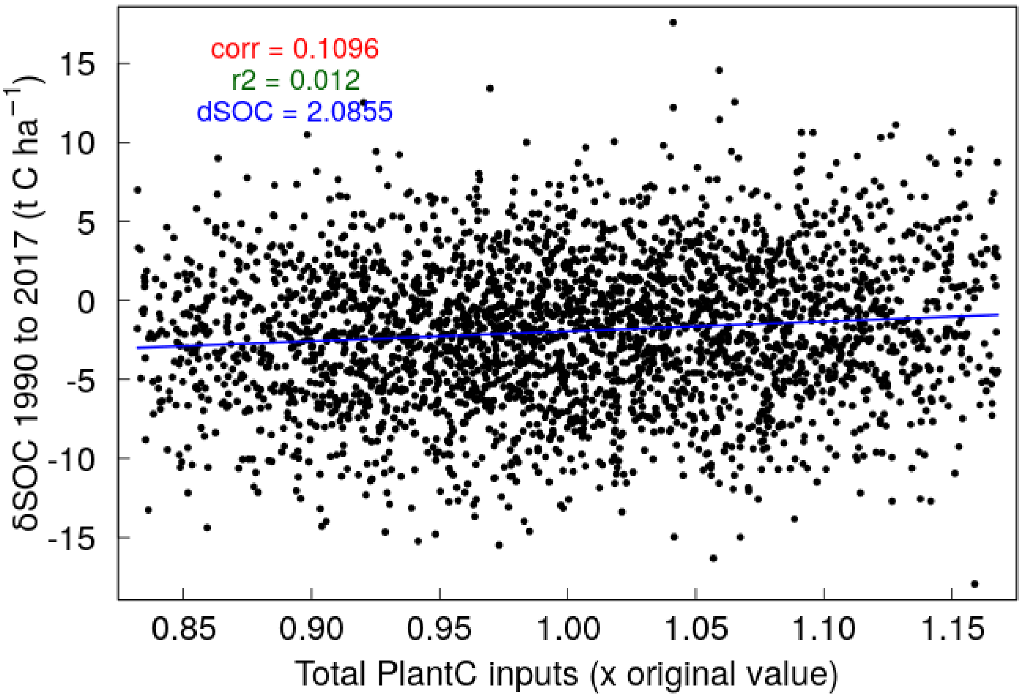

Figure A - 23 The relationship between plant C inputs and SOC stock changes

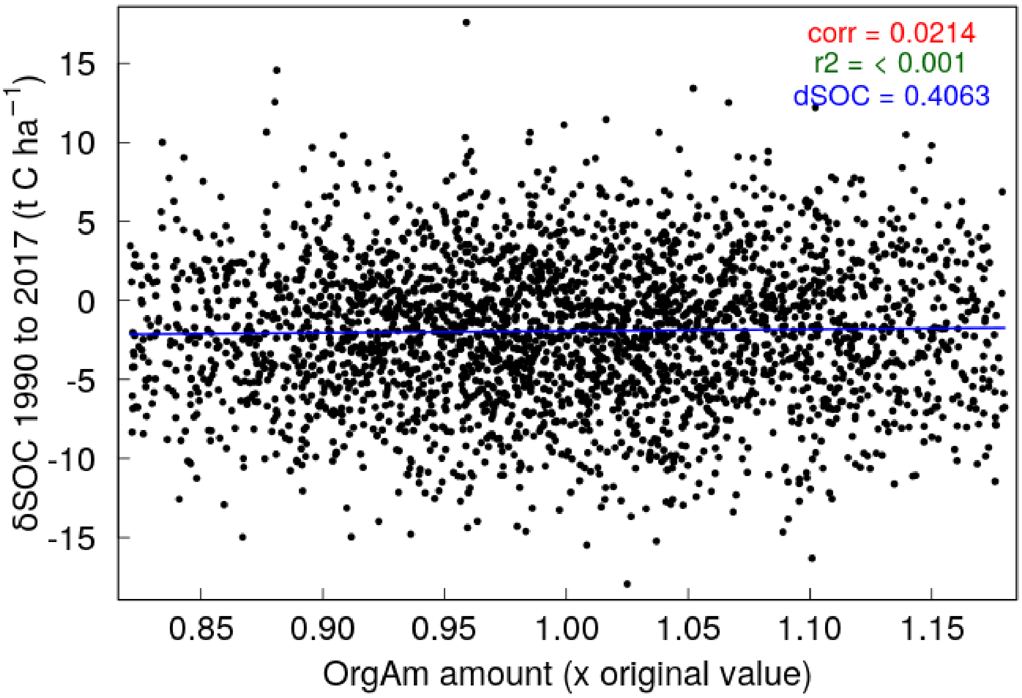

Figure A - 24 The relationship between OrgAm-C inputs and SOC stock changes

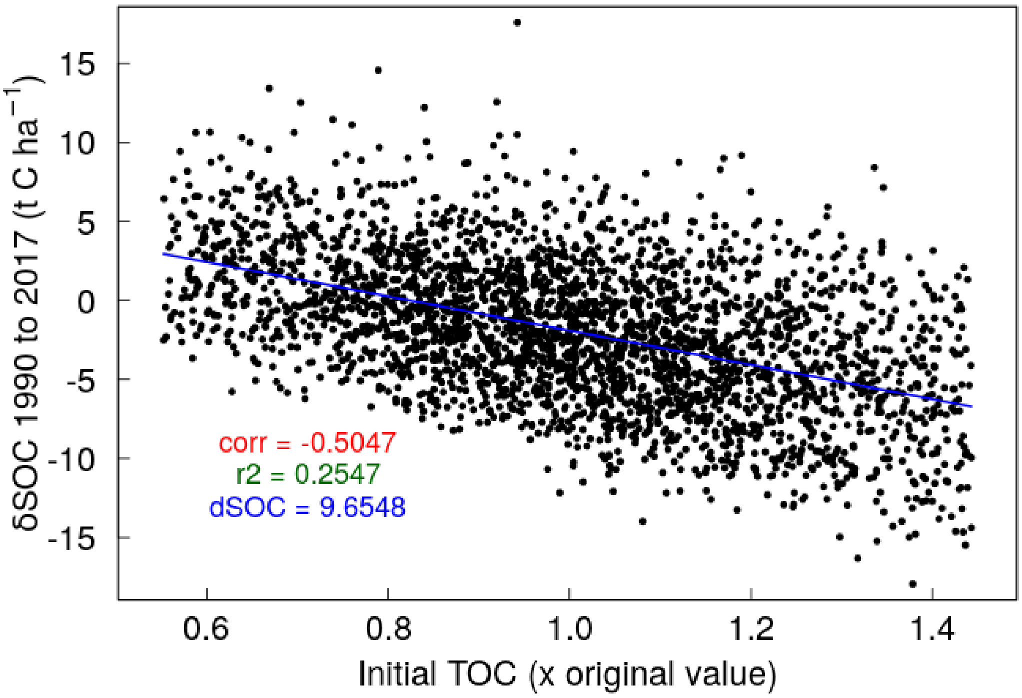

Figure A - 25 The relationship between initial SOC stocks and SOC stock changes

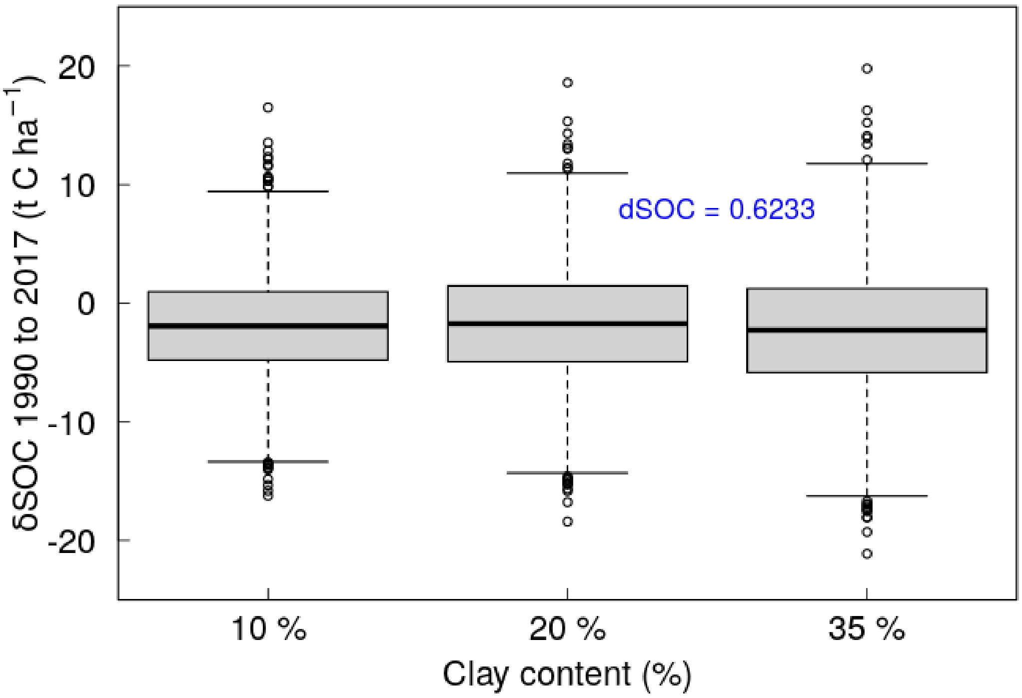

Figure A - 26 The relationship between the clay content of the soil and SOC stock changes; dSOC refers to the largest difference between the three mean dSOC values of the clay content classes

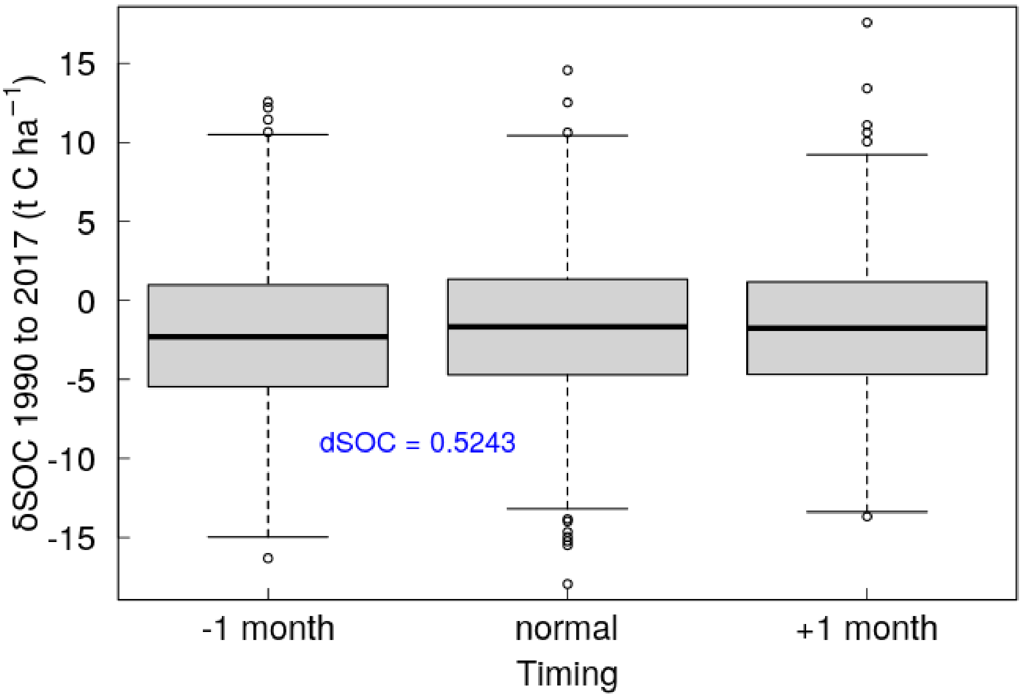

Figure A - 27 The relationship between the timing of C additions and SOC stock changes; dSOC refers to the largest difference between the three mean dSOC values

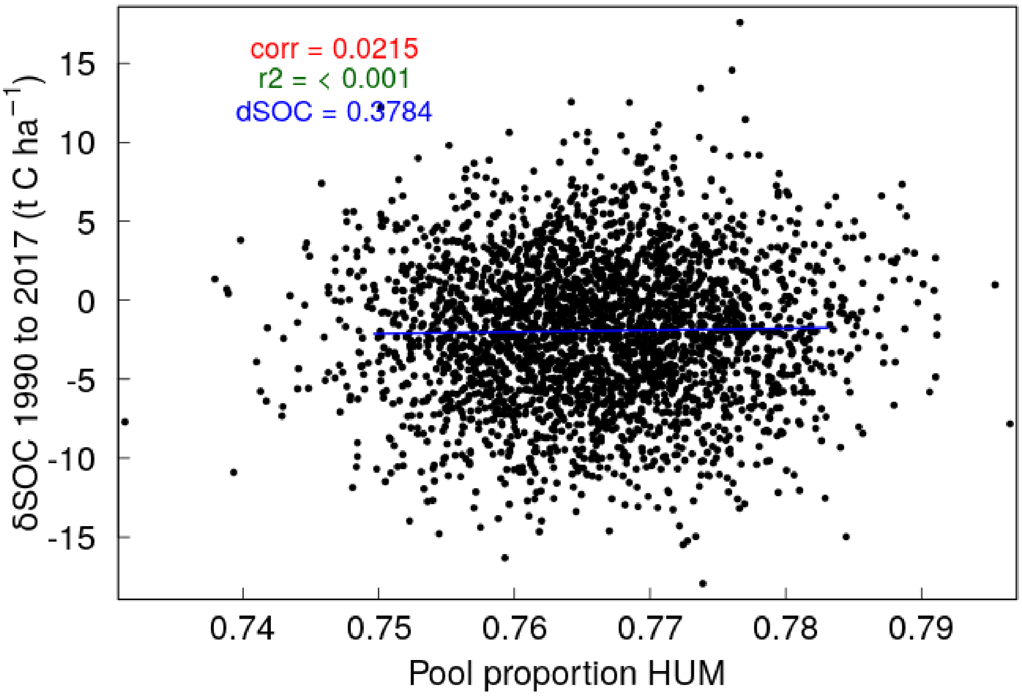

Figure A - 28 The relationship between the initial HUM pool size and SOC stock changes

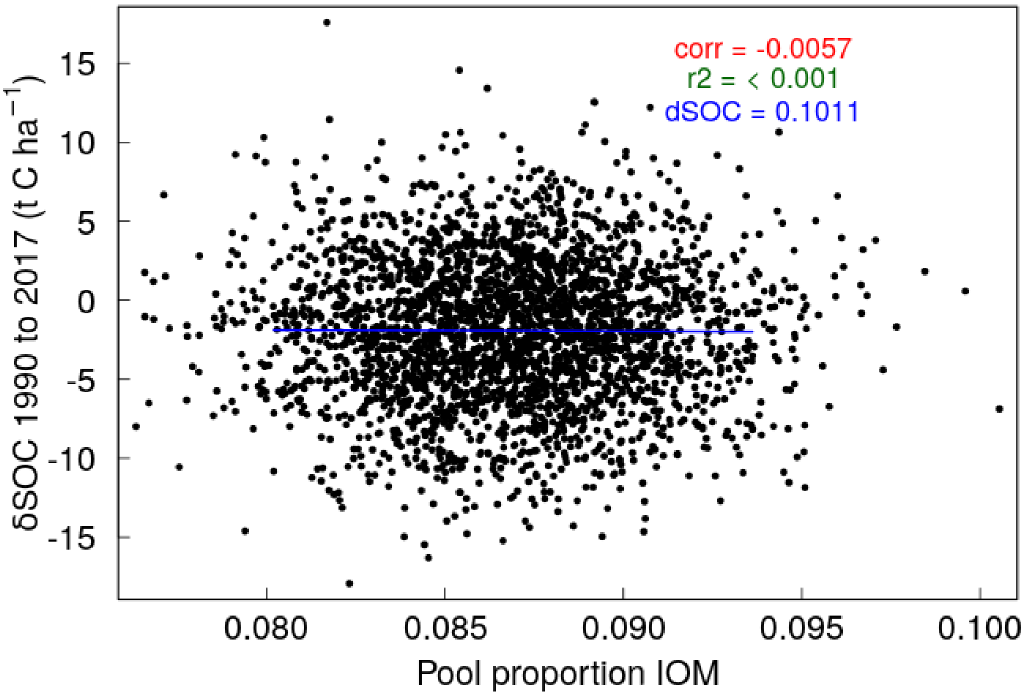

Figure A - 29 The relationship between the initial IOM pool size and SOC stock changes

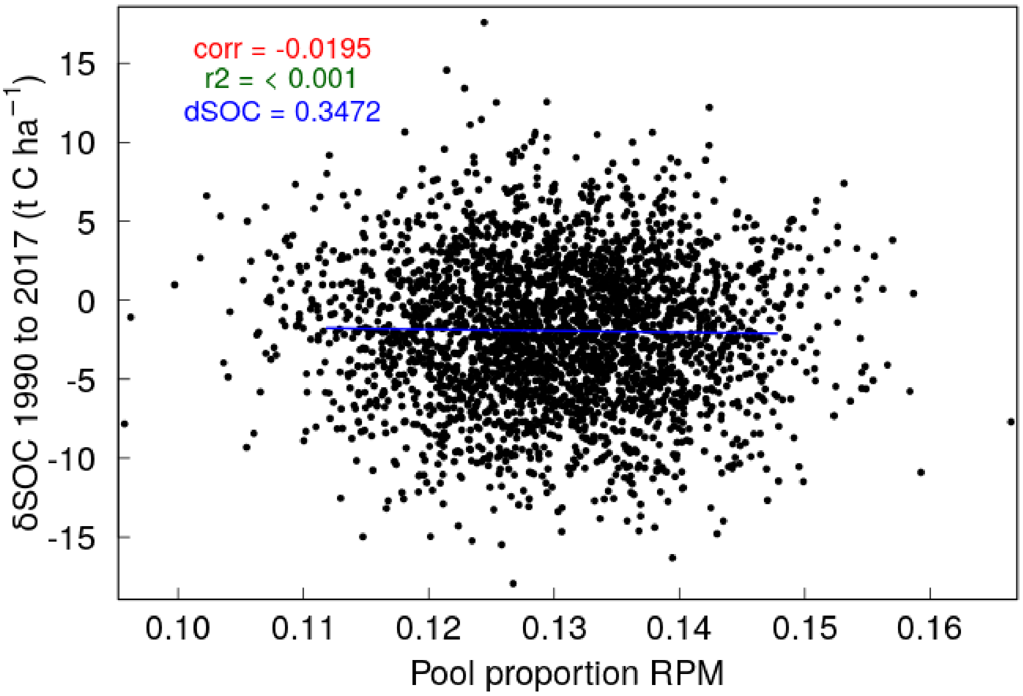

Figure A - 30 The relationship between the initial RPM pool size and SOC stock changes

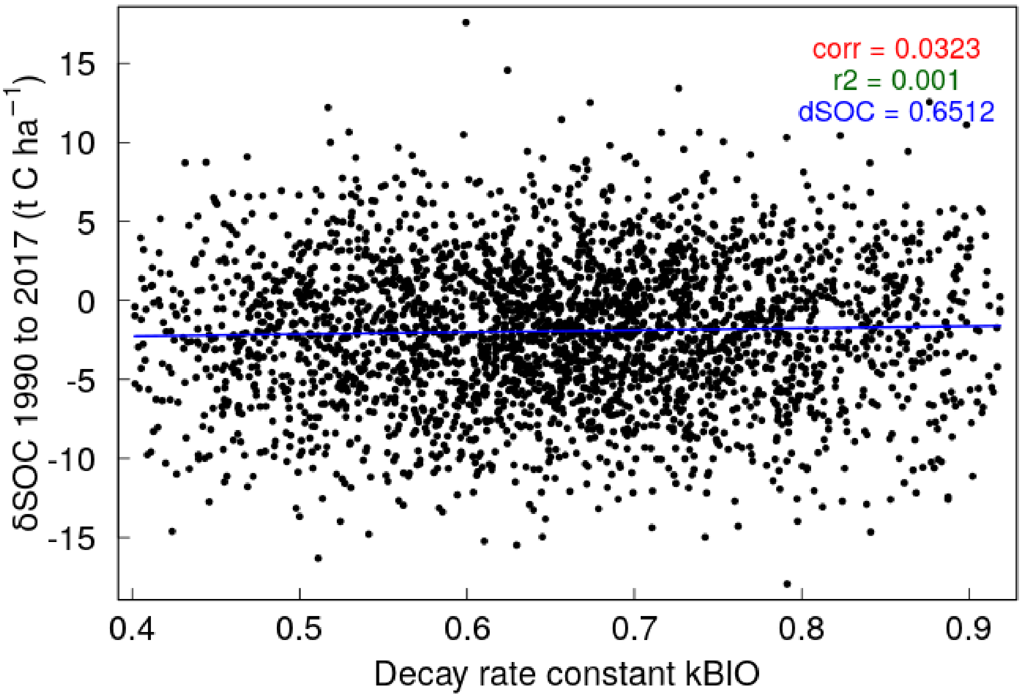

Figure A - 31 The relationship between the BIO pool decay rate constant and SOC stock changes

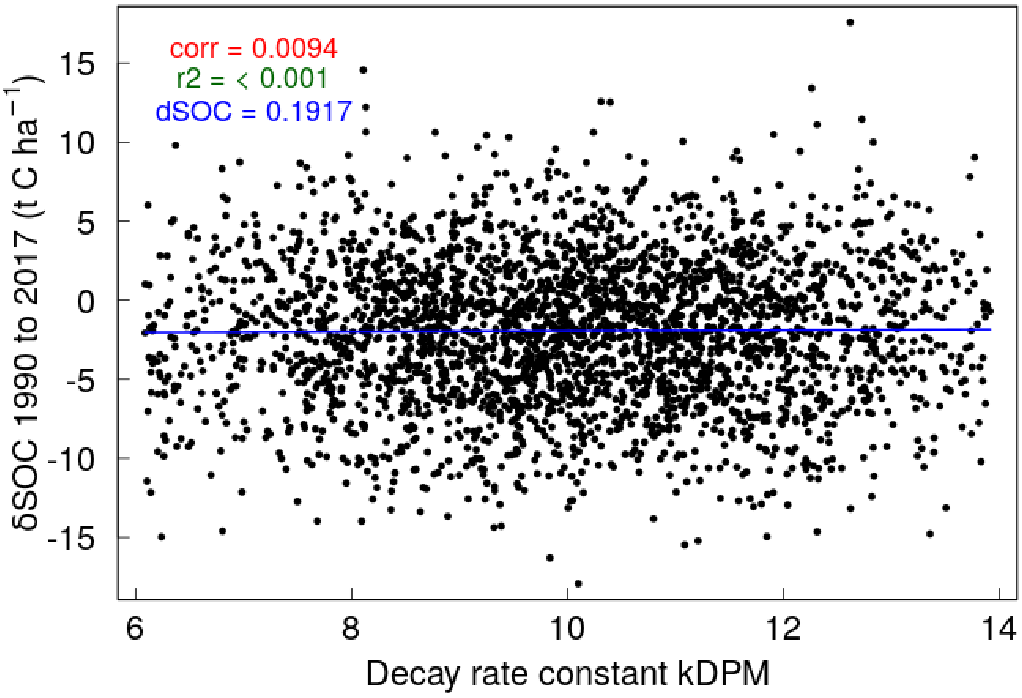

Figure A - 32 The relationship between the DPM pool decay rate constant and SOC stock changes

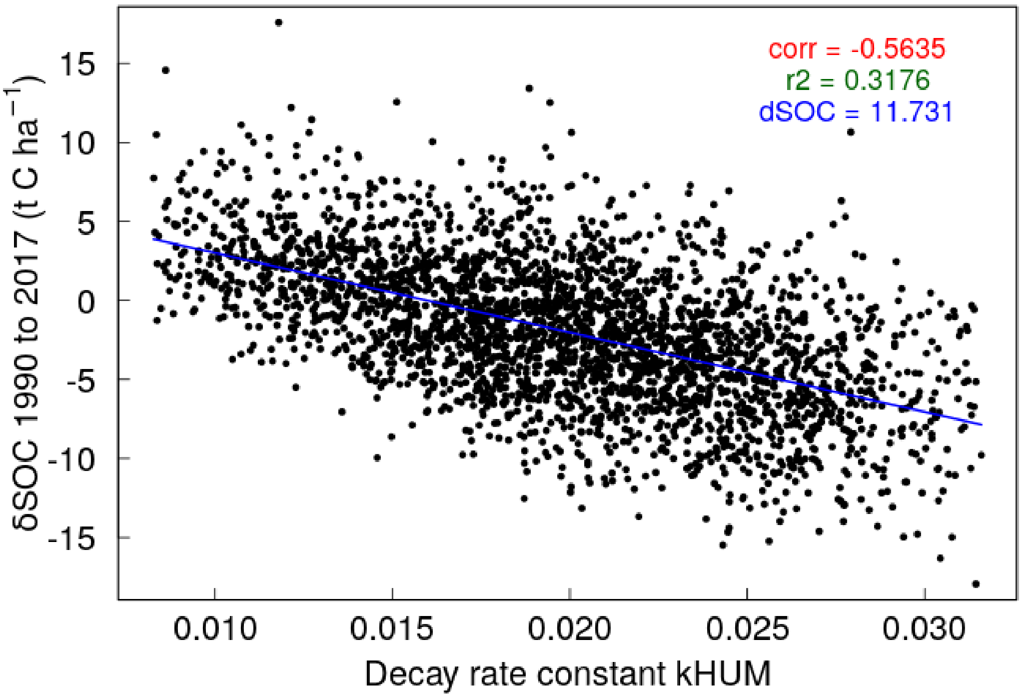

Figure A - 33 The relationship between the HUM pool decay rate constant and SOC stock changes

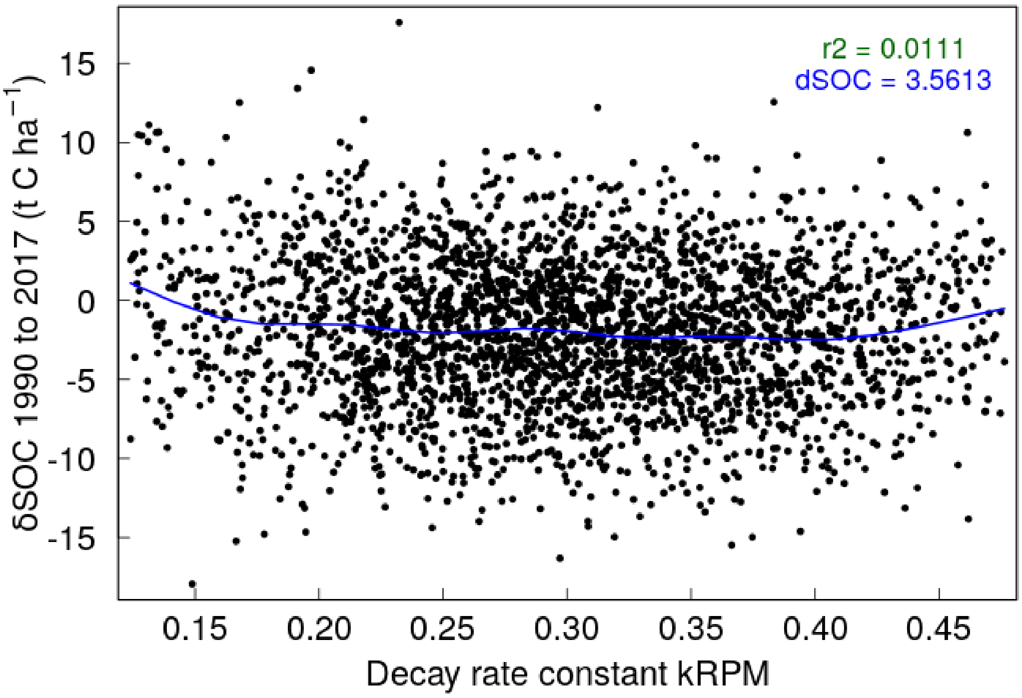

Figure A - 34 The relationship between the RPM pool decay rate constant and SOC stock changes

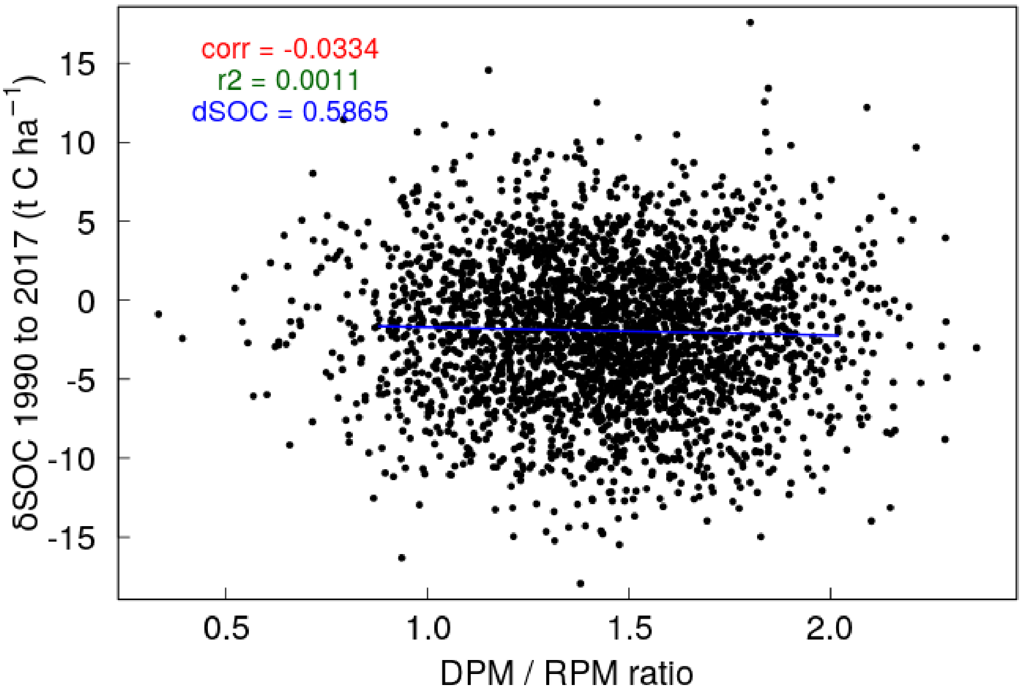

Figure A - 35 The relationship between the DPM / RPM ratio and SOC stock changes

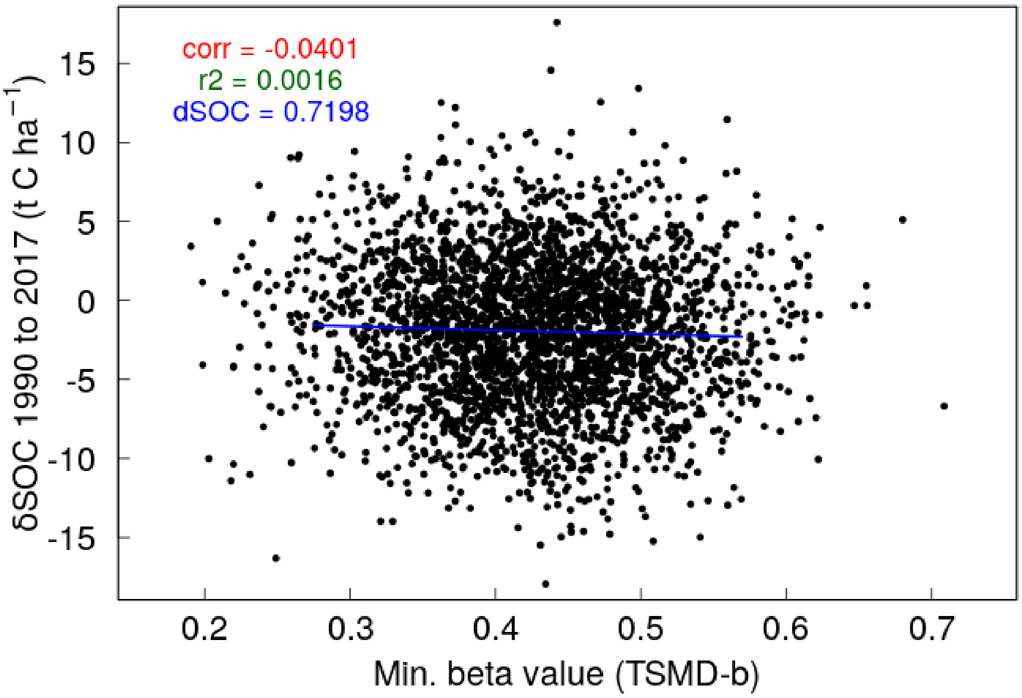

Figure A - 36 The relationship between TSMD-b (applied by RothC during periods of strong topsoil moisture deficit) and SOC stock changes

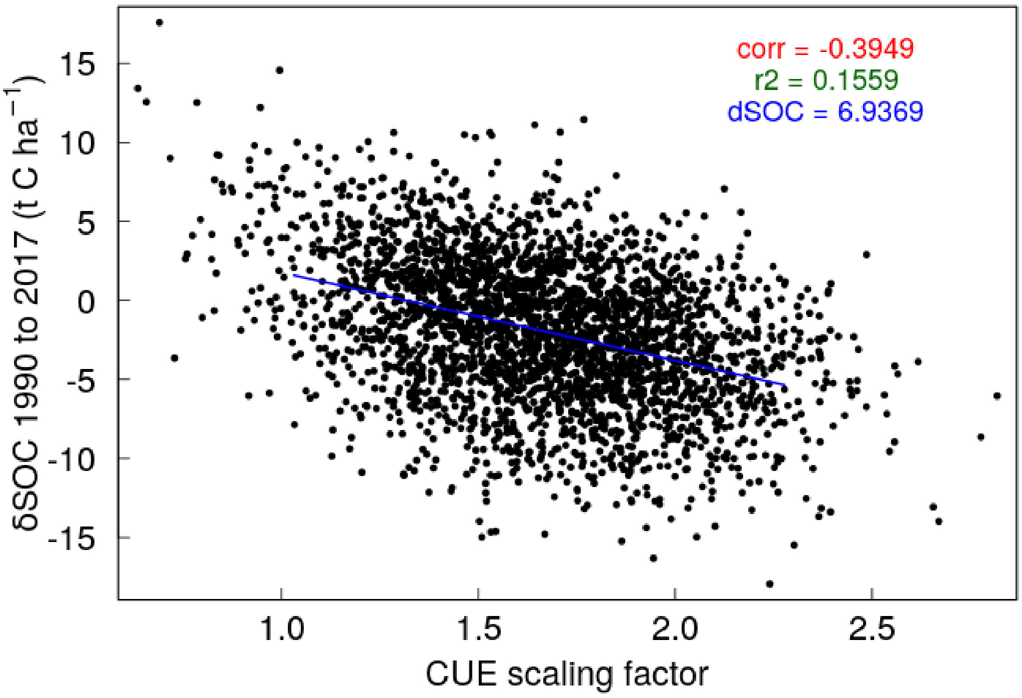

Figure A - 37 The relationship between the CUE scaling factor and SOC stock changes

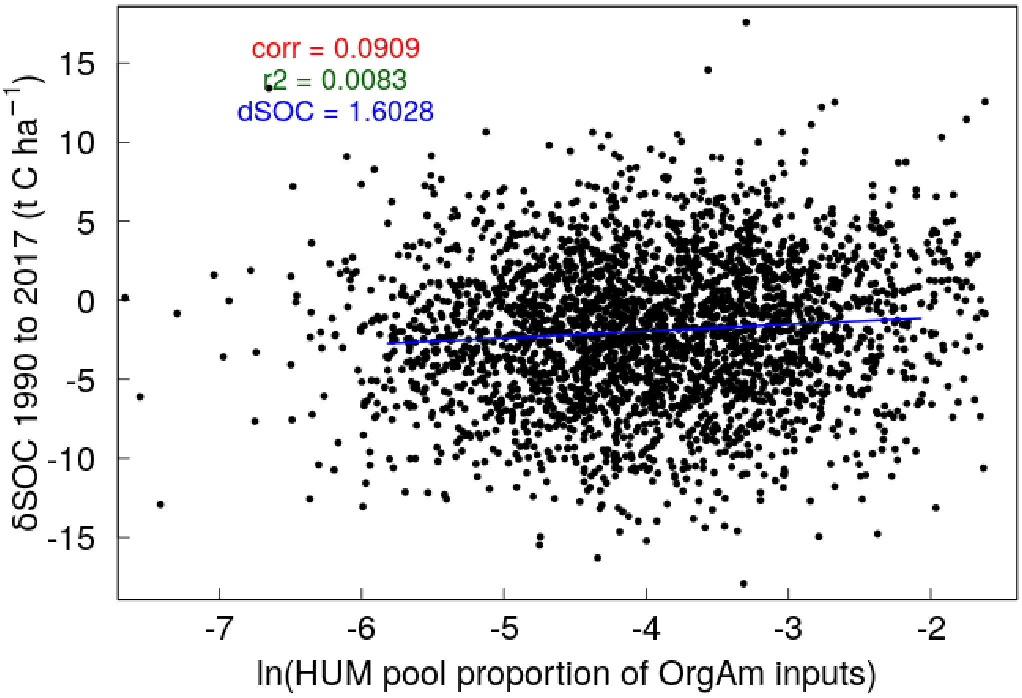

Figure A - 38 The relationship between the proportion of OrgAm inputs going to the HUM pool and SOC stock changes; note the natural log x-axis

10 Appendix E – Results of summer pasture area

In the following section the SOC stock changes of the individual replicates (total replicates = 3000) are plotted against the variation in each parameter. For all plots, “corr” refers to the pearson correlation coefficient, “r2” refers to the goodness of fit of the linear model or generalised additive model and “dSOC” refers to the range (maximum – minimum) in SOC stock changes across the range of the parameter in question, as predicted by the model and as indicated by the blue line. For parameters for which a truncated distribution was applied (Table 2), the calculation of dSOC was carried out for the whole range of the parameter values. For all other parameters, the calculation of dSOC was carried out for 95 % of the values of that parameter. Unless otherwise stated, SOC stock changes were modelled with a linear model.

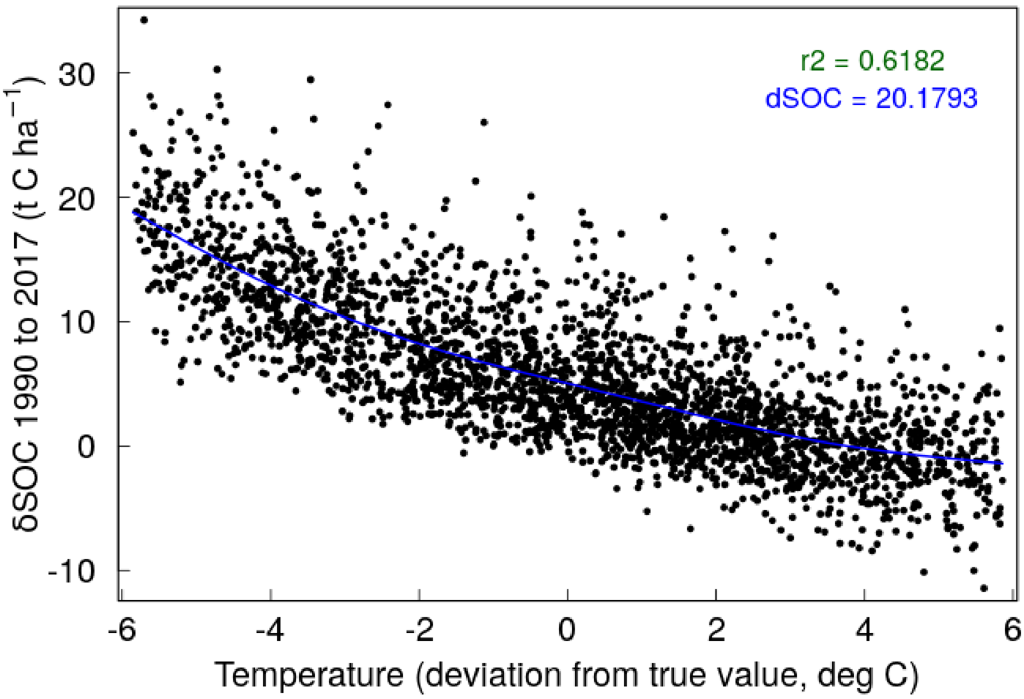

Figure A - 39 The relationship between temperature and SOC stock changes

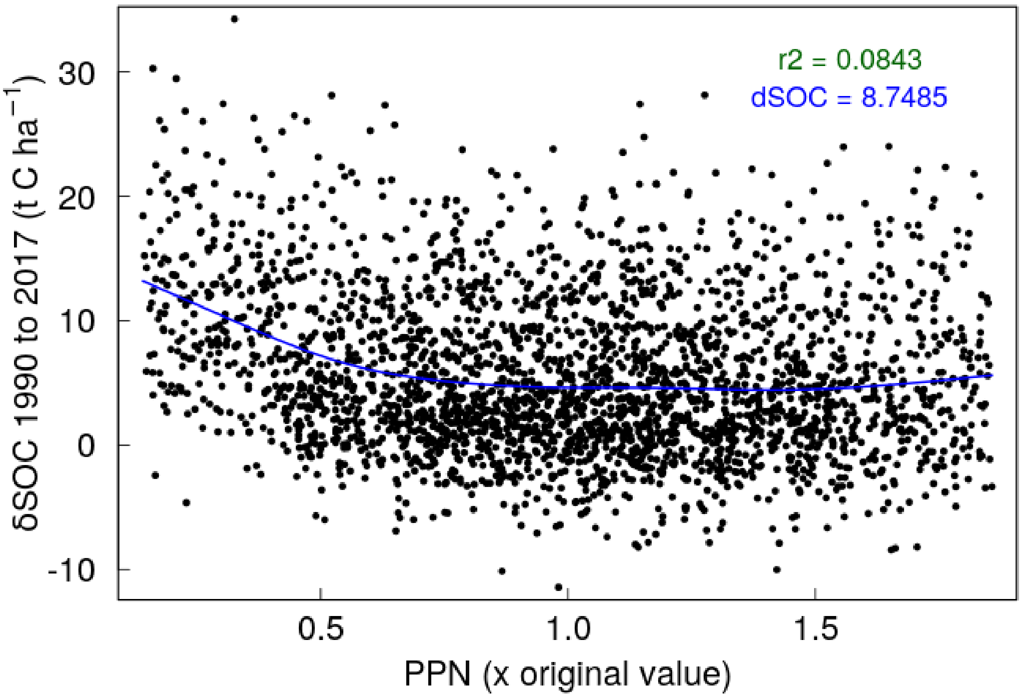

Figure A - 40 The relationship between precipitation (PPN) and SOC stock changes

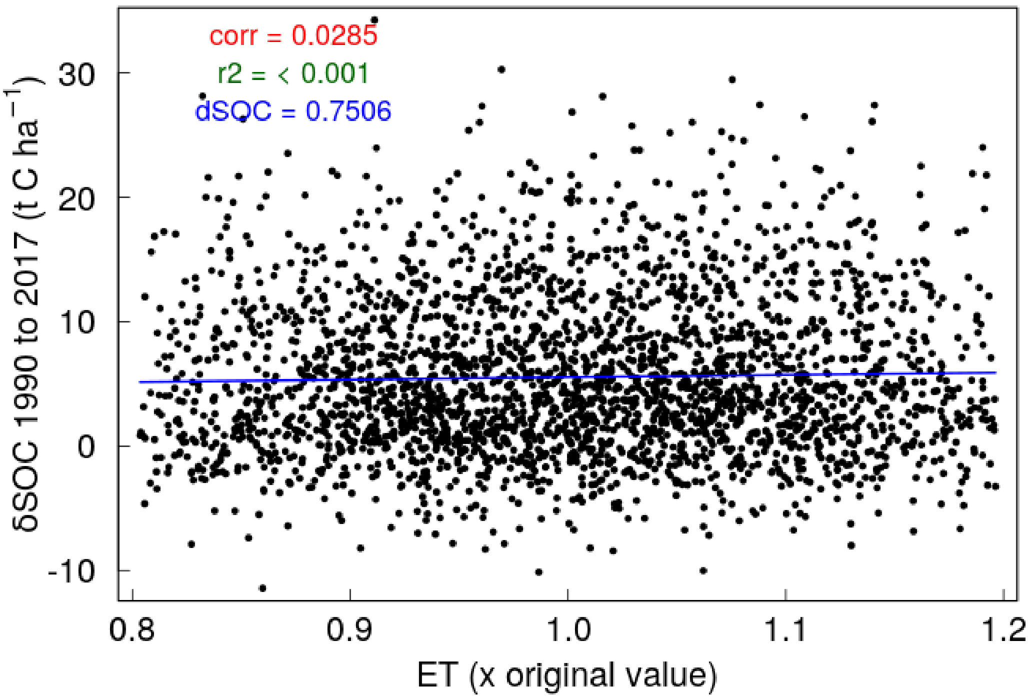

Figure A - 41 The relationship between evapotranspiration (ET) and SOC stock changes

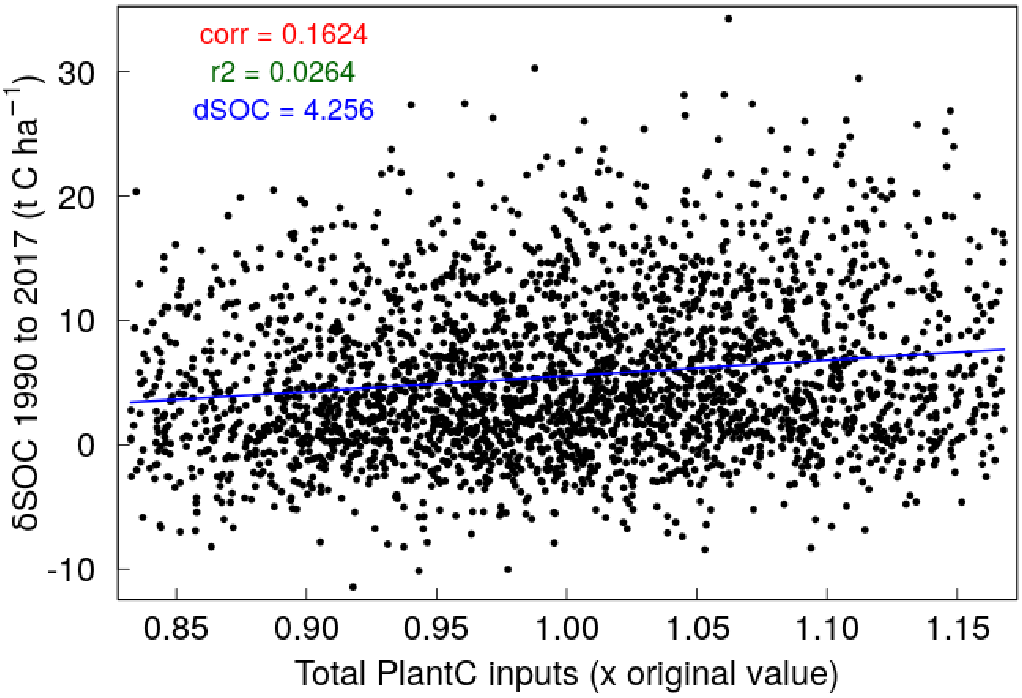

Figure A - 42 The relationship between total plant C inputs and SOC stock changes

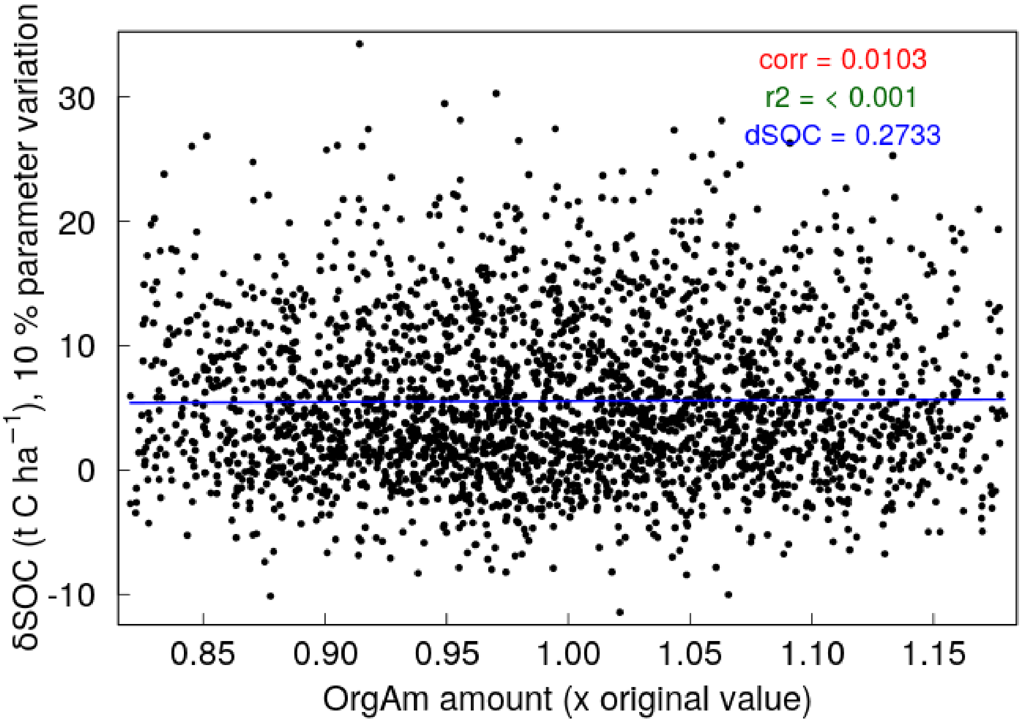

Figure A - 43 The relationship between OrgAm-C inputs and SOC stock changes

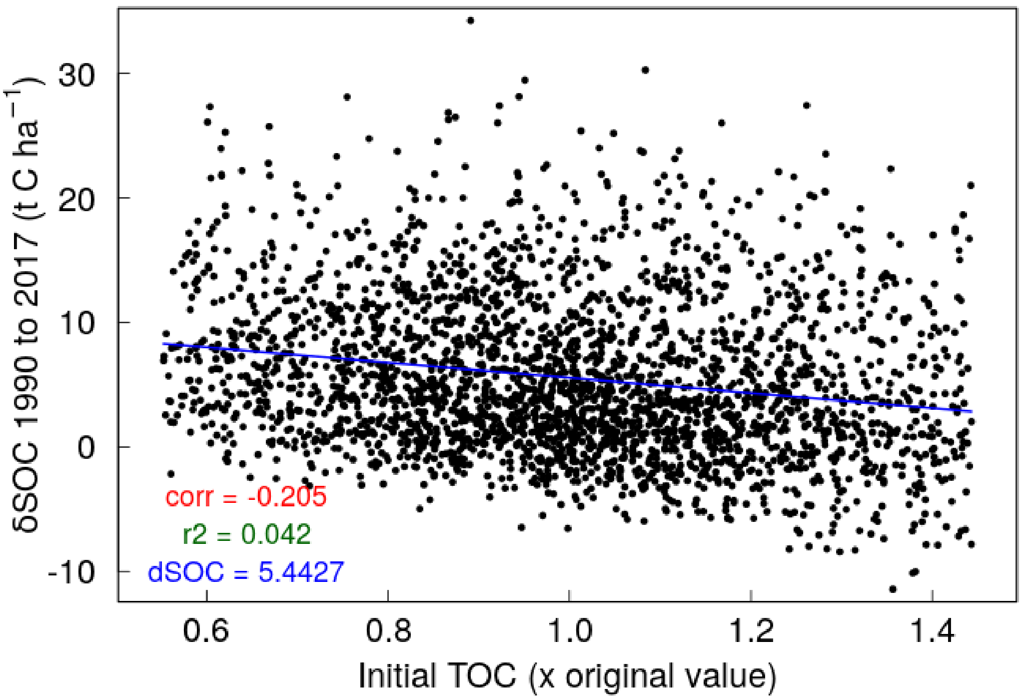

Figure A - 44 The relationship between initial SOC stocks and SOC stock changes

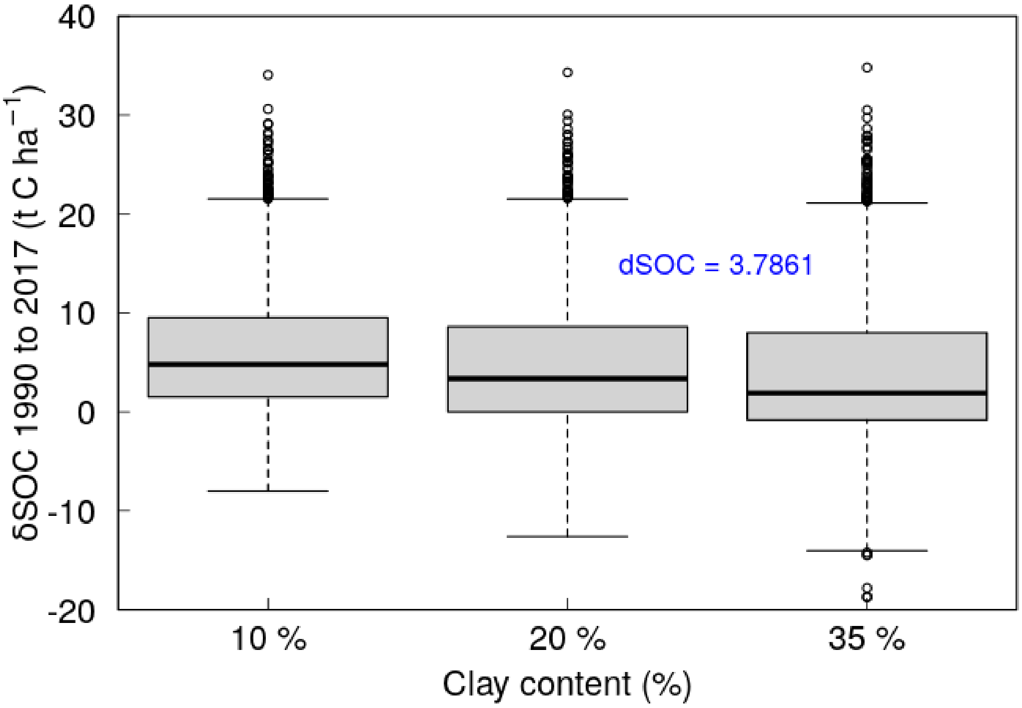

Figure A - 45 The relationship between the clay content of the soil and SOC stock changes; dSOC refers to the largest difference between the three mean dSOC values of the clay content classes

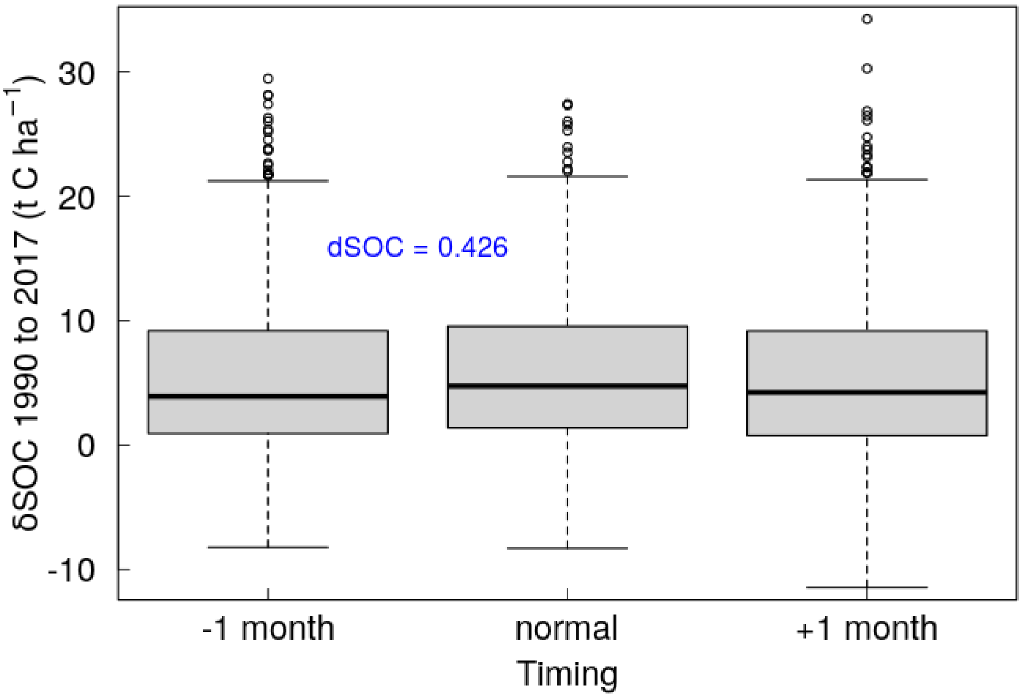

Figure A - 46 The relationship between the timing of C additions and SOC stock changes; dSOC refers to the largest difference between the three mean dSOC values

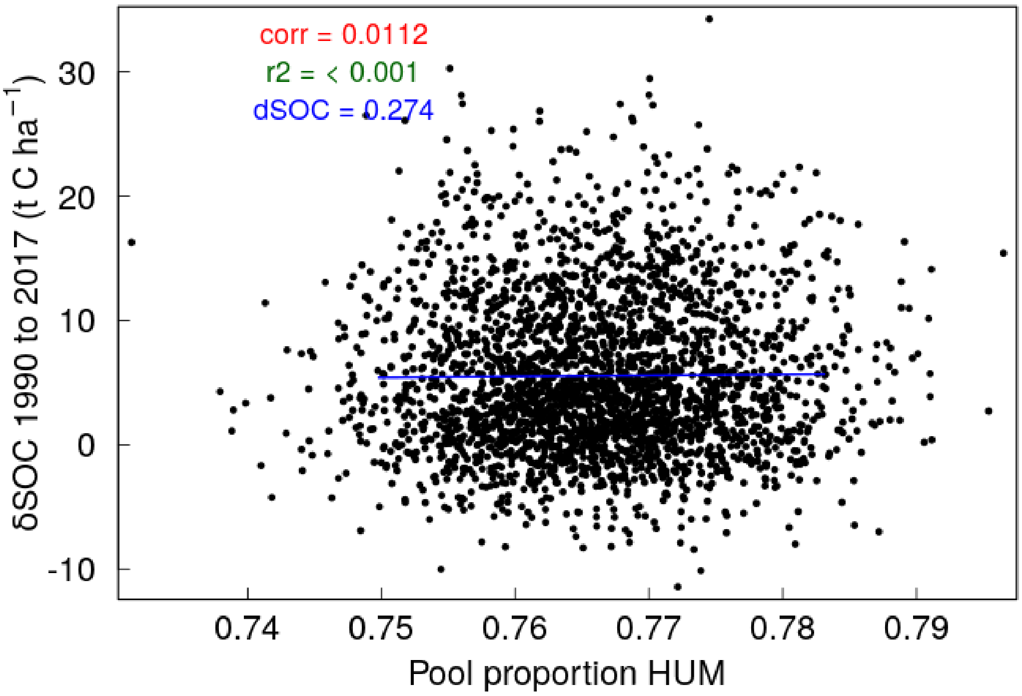

Figure A - 47 The relationship between the initial HUM pool size and SOC stock changes

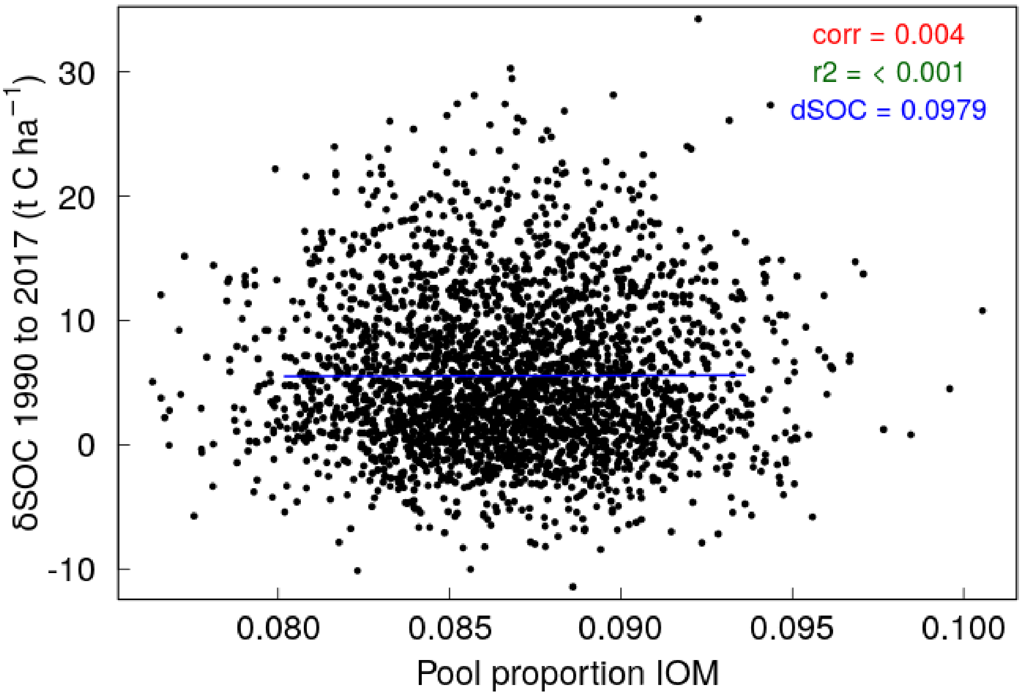

Figure A - 48 The relationship between the initial HUM pool size and SOC stock changes

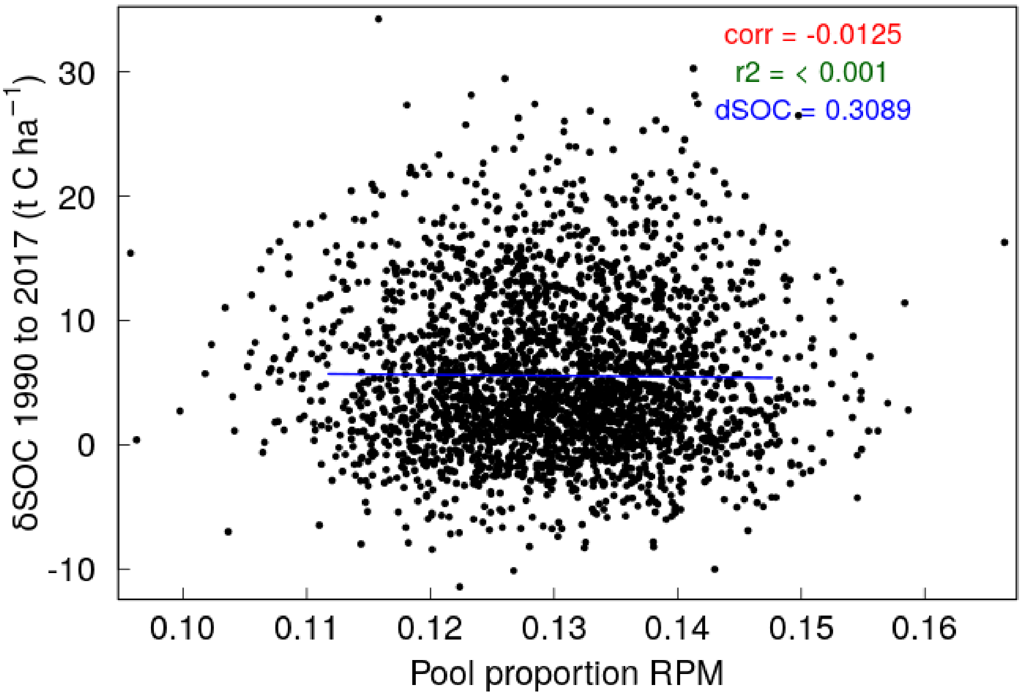

Figure A - 49 The relationship between the initial RPM pool size and SOC stock changes

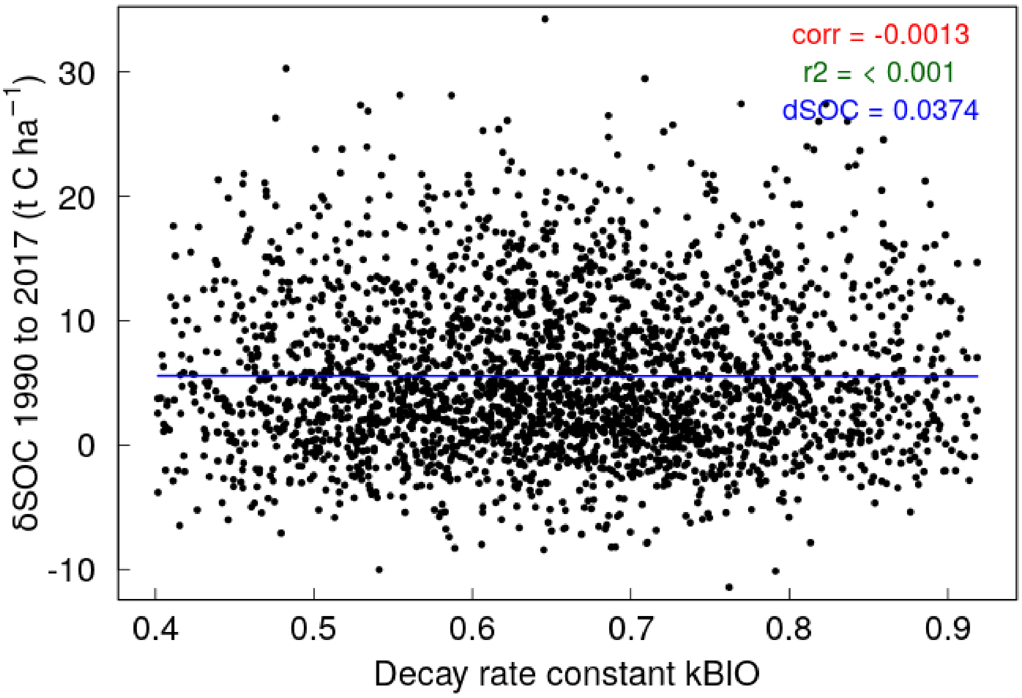

Figure A - 50 The relationship between the decay rate of the BIO pool and SOC stock changes

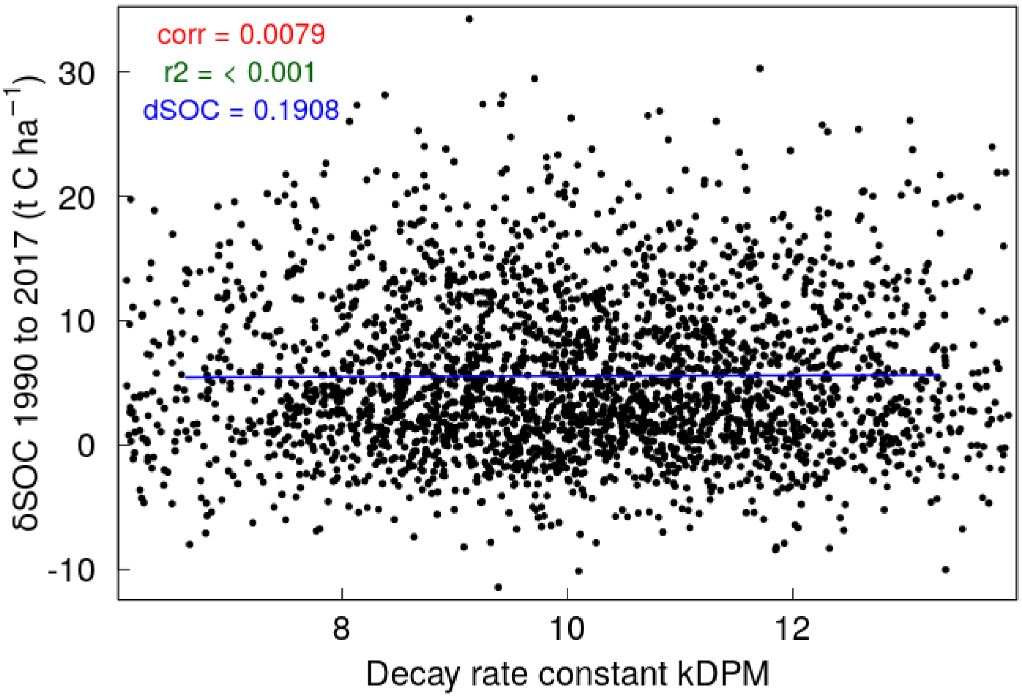

Figure A - 51 The relationship between the decay rate of the DPM pool and SOC stock changes

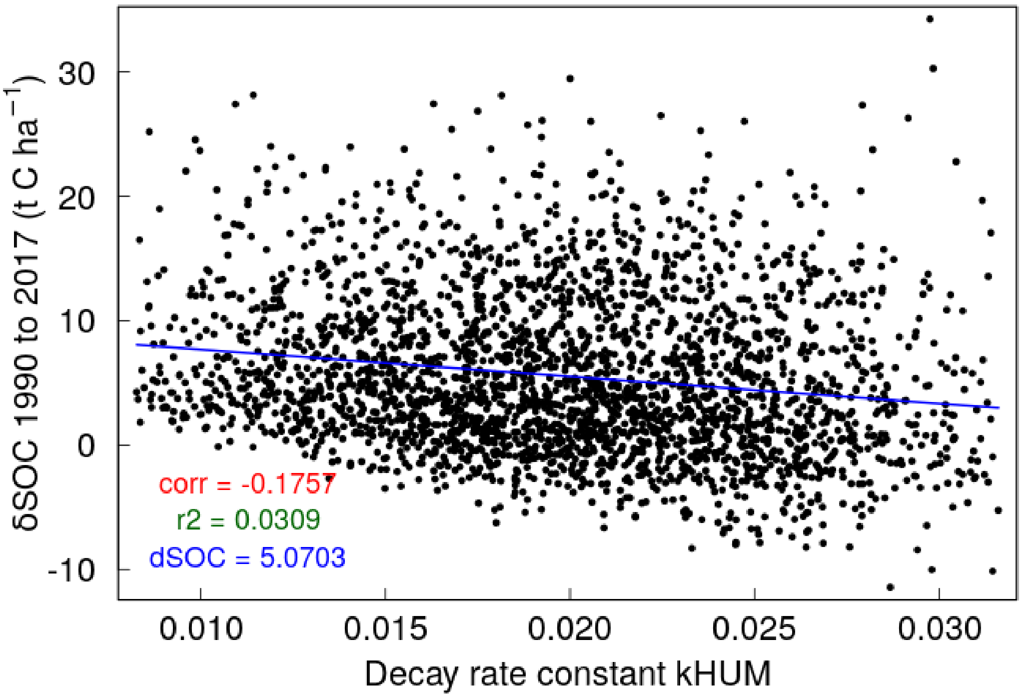

Figure A - 52 The relationship between the decay rate of the HUM pool and SOC stock changes

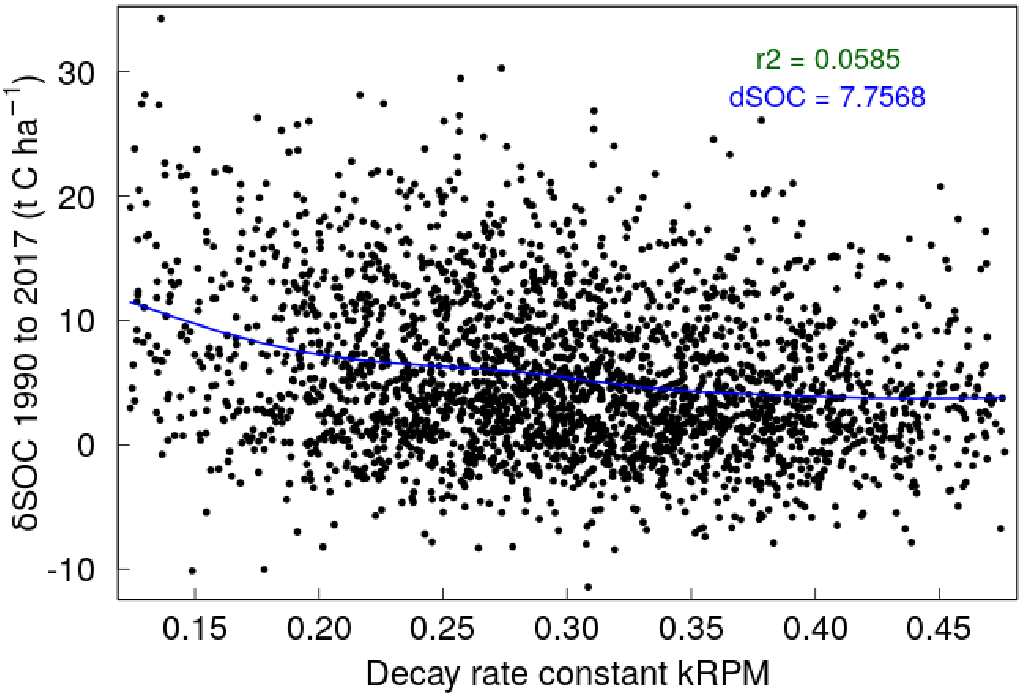

Figure A - 53 The relationship between the decay rate of the RPM pool and SOC stock changes

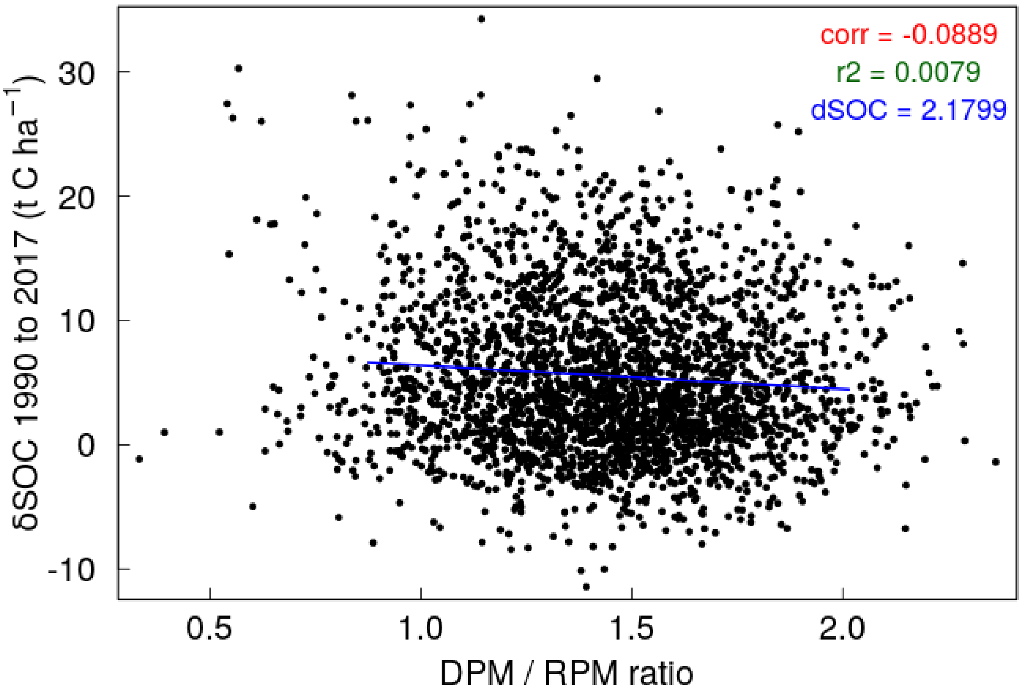

Figure A - 54 The relationship between the DPM / RPM ratio and SOC stock changes

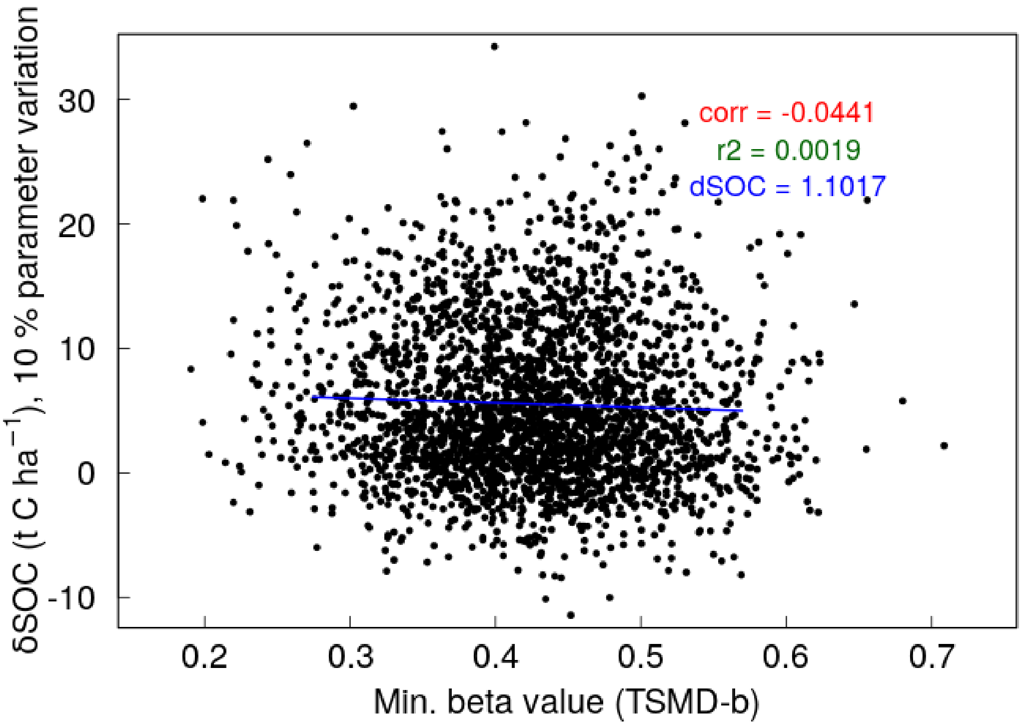

Figure A - 55 The relationship between TSMD-b (applied by RothC during periods of strong topsoil moisture deficit) and SOC stock changes

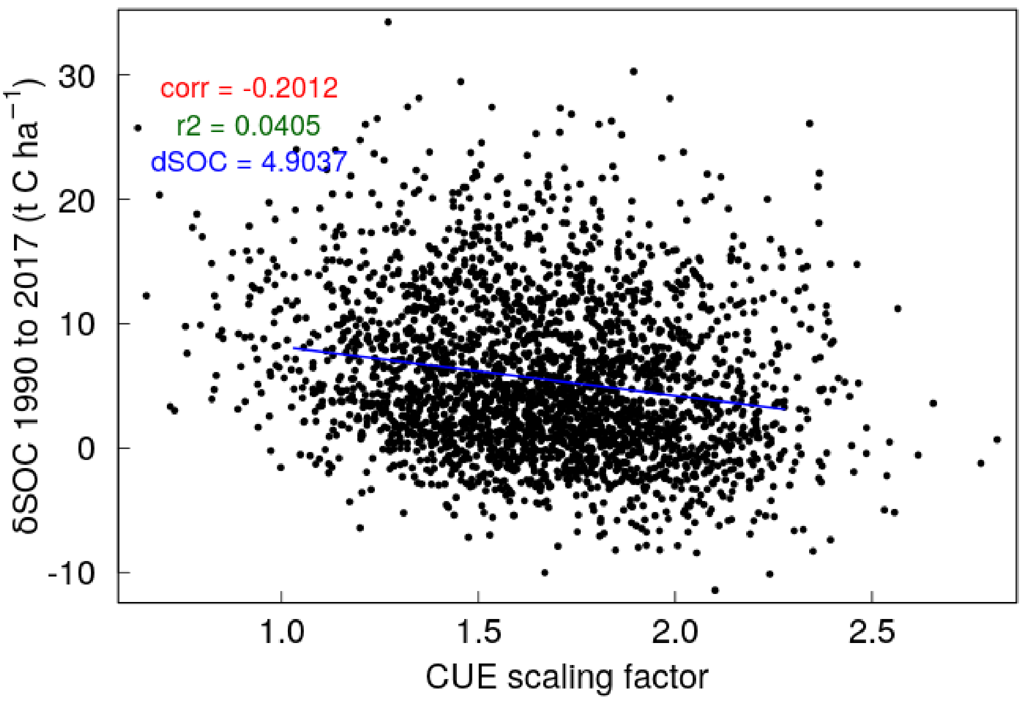

Figure A - 56 The relationship between the CUE scaling factor and SOC stock changes

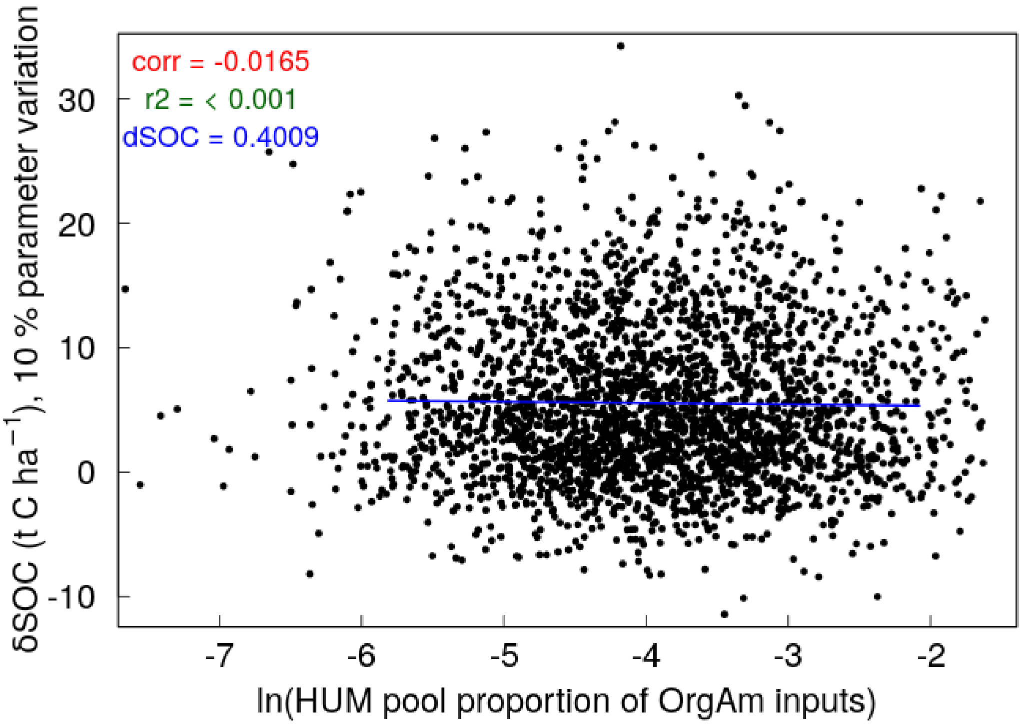

Figure A - 57 The relationship between the proportion of OrgAm inputs going to the HUM pool and SOC stock changes; note the natural log x-axis