extended Rdocumentation

of function sorcering()

from package 'sorcering'

October 8, 2024

Description

SORCERING can be used to model the fate of soil organic carbon (SOC) and soil organic nitrogen (SON) and to calculate N mineralisation rates. It provides a framework that numerically solves differential equations of SOC models based on first-order kinetics. An SOC model can be simply defined or a predefined existing SOC model can be chosen and then run to predict the temporal development of SOC. Beyond this, SORCERING determines the fluxes of SON and N mineralisation / immobilisation. Basic inputs are (1) the model parameters of a given SOC model expressed as the C transfer matrix (including information on decomposition and transfer rates between model pools), (2) either the initial distributions of C and N among model pools as a direct input or time series of at least three C and N measurement points with which these initial distributions can be calculated using linear regression, and (3) time series of C and N inputs and rate modifying environmental factors. In case a predefined SOC model is used, instead of model parameters and time series of rate modifying factors, modelspecific environmental and stand data must be passed for the calculation of decomposition and transfer rates. Moreover, SORCERING provides the options to cover statistical uncertainties by using stochastic repetitions for many input data and parameters as well as to perform model spin-up runs. The fourthorder Runge-Kutta algorithm is used to numerically solve the system of differential equations.

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Contents

Usage

sorcering($A = NULL$, tsteps = $"monthly",$ $CO = NULL,$ $NO = NULL$ $Cin = NULL$, Nin = NULL, Cin_wood = NULL, Nin_wood = NULL, wood_diam = NULL, $xi = NULL,$ $env_in = NULL,$ site = NULL, theta = NULL, theta_unc = NULL, theta_n_unc = 1 , meas_data = NULL, $A_s1 = NULL,$ $CO_S1 = NULL,$ $N\emptyset_S1 = NULL,$ $Cin_S1 = NULL,$ $Nin_S1 = NULL,$ Cin_wood_sl = NULL, Nin_wood_sl = NULL, $wood_diam_s1 = NULL$, $xi_s1 = NULL,$ $env_in_s1 = NULL,$ $site_s1 = NULL,$ sitelist = NULL, meas_data_sl = NULL, calcN = FALSE, calcNbalance = FALSE, $cal₀ = FALSE,$ $calcC₀ = FALSE,$ calcCN_fast_init = FALSE, CTool_input_raw = FALSE, RothC_Cin4C0 = FALSE, C0_fracts = NULL, multisite = FALSE, pooltypes = NULL, $CN_fast_init = 40$, $CN_bio = 9$, CN_spin = NULL, CN_fast_init_sl = NULL, $CN_bio_s1 = NULL,$ CN _spin_sl = $NULL$, init_info = FALSE, model = $"$, spinup = FALSE, t _spin = 2, t _spin_sl = 2)

Arguments

In addition to the arguments descriptions below, Fig. 1 provides a visualisation of the list structure and Fig. 2 provides a visualisation of the content structure of the arguments.

site vector of model-specific length. Contains site-specific information to calculate rate modifying factors (instead of passing them with x i) and initial distributions. When model = "RothC", it must be of length four: sample depth $[mm]$, clay content $[\%]$, black sand status (0 or 1, 0 if unknown or if black sand method is not desired) and CN ratio (0 if unknown, but then either \circ and θ must be passed or calcC0 = TRUE and calcN0 = TRUE, information on CN ratio given in site always takes precedence over internally calculated CN ratios). When model = "C-Tool" or model = "C-Tool-org", it must be of length one: clay content [%]. Only used when model = "RothC" or model = "C-Tool" or model = "C-Tool-org".

- theta either vector with model parameters for predefined models or matrix with rows of such parameters. If it is a matrix, each row is expected to represent a stochastic repetition that covers input uncertainties. If uncertainties are defined by another argument, e.g. Cin or Nin, these determine the number of stochastic repetitions and not theta. Then, if theta is a matrix, a parameter vector is randomly drawn for each uncertainty loop. Each vector (or row of matrix) must be of length 7 when model = "RothC", of length 10 when model = "C-Tool" or model = "C-Tool-org", of length 21 when model = "Yasso07" and of length 30 when model = "Yasso15" or model = "Yasso20". If NULL, model-specific standard parameters are used instead. Only used when model is not NULL. See section 3.3 for details and standard parameters used.
- theta_unc either number or vector of percentage values. If it is a vector, the same modelspecific lengths as described for theta must be used. When used, model parameters modified by taking from the normal distribution around given values (either from theta or predefined values) with a standard deviation of theta_unc. This will be repeated as many times as defined in the ta_n_unc or as defined by uncertainty dimensions of a carbon or nitrogen input argument (e.g. Cin) and lead to unique model results and output list elements. Only used when model is not NULL and theta is not a matrix.
- theta_n_unc number of stochastic repetitions when model parameters for predefined models should be determined from a random distribution. Only used when the number of stochastic repetitions is not defined by another argument (e.g. Cin). Only used when model is not NULL, theta_unc is not NULL and theta is not a matrix.
- meas_data matrix with a number of rows equal to the number of measurement points. The first column defines the time of measurement, the metric of which is based on simulation time steps. The second row must contain values of measured soil organic carbon stock. The third row must contain values of measured soil organic nitrogen and is only used when calcN0 = TRUE. Only used when calc $Co =$ TRUE.
- A_sl list with a length of number of sites to simulate. Each list element represents a site and must be in A format. Only used when multisite = TRUE and model is NULL. When multisite = TRUE, A can be passed instead of A_sl to have the same argument for all sites.

Figure 1: List structure of SORCERING arguments. The arguments listed can either include uncertainties (orange structure path) or not (blue structure path). Arguments marked with an asterisk refer to those in matrix format.

Figure 2: Content structure of SORCERING arguments. Arguments with grey frames depend on using predefined models. Black arrows indicate direct definitions or direct influences. Blue arrows indicate indirect influences that are based on internal function calculations or definitions and can serve as an alternative to the direct definitions.

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Value

sorcering() returns either a list of carbon and nitrogen output values or, when multisite = TRUE, a list broken down by site with result lists for each site. When uncertainties are modeled (as can be defined by passing e.g. Cin, Nin, xi or theta), the output is even extended to include another list dimension that covers these uncertainties. The lowest output list-level contains the following components:

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Package Building Information

The SORCERING code was written in C++ using the R packages Rcpp (Eddelbuettel et al. 2021a) and RcppArmadillo (Eddelbuettel et al. 2021b).

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Details

1 Introduction

SORCERING is a general model framework to describe soil organic carbon (SOC) dynamics and soil organic nitrogen (SON) dynamics based on models of first-order kinetics. It can be applied to any given SOC first-order kinetics model. The approach has already been successfully tested to describe SOC dynamics of Yasso (Tuomi et al. 2009, Viskari et al. 2020; 2022), RothC (Coleman and Jenkinson 1996) and C-Tool (Taghizadeh-Toosi et al. 2014). Moreover, it additionally offers the possibility of modelling N immobilisation and mineralisation by enhancing given SOC models by an additional N module. SORCERING was created using the C++ interface Rcpp (Eddelbuettel et al. 2021a) and can handle multiple sites and multiple stochastic representations with just one function call. This makes SORCERING a computationally efficient SOC and SON modelling tool.

In the following a description of each output value (see section 'Value') is given, details of the optional calculation of initial SOC and SON are presented, and predefined existing models and their functions are described.

2 Output Calculation

2.1 Value C

SORCERING calculates SOC applying a given SOC model for every simulation time step defined by passing tsteps and the number of rows of Cin (or number of rows of matrix elements in Cin_sl). SOC models applied here are defined by a number of pools, each characterised by specific decomposition and turnover rates. The underlying equation of first-order kinetics defines the change of SOC concentration in time as:

$$
\frac{dC(t)}{dt} = Cin(t) + A_e(t) \cdot C(t)
$$
\n(1)

The boundary condition $Cin(t)$ and the initial condition $C(0)$ must be defined beforehand (by passing Cin and C0, or by calculating with SORCERING-specific functions). $A_e(t)$ is composed of transfer matrix *A* (as passed with A or provided by model) and the model-specific generated rate modifying factor series $xi(t)$ (as passed with x_i or calculated for a predefined model):

$$
A_e(t) = (A^T \cdot x i(t))^T
$$

= $A \cdot diag(x i(t))$ (2)

with superscript *^T* denoting transposed matrices. Eq. 1 is valid for scalar values of *A*, *C*, *xi* and *Cin*, as well as for a square matrix *A* with side length of number of SOC pools *n* and related one dimensional vectors *C*, *xi* and *Cin* with length *n*. Each element of *C*, *xi* and *Cin* and each row and column of *A* thus stands for a specific pool. Off-diagonal elements of *A* describe SOC fluxes and diagonal elements describe SOC decomposition. Analytical solutions of eq. 1 are exponential functions and can be very complex with *A* containing many off-diagonals, i.e. SOC transfer between many pool pairs. Therefore, numerical solutions are an efficient way to solve the resulting complex equation system. In SORCERING, this equation system is solved by applying the fourth-order Runge-Kutta method:

$$
C(t) = C(t-1) + \frac{1}{6}(K_1 + 2K_2 + 2K_3 + K_4)
$$
\n(3)

with

$$
K_1 = Cin(t-1) + A \cdot diag(xi(t-1)) \cdot C(t-1)
$$

\n
$$
K_2 = Cin(t-1) + A \cdot diag\left(\frac{xi(t-1) + xi(t)}{2}\right) \cdot \left(C(t-1) + \frac{K_1}{2}\right)
$$

\n
$$
K_3 = Cin(t-1) + A \cdot diag\left(\frac{xi(t-1) + xi(t)}{2}\right) \cdot \left(C(t-1) + \frac{K_2}{2}\right)
$$

\n
$$
K_4 = Cin(t-1) + A \cdot diag(xi(t)) \cdot \left(C(t-1) + K_3\right)
$$
\n(4)

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2.2 Values N and Nloss

As an extension to SOC modelling, SORCERING allows the modelling of SON coupled to the modelling of SOC. Its implementation is based on the following simplifying assumptions: (1) Nitrogen transfer and turnover rates are equal to carbon decomposition and transfer rates. (2) There is no N limitation in the soil, i.e. mineral N is always available for N immobilisation processes. (3) CN ratios of single pools are only affected by external inputs of C and N. The transfer of organic matter among pools does not affect CN ratios. As for SOC, the development of SON depends on boundary and initial conditions: $Nin(t)$ and $N(0)$ (passed with Nin and N0, or calculated with SORCERING-specific functions).

Given the input-considered SOC losses

$$
C_{loss} = C(t-1) + Cin(t-1) - C(t)
$$
\n(5)

and the input-considered NOC losses

$$
N_{loss} = N(t-1) + Nin(t-1) - N(t)
$$
\n(6)

between time points t and $t - 1$, and assuming equal C and N decomposition rates

$$
\frac{C_{loss}}{C(t)} = \frac{N_{loss}}{N(t)}\tag{7}
$$

the amount of SON at each simulation time step is then calculated pool-wise as:

$$
N(t) = \frac{N(t-1) + Nin(t-1)}{\left(\frac{C_{loss}}{C(t)} + 1\right)}
$$
\n(8)

2.3 Values Nmin, Nmin.sink $\langle 1 \rangle$, ..., Nmin.sink $\langle n \rangle$

Along with modelling SON, further quantities such as mineralisation rates are determined. In the following mineralisation is mentioned as if it includes mineralisation (positive values) and immobilisation (negative values). In contrast to nitrogen losses (eq. 6), mineralisation rates contain information about sources and sinks of SON. Pool-specific N mineralisation *Nmin*.*sink* ⟨*j*⟩ and N mineralisation *Nmin* are related as follows:

$$
Nmin_j(t) = \sum_{p=1}^{n} Nmin.sink \langle j \rangle_p(t)
$$
\n(9)

for each simulation time point *t*, each pool $j = 1, ..., n$ and each pool $p = 1, ..., n$ and *n* total pools. Or in other words, the row sum of *Nmin.sink* $\langle j \rangle$ at one simulation time point equals the jth column of *Nmin* at that time point. Mineralisation rates and sinks are read from a mineralisation rates matrix *Nmin*.*mat*:

$$
Nmin_1(t), ..., Nmin_n(t) = \sum_{i=1}^n Nmin_matrix_i(t), ..., \sum_{i=1}^n Nmin_matrix_i(t)
$$
\n(10)

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$$
Nmin.sink\langle j \rangle_1(t),..., Nmin.sink\langle j \rangle_n(t) = Nmin.mat_{j,1}(t),..., Nmin.mat_{j,n}(t)
$$
\n(11)

and using the fourth-order Runge-Kutta Method *Nmin*.*mat* at time point *t* is calculated as follows:

$$
Nmin.max(t) = -\frac{1}{6}(Kn_1 + 2Kn_2 + 2Kn_3 + Kn_4)
$$
\n(12)

with

$$
Kn_1 = (A \cdot diag(xi(t-1) \cdot C(t-1)))^T \cdot diag\left(\frac{1}{CN(t)}\right)
$$

\n
$$
Kn_2 = \left(A \cdot diag\left(\frac{xi(t-1) + xi(t)}{2} \cdot \left(C(t-1) + \frac{K_1}{2}\right)\right)\right)^T \cdot diag\left(\frac{1}{CN(t)}\right)
$$

\n
$$
Kn_3 = \left(A \cdot diag\left(\frac{xi(t-1) + xi(t)}{2} \cdot \left(C(t-1) + \frac{K_2}{2}\right)\right)\right)^T \cdot diag\left(\frac{1}{CN(t)}\right)
$$

\n
$$
Kn_4 = (A \cdot diag(xi(t) \cdot (C(t-1) + K_3)))^T \cdot diag\left(\frac{1}{CN(t)}\right)
$$
\n(13)

and superscript *^T* denoting transposed matrices and

$$
CN(t) = \begin{cases} \frac{C(t)}{N(t)}, & \forall N(t) > 0\\ n.c., & \text{otherwise} \end{cases}
$$
 (14)

and K_1 - K_3 taken from eq. system (4). Note that $Kn_{1...4}$ are matrices and $K_{1...3}$ are vectors. As changes in SON must match the sums of all mineralisation paths, the sums over soil pools of Nloss and Nmin, respectively, must be approximately equal for all simulation time points:

$$
\sum_{p=1}^{n} N loss_p(t) \approx \sum_{p=1}^{n} N min_p(t)
$$
\n(15)

A verification of this relation is given by Nbalance (see below).

2.4 Value Nbalance

The overall N change between two time steps is calculated as:

$$
\Delta N(t) = \sum_{p=1}^{n} N_p(t-1) - \sum_{p=1}^{n} N_p(t)
$$
\n(16)

The total system N balance serves as a verification output. Both of the following equations should always give results close to zero:

$$
N_{bal1}(t) = \sum_{p=1}^{n} Nin_p(t-1) + \Delta N(t) - \sum_{p=1}^{n} Nloss_p(t) \approx 0
$$
 (17)

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$$
N_{bal2}(t) = \sum_{p=1}^{n} N i n_p(t-1) + \Delta N(t) - \sum_{p=1}^{n} N m i n_p(t) \approx 0
$$
\n(18)

 $\Delta N(t)$ is saved in the first column, $N_{bal1}(t)$ in the second and $N_{bal2}(t)$ in the third column of Nbalance.

3 Additional Features and Input Processing

3.1 Estimation of Initial Soil Organic Carbon

If there is no initial SOC data, total initial SOC $\Sigma C(0)_{est}$ can be estimated if there are more than two SOC measurement points (passed with meas_data) and the model is called with calc $C0 = TRUE$. Then, $\Sigma C(0)_{est}$ is the intercept value (at the first time point) of the linear regression line through measured SOC data. In order to derive the initial SOC for each model pool, information about the initial SOC shares among pools CO_{fracts} is required. It can be passed with CO_{rfacts} or, when a predefined SOC model is used, the model's standard fractions are taken (see section 3.3). The initial SOC distribution among the pools is then calculated with:

$$
C(0)^n_{p=1} = \Sigma C(0)_{est} \cdot C0_{fracts,p} \tag{1}
$$

with *n* being the number of SOC pools.

3.2 Estimation of Initial Soil Organic Nitrogen

If there is no initial SON data, similarly to SOC, total initial SON Σ*N*(0)*est* can be estimated if there are more than two SON measurement points (passed with meas_data) and the model is called with calcN0 $=$ TRUE. Likewise, $\Sigma N(0)$ _{*est*} is the intercept value (at the first time point) of the linear regression line through measured SON data. To estimate the initial pool distribution of SON the model used must be classified into fast, slow and resistant pools (either via pooltypes or automatically when a predefined SOC model is used). Then, the initial SON in fast pools is calculated as:

$$
N_{fast}(0) = \frac{C_{fast}(0)}{CN_{fast}(0)}
$$
\n
$$
(2)
$$

If calcCN_fast_init = FALSE (default), the initial CN ratio of fast pools $CN_{fast}(0)$ is defined in CN_fast_init (40 by default). If calcCN_fast_init = TRUE, *CNf ast*(0) is estimated from organic inputs, or more specifically, it is thought to be typically the result of the direct input of organic C and N into these pools. Consequently, this method assumes that there has been similar management or natural input in the past, and the organic input during the simulation is used to estimate the initial CN ratio:

$$
CN_{fast}(0) = \sum_{t=t_{in,first}}^{t_{in,last}} CN_{in}(t) \cdot weight(t)
$$
\n(3)

However, not each input should have the same impact. Therefore, higher weights for early inputs and for higher amounts of inputs are used:

$$
weight(t) = \frac{weight_t(t) \cdot weight_c(t)}{\sum_{T=t_{in,first}}^{t_{in,last}} (weight_t(T) \cdot weight_c(T))}
$$
(4)

trivially with

$$
\sum_{t=t_{in,first}}^{t_{in,last}} weight(t) = 1
$$
\n(5)

and with mass weight defined as:

$$
weight_c(t) = \frac{C_{in}(t)}{\sum_{t=t_{in,first}}^{t_{in,last}} C_{in}(t)}
$$
\n(6)

and temporal weight defined as:

$$
weight_t(t) = \frac{1}{t^2}
$$
 (7)

If the sum of total carbon input during the simulation is smaller than the initial SOC, it is assumed that calculating the CN ratio from the inputs alone would lead to unrealistic results. As a solution, the missing amount of carbon is placed at the beginning of the *Cin* vector and CN_fast_init at the beginning of the CNfast vector for the calculations of equations 3 and 6. The user will be informed about those events when init_info = TRUE.

The initial amount of SON in slow and resistant pools $N_{slow}(0)$ and $N_{res}(0)$ are calculated as follows:

$$
N_{slow}(0) = \frac{C_{slow}(0)}{CN_{slow}(0)}
$$
\n(8)

$$
N_{res}(0) = \frac{\Sigma C(0)}{\Sigma CN(0)_{est}} - (N_{fast}(0) + N_{slow}(0))
$$
\n(9)

with *CNslow* initially starting with the given value of CN_bio (9 by default). If unrealistic values result out of the calculation, i.e. $N_{res}(0) < 0$ or $CN_{res}(0) = \frac{C_{res}(0)}{N_{res}(0)} > 100$, $CN_{slow}(0)$ iteratively gets raised by 0.1 and eqs. 8 and 9 are iteratively repeated until realistic results are achieved. Assuming higher CN values in resistant pools than in slow pools, if *CNres*(0) is smaller than *CNslow*(0), *CNslow*(0) iteratively gets lowered by 0.1 and eqs. 8 and 9 are iteratively repeated until *CNres*(0) is not smaller than $CN_{slow}(0)$. Initial total CN ratio $CN(0)$ is calculated as follows:

$$
\Sigma CN(0)_{est} = \frac{\Sigma C(0)_{est}}{\Sigma N(0)_{est}}\tag{10}
$$

and $C_i(0)$ and $N_i(0)$ being the intercept values by applying linear regressions through measured SOC and SON values, respectively. One should note that $\Sigma C(0)$ may not be the same as $\Sigma C(0)_{est}$ and therefore use the estimated SOC for the measured data-based calculation of *N*(0).

3.3 Predefined Models

SORCERING can be run using existing predefined SOC models. The information about the transfer matrix and the rate modifying factors, which are formerly passed with \land and $\times i$, are then calculated based on environment-specific information env_in (mandatory) and model parameters theta (when not passed, standard values will be used). At the moment one can choose among five models: Yasso07 (Tuomi et al. 2009), Yasso15 (Viskari et al. 2020), Yasso20 (Viskari et al. 2022), RothC (Coleman and Jenkinson 1996) or C-Tool (Taghizadeh-Toosi et al. 2014).

According to the definitions given in section 2.1, *A* is a matrix of size $n \times n$ and $xi(t)$ is a vector of length *n*, with *n* being the number of pools. For all predefined models, $n = 5$, except for C-Tool, where $n = 6$. When using predefined models, the *xi*(*t*) vectors are calculated based on annual decomposition rates. Using the default value of tsteps = "monthly", $xi(t)$ is divided by 12, which is not taken into account below.

When using predefined SOC models, the pooltypes vector does not need to be passed since default values are used. These values were created be the SORCERING developers out of logical considerations and with the aim of SON initialization.

3.3.1 Yasso

When modelling with Yasso, the user must pass either model = "Yasso07", model = "Yasso15" or model = "Yasso20" according to the three versions provided.

Parameters

When model = $"Y$ asso07", a theta default vector of

$$
\Theta_{Y07} = (kA, kW, kE, kN, kH, p_1...p_{12}, pH, \beta_1, \beta_2, \gamma) \tag{11}
$$

is used, and when model = "Yasso15" or model = "Yasso20", a theta default vector of

$$
\Theta_{Y15} = \Theta_{Y20} = (kA, kW, kE, kN, kH, p_1...p_{12}, pH, \beta_1, \beta_2, \beta_{N1}, \beta_{N2}, \beta_{H1}, \beta_{H2}, \gamma, \gamma_N, \gamma_H, \theta_1, \theta_2, r) \tag{12}
$$

is used, with standard values listed in Table 1.

 $\overline{}$

Transfer Matrix

For all Yasso versions *A* looks like this:

$$
A = \begin{pmatrix} -kA & p_1 & p_2 & p_3 & 0 \\ p_4 & -kW & p_5 & p_6 & 0 \\ p_7 & p_8 & -kE & p_9 & 0 \\ p_{10} & p_{11} & p_{12} & -kN & 0 \\ pH & pH & pH & pH & -kH \end{pmatrix}
$$
(13)

Environmental Factors

When model = $"Y$ asso $07"$, $xi(t)$ is calculated as follows:

$$
xi_1(t) = xi_2(t) = xi_3(t) = xi_4(t) = xi_5(t)
$$

= $e^{\beta_1 T + \beta_2 T^2} (1 - e^{\gamma p})$ (14)

When model = "Yasso15" or model = "Yasso20", $xi(t)$ is calculated as follows:

$$
xi_1(t) = x i_2(t) = x i_3(t)
$$

= $e^{\beta_1 T(t) + \beta_2 T(t)^2} \left(1 - e^{\gamma p(t)}\right)$ (15)

$$
xi_4(t) = e^{\beta_{N1}T(t) + \beta_{N2}T(t)^2} \left(1 - e^{\gamma_N p(t)}\right)
$$
\n(16)

$$
xi_5(t) = e^{\beta_{H1}T(t) + \beta_{H2}T(t)^2} \left(1 - e^{\gamma_{H}p(t)}\right)
$$
\n(17)

with T in degrees Celsius and p in mm, both passed with env_in .

Initial Pool Properties

Initial pool properties described here apply equally to all three Yasso versions. When calcN0 = TRUE, a pooltypes default vector of $(1,1,1,2,3)$ is used. When calcC0 = TRUE and C0_fracts = Null, a C_0 fracts default vector of $(0.15, 0.025, 0.025, 0.35, 0.45)$ is used, which could be a plausible initial carbon distribution for the Yasso pools. However, these values are not intended by the Yasso developers. It is recommended to perform model spinup runs for the initialisation of SOC.

Input from Woody Litter

Woody litter is only considered when model = "Yasso15" or model = "Yasso20". Then instead of Cin or Cin_sl, and instead of Nin or Nin_sl, Cin_wood or Cin_wood_sl, and Nin_wood or Nin_wood_sl must be passed. When model = "Yasso15" or model = "Yasso20", by default an additional set of rate modifying factors $xi_w(t)$ for each wood diameter class is calculated:

$$
xi_w(t) = min(1, \left(1 + \theta_1 \cdot diam + \theta_2 \cdot diam^2\right)^{-r})
$$
\n(18)

with θ_1, θ_2 and *r* as described in section 3.3.1 and *diam* being the wood diameter as described in wood_diam or wood_diam_sl. Equation 2 then is exchanged with:

$$
A_e(t) = (A^T \cdot x i(t) \cdot x i_w(t))^T
$$

= $A \cdot diag(x i(t) \cdot x i_w(t))$ (19)

Since each wood diameter produces a new $xi_w(t)$ the model calculation for each wood class is automatically run separately and after each time step the overall new SOC and SON are calculated as weighted means over all wood diameter input runs. The idea behind this separation of input diameter classes is that woody components are subject to delayed decomposition.

3.3.2 RothC

The RothC application used here uses standard RothC parameters and properties for agricultural soils (Coleman and Jenkinson 2014). This particularly affects the estimation of initial SOC. Therefore, especially if modelling non-agricultural soils, it is recommended to use the SOC input and pass RothC_Cin4C0 = TRUE to estimate the initial SOC.

Parameters

When model = $"RothC",$ a theta default vector of

$$
\Theta_R = (k_{DPM}, k_{RPM}, k_{BIO}, k_{HUM}, k_{IOM}, R_{W,max}, R_{W,min})
$$
\n(20)

is used, with standard values listed in Table 2. Note that $R_{W,max}$ and $R_{W,min}$ are not typically intended by RothC developers to be modifiable parameters.

Transfer Matrix

A is build as follows:

 $A =$ $\sqrt{ }$ $\overline{}$ $-k$ *DPM* 0 0 0 0 0 0 −*kRPM* 0 0 0 $B \cdot k_{DPM}$ $B \cdot k_{RPM}$ $B \cdot k_{BIO} - k_{BIO}$ $B \cdot k_{HUM}$ 0 $H \cdot k_{DPM}$ $H \cdot k_{RPM}$ $H \cdot k_{BIO}$ $H \cdot k_{HUM} - k_{HUM}$ 0 0 0 0 0 −*kIOM* \setminus $\begin{array}{c} \hline \end{array}$ (21)

with

$$
B = \frac{0.46}{1 + 1.67 \left(1.85 + 1.6e^{-0.0786 \cdot clay} \right)}\tag{22}
$$

$$
H = \frac{0.54}{1 + 1.67 \left(1.85 + 1.6e^{-0.0786 \text{ }c \text{ }l \text{ }a \text{y}}\right)}\tag{23}
$$

and *clay* as defined in site.

Environmental Factors

 $xi(t)$ is calculated as follows:

$$
xi_1(t) = x i_2(t) = x i_3(t) = x i_4(t) = x i_5(t)
$$

= $R_T(t) \cdot R_C(t) \cdot R_W(t)$ (24)

with $R_T(t)$ being the rate modifying factor series for temperature:

$$
R_T(t) = \begin{cases} \frac{47.91}{1 + e^{\left(\frac{106.06}{T(t) + 18.27}\right)}}, & \forall T(t) > -18.27\\ 0, & \text{otherwise} \end{cases}
$$
(25)

and $R_C(t)$ being the soil cover rate modifying factor:

$$
R_C(t) = \begin{cases} 1, & \forall s_{cover}(t) = 0 \text{ or } s_{cover}(t) = 2\\ 0.6, & \forall s_{cover}(t) = 1 \end{cases}
$$
(26)

and $R_W(t)$ being the topsoil moisture deficit (TSMD) rate modifying factor:

$$
R_W(t) = \begin{cases} R_{W,max}, & \forall TSMD_{acc}(t) \ge 0.444 \cdot TSMD(t) \\ R_{W,min} + (R_{W,max} - R_{W,min}) \frac{TSMD_{max, pot} - TSMD_{acc}(t)}{TSMD_{max, pot} - 0.444 \cdot TSMD_{max, pot}}, & \text{otherwise} \end{cases}
$$
(27)

and $TSMD_{max, pot}(t)$ being the potentially, regardless of land cover, on the maximum remaining TSMD

$$
TSMD_{max,pot}(t) = \begin{cases} TSMD_{max}(t)/1.8, & \forall s_{cover}(t) = 0\\ TSMD_{max}(t), & \forall s_{cover}(t) = 1 \text{ or } s_{cover}(t) = 2 \end{cases}
$$
(28)

and *T SMDmax*(*t*) being the maximum TSMD

$$
TSMD_{max}(t) = -(20 + 1.3 \cdot clay - 0.01 \cdot clay^2) \frac{depth}{23}
$$
 (29)

and *T SMDacc*(*t*) being the accumulated TSMD

$$
TSMD_{acc}(t) = \n\begin{cases}\n\max(TSMD(t), WF(t)), & \forall WF(t) < 0 \text{ and } t = 0 \\
\max(TSMD(t), TSMD_{acc}(t-1) + WF(t)), & \forall TSMD_{acc}(t-1) + WF(t) < 0 \text{ and } t > 0 \\
0, & \text{otherwise}\n\end{cases}\n\tag{30}
$$

with

$$
TSMD(t) = \begin{cases} TSMD_{max}(t)/1.8, & \forall s_{cover}(t) = 0 \text{ or } s_{cover}(t) = 2\\ TSMD_{max}(t), & \forall s_{cover}(t) = 1 \end{cases} \tag{31}
$$

and $WF(t)$ describing the water flux

$$
WF(t) = p(t) - ETP(t)
$$
\n(32)

with *clay* and *depth* as defined in site and temperature *T*, precipitation *p*, evapotranspiration *ET P* and soil cover index s_{cover} as defined in env_in. Please note that $TSMD_{max,pot}(t)$ only differs from *TSMD*(*t*) when $s_{cover}(t) = 2$.

Initial Pool Properties

When calcN0 = TRUE, a pooltypes default vector of $(1,1,2,2,3)$ is used. When calcC0 = TRUE and CO_f fracts = Null, initial SOC fractions are calculated for the first four SOC pools, and the initial SOC of the fifth pool $C(0)_{IOM}$ (inert pool IOM, as described by Falloon et al. 1998) is calculated directly out of the total $C(0)$:

$$
C(0)_{IOM} = 0.049(C(0) - C0_{rel})^{1.139} + C0_{rel}
$$
\n(33)

with *C*0*rel* increasing the SOC in the inert pool of black sands based on a method of Springob and Kirchmann (2010):

$$
CO_{rel} = \begin{cases} 0, & \forall CN(0) \le 11 \vee bs_{flag} = 0\\ \frac{C(0)(11 - CN(0))}{CN(0)(\frac{11}{35} - 1)}, & \forall CN(0) > 11 \wedge bs_{flag} = 1 \end{cases}
$$
(34)

and *bsf lag* being the identifier of black sand soils as defined in site, and *CN*(0) being the CN ratio as defined in site or, if specified there by entry $= \emptyset$, as calculated. In the letter case, the CN ratio is calculated either as in eq. 10 or from *C*0 and *N*0, depending on whether measured data should be used to estimate the initial CN ratio.

The initial state of the remaining carbon pools is calculated using a simplified version of the analytical solution from Dechow et al. (2019) assuming steady-state conditions. The initial SOC distribution among the five pools is then calculated as:

$$
(C(0)_1, C(0)_2, C(0)_3, C(0)_4, C(0)_5) = (f_1 \cdot C(0), f_2 \cdot C(0), f_3 \cdot C(0), f_4 \cdot C(0), C(0)_{IOM})
$$
(35)

with

$$
(f_1, f_2, f_3, f_4) = (f_{dpm}, f_{rpm}, f_{bio}, f_{hum}) \cdot \frac{C(0) - C(0)_{IOM}}{C(0)}
$$
(36)

and

$$
f_{\text{dpm}} + f_{\text{rpm}} + f_{\text{bio}} + f_{\text{hum}} = 1 \tag{37}
$$

Following Dechow et al. (2019), these fractions are calculated as:

$$
f_{dpm} = \frac{fractI_1 \cdot k_{DPM}^{-1}}{fractI_1 \cdot u_{dpm} + fractI_2 \cdot u_{rpm}}
$$
(38)
\n
$$
f_{rpm} = \frac{fractI_2 \cdot k_{RPM}^{-1}}{fractI_1 \cdot u_{dpm} + fractI_2 \cdot u_{rpm}}
$$

\n
$$
f_{bio} = \frac{fractI_1 \cdot u_{bio,dpm} + fractI_2 \cdot u_{bio,rpm}}{fractI_1 \cdot u_{dpm} + fractI_2 \cdot u_{ppm}}
$$

\n
$$
f_{hum} = \frac{fractI_1 \cdot u_{hum,dpm} + fractI_2 \cdot u_{hum,rpm}}{fractI_1 \cdot u_{dpm} + fractI_2 \cdot u_{rpm}}
$$

with

$$
fractI_1 = \begin{cases} 0.59, & \text{RothC_Cin4C0 = FALSE} \\ \frac{C_{in, tot,DPM}}{C_{in, tot,DPM} + C_{in, tot,RPM}}, & \text{RothC_Cin4C0 = TRUE} \end{cases} \tag{39}
$$

and

$$
fractI_2 = 1 - fractI_1 \tag{40}
$$

and *Cin*,*tot*,*DPM* and *Cin*,*tot*,*RPM* being the total SOC inputs (during the following simulation) into DPM and RPM pools, and

 $u_{dpm} = k_{DPM}^{-1} + u_{bio,dpm} + u_{hum,dpm}$ (41) $u_{rpm} = k_{RPM}^{-1} + u_{bio,rpm} + u_{hum,rpm}$

and

$$
u_{hum,dpm} = u_{hum,rpm} = \frac{1}{a_{1,2}} (-u_{bio,dpm}) \cdot a_{1,1} - \alpha_1
$$
\n(42)

and

$$
u_{bio,4pm} = u_{bio,rpm} = \frac{\alpha_2 \cdot a_{1,2} - \alpha_1 \cdot a_{2,2}}{a_{1,1} \cdot a_{2,2} - a_{1,2} \cdot a_{2,1}} \tag{43}
$$

and

$$
a_{1,1} = k_{BIO} \cdot (\alpha_1 - 1)
$$

\n
$$
a_{1,2} = k_{HUM} \cdot \alpha_1
$$

\n
$$
a_{2,1} = k_{BIO} \cdot \alpha_2
$$

\n
$$
a_{2,2} = k_{HUM} \cdot (\alpha_2 - 1)
$$
\n(44)

and

$$
\alpha_1 = cue \cdot 0.46
$$

\n
$$
\alpha_2 = cue \cdot 0.54
$$
\n(45)

and carbon use efficiency

$$
cue = \frac{1}{1 + 1.67(1.85 + 1.6e^{-0.0786 \cdot clay})}
$$
(46)

and *clay* being the clay content as defined in site.

3.3.3 C-Tool

C-Tool typically needs to be run twice, one time with model = "C-Tool" with Cin (and if desired Nin) of crop input and one time with model = "C-Tool-org" with Cin (and Nin) of organic input. In case of model = "C-Tool-org", $CØ$ (and $NØ$) should be zero. The user must calculate the overall C-Tool result independently as the sum of both runs. Thus, "C-Tool-org" is not a separate model, but rather a running mode of C-Tool.

Parameters

When model = "C-Tool" or model = "C-Tool-org", a theta default vector of

$$
\Theta_C = (k_{FOMt}, k_{HUMt}, k_{ROMt}, k_{FOMs}, k_{HUMs}, k_{ROMs}, t_f, f_{CO_2}, f_{ROM}, f_{HUM})
$$
\n
$$
\tag{47}
$$

is used, with standard values taken from Taghizadeh-Toosi (2015) listed in Table 3.

Table 3: C-Tool standard parameters.

Transfer Matrix

A is build as follows:

$$
A = \begin{pmatrix} -k_{FOMt} & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & -k_{HUMt} & 0 & 0 & 0 & 0 & 0 \\ 0 & a_{32} & -k_{ROMt} & 0 & 0 & 0 & 0 \\ a_{41} & 0 & 0 & -k_{FOMs} + a_{44} & 0 & 0 & 0 \\ 0 & a_{52} & 0 & a_{54} & -k_{HUMs} + a_{55} & 0 \\ 0 & 0 & a_{63} & 0 & a_{65} & -k_{ROMs} + a_{66} \end{pmatrix}
$$
 (48)

with

$$
ai_{21} = (1 - t_f) \cdot h \cdot k_{FOMt}
$$
\n
$$
ai_{41} = t_f \cdot k_{FOMt}
$$
\n
$$
ai_{32} = f_{ROM} \cdot k_{HUMt}
$$
\n
$$
ai_{52} = (1 - f_{CO_2} - f_{ROM}) \cdot k_{HUMt}
$$
\n
$$
ai_{63} = (1 - f_{CO_2}) \cdot k_{ROMt}
$$
\n
$$
ai_{44} = t_f \cdot k_{FOMs}
$$
\n
$$
ai_{54} = (1 - t_f) \cdot h \cdot k_{FOMs}
$$
\n
$$
ai_{65} = f_{ROM} \cdot k_{HUMs}
$$
\n
$$
ai_{66} = (1 - f_{CO_2}) \cdot k_{ROMs}
$$

and *h* being a factor that depends on clay content:

$$
h = \frac{1}{1 + 1.67(1.85 + 1.6 \cdot e^{-7.86 \frac{clay}{100}})}
$$
(50)

and *clay* being the clay content as defined in site.

Input Transformation

If the input of SOC and SON is not defined for the single pools but only for topsoil and subsoil fractions (CTool_input_raw = TRUE) the standard way of distributing the fractions among the pools is used:

$$
Cin(t) =
$$

\n
$$
(Cin_{raw,top} \cdot (1 - F_{hum,clay}), Cin_{raw,top} \cdot F_{hum,clay}, 0, Cin_{raw,sub} \cdot (1 - F_{hum,clay}), Cin_{raw,sub} \cdot F_{hum,clay}, 0)
$$

\n
$$
Nin(t) =
$$

\n
$$
(Nin_{raw,top} \cdot (1 - F_{hum,clay}), Nin_{raw,top} \cdot F_{hum,clay}, 0, Nin_{raw,sub} \cdot (1 - F_{hum,clay}), Nin_{raw,sub} \cdot F_{hum,clay}, 0)
$$

\n(51)

with

$$
F_{hum,clay} = max(0, f_{HUM} - h)
$$
\n⁽⁵²⁾

and *fhum* and *h* as defined above, and with *Cinraw*,*top* and *Ninraw*,*top* being topsoil inputs and *Cinraw*,*sub* and *Ninraw*,*sub* being subsoil inputs.

Environmental Factors

 $xi(t)$ is calculated as follows:

32 sorcering and the set of the set

 (54)

$$
xi_1(t) = xi_2(t) = xi_3(t) = ft_t(t)
$$

\n
$$
xi_4(t) = xi_5(t) = xi_6(t) = ft_s(t)
$$
\n(53)

and

$$
ft_{t} = 7.24 \cdot e^{-3.432 + 0.168T_{est,t}(t)(1 - \frac{T_{est,t}(t)}{73.8})}
$$

$$
ft_{s} = 7.24 \cdot e^{-3.432 + 0.168T_{est,s}(t)(1 - \frac{T_{est,s}(t)}{73.8})}
$$

and

$$
T_{est,t} = \bar{T} + amp \cdot e^{-\frac{d_t}{10 \cdot d_{damp}} \cdot \sin(\rho \cdot (doy - of fset)) \cdot 86400 - \frac{d_t}{10 \cdot d_{damp}}}
$$
(55)

$$
T_{est,s} = \bar{T} + amp \cdot e^{-\frac{d_s}{10 \cdot d_{damp}} \cdot \sin(\rho \cdot (doy - of fset)) \cdot 86400 - \frac{d_s}{10 \cdot d_{damp}}
$$

with \bar{T} being the average annual temperature, *amp* being the temperature range that lays between the 25% and the 75% quantile, *d^t* the number of the decimeter-wide soil layer that is relevant for the topsoil, *d*_{*s*} the one that is relevant for the subsoil (with standard values $d_t = 2 \text{ dm}$ and $d_s = 3 \text{ dm}$), furthermore with d_{damp} being the damping depth, ρ being the angular frequency (= $\pi \cdot 2/365/24/3600 = 1.992385$ · 10−⁷ sec−¹), *doy* being the day of the year and *o f f set* being defined as 110 days. *T*¯ is calculated using data from tsteps and env_in. Since *amp* is based on within-year fluctuations it is recommended to use a temporal resolution not coarser than a monthly one. Note that the function from RcppArmadillo (Eddelbuettel et al. 2021b) used to calculate the quantiles is equivalent to type 5 of the R quantile function. *ddamp* is calculated as follows:

$$
d_{damp} = \sqrt{\frac{2Th_{diff}}{\rho}} = 1.874401 \,\text{m} \tag{56}
$$

with default thermal diffusivity of solid soil Th_{diff} of $0.35 \cdot 10^{-6}$ m²sec⁻¹.

Initial Pool Properties

When calcN0 = TRUE, a pooltypes default vector of $(1,2,3,4,5,6)$ is used. When calcC0 = TRUE and C0_fracts = Null, a C0_fracts default vector of

$$
COfracts = (fFOMt, fHUMt, fROMt, fFOMs · sf, fHUMs · sf, fROMs · sf)
$$
(57)
= (0.0316, 0.4804, 0.488, 0.003 · sf, 0.3123 · sf, 0.6847 · sf)
= (0.0316, 0.4804, 0.488, 0.00338298, 0.35216822, 0.77210880)

is used, with *fFOMt*, *fHUMt* and *fROMt* being the fresh organic, humus and resistant topsoil matter fractions, and *fFOMt*, *fHUMt* and *fROMt* being those of the subsoil, and with *s f* being the subsoil factor defined as

$$
sf = \frac{0.53}{0.47} = 1.12766\tag{58}
$$

Note that by default the first three pools in C-Tool represent the upper soil. Thus, to compare with other SOC models only the first three pools of the C-Tool output are relevant.

Examples

```
#1 RothC application with fictional input for a single site
```
#1.1 Input

```
data(RothC_Cin_ex, RothC_Nin_ex, RothC_N0_ex, RothC_C0_ex, RothC_xi_ex,
 RothC_site_ex, RothC_env_in_ex) #fictional data
```
#1.2 Simulations

#In the following two methods are presented, one with a RothC as a predefined #model (1.2.1), one where the RothC rate modifying factors must be calculated #beforehand (1.2.2). Both methods lead to the same results.

#1.2.1 Simulation with predefined model

```
out_rothC <- sorcering( model="RothC", site=RothC_site_ex, env_in=RothC_env_in_ex,
 Cin=RothC_Cin_ex, Nin=RothC_Nin_ex, N0=RothC_N0_ex, C0=RothC_C0_ex,
  calcN=TRUE, tsteps="monthly")
```
#1.2.2 Simulation with own model definition and rate modifying factor definition

A_RothC <- fget_A_RothC(clay=30) #create transfer matrix for RothC out_rothC_own <- sorcering(A=A_RothC , xi=RothC_xi_ex, Cin=RothC_Cin_ex,

Nin=RothC_Nin_ex, N0=RothC_N0_ex, C0=RothC_C0_ex, calcN=TRUE, tsteps="monthly") #Note that RothC_xi_ex contains site and model specific rate modifying factors that #are only valid in this specific example. Generally, xi must be calculated by the #user for different environmental conditions and SOC models used.

#1.3 Results

```
#output structure summary
summary(out_rothC)
#show that results of 1.2.1 and 1.2.2 differ negligibly
all( abs(out_rothC$C-out_rothC_own$C) < 1e-14)
all( abs(out_rothC$N-out_rothC_own$N) < 1e-14)
#example plot
  oldpar <- par(no.readonly=TRUE) #save old par
par(mfrow=c(1,1),mar=c(4,4,1,4))
plot(rowSums(out_rothC$N),axes=FALSE, col=1, cex.lab=2,xlab="",ylab="",ylim=c(0,9),
  pch=20)
par(new=TRUE)
plot(rowSums(RothC_Cin_ex)/rowSums(RothC_Nin_ex),
  axes=FALSE,col=2, cex.lab=2,xlab="",ylab="",ylim=c(0,60),pch=20)
axis(side=2, pos=0,
  labels=(0:6)*1.5, at=(0:6)*10, hadj=0.7, padj=0.5, cex.axis=2,las=1,col.axis=1)
axis(side=4, pos=60,
  labels=(0:6)*10, at=(0:6)*10, hadj=0, padj=0.5, cex.axis=2, las=1,col.axis=2)
axis(side=1, pos=0,
 labels= (0:6)*10 , at=(0:6)*10, hadj=0.5, padj=0, cex.axis=2)
title(ylab=expression("total N [t ha"^-1*"]"), line=2, cex.lab=2)
mtext("C input / N input", side=4, line=2, cex=2,col=2)
title(xlab="time", line=2, cex.lab=2)
par(oldpar) #back to old par
```

```
#2 RothC application with fictional input for a multiple site application
```
#2.1 Input

```
data(RothC_Cin_ex_sl, RothC_Nin_ex_sl, RothC_N0_ex, RothC_C0_ex, RothC_site_ex,
 RothC_env_in_ex) #fictional data
```

```
#2.2. Simulation
```

```
out_multi_rothC <- sorcering( model="RothC", site_sl=rep(list(RothC_site_ex),3),
  env_in_sl=rep(list(RothC_env_in_ex),3), Cin_sl=RothC_Cin_ex_sl,
 Nin_sl=RothC_Nin_ex_sl, N0_sl=rep(list(RothC_N0_ex),3),C0_sl=rep(list(RothC_C0_ex),3),
 calcN=TRUE, tsteps="monthly", multisite=TRUE,
  sitelist=list("normal","half_input","double_Cin"))
```

```
#2.3 Results
```

```
#output structure summary
summary(out_multi_rothC$normal)
summary(out_multi_rothC$half_input)
summary(out_multi_rothC$double_Cin)
```

```
#example plot
oldpar <- par(no.readonly=TRUE) #save old par
par(mfrow=c(1,1),mar=c(4,4,1,4))
for (listelement in c(1:3))
{
 lwidth<-1
 if (listelement==2)lwidth<-3
 plot(rowSums(out_multi_rothC[[listelement]]$N),axes=FALSE, col=1,type="l", lwd=lwidth,
     lty=listelement+2,cex.lab=2,xlab="",ylab="",ylim=c(0,18))
  par(new=TRUE)
  plot(rowSums(RothC_Cin_ex_sl[[listelement]])/rowSums(RothC_Nin_ex_sl[[listelement]]),
      type="l", lwd=lwidth, lty=listelement+2,axes=FALSE,col=2, cex.lab=2,xlab="",
     ylab="",ylim=c(0,120))
 par(new=TRUE)
}
axis(side=2, pos=0,
 labels=(0:6)*3, at=(0:6)*20, hadi=0.7, pad=0.5, cex.axis=2, las=1, col.axis=1)axis(side=4, pos=60,
 labels=(0:6)*20, at=(0:6)*20, hadj=0, padj=0.5, cex.axis=2, las=1,col.axis=2)
axis(side=1, pos=0,
 labels= (0:6)*10 , at=(0:6)*10, hadj=0.5, padj=0, cex.axis=2)
title(ylab=expression("total N [t ha"^-1*"]"), line=2, cex.lab=2)
mtext("C input / N input", side=4, line=2, cex=2,col=2)
title(xlab="time", line=2, cex.lab=2)
legend(x=40,y=100,legend=c("normal","half_input","double_Cin"),lty=c(3,4,5),
lwd=c(1,3,1))par(oldpar) #back to old par
```

```
#3 RothC application with fictional input
#and fictional measurement data to calculate C0 and N0
#3.1 Input
#fictional data
data(RothC_Cin_ex_sl, RothC_Nin_ex_sl, RothC_site_ex, RothC_env_in_ex, meas_data_ex)
#3.2. Simulation
out_rothC_C0<-sorcering( model="RothC", site=RothC_site_ex, env_in=RothC_env_in_ex,
  Cin=RothC_Cin_ex, Nin=RothC_Nin_ex, calcC0=TRUE, calcN=TRUE, calcN0=TRUE,
  tsteps="monthly", meas_data=meas_data_ex)
#3.3 Results
#output structure summary
summary(out_rothC_C0)
#example plot
oldpar <- par(no.readonly=TRUE) #save old par
par(mfrow=c(1,1),mar=c(4,4,1,4))
plot(rowSums(out_rothC_C0$N),axes=FALSE, col=1, cex.lab=2,xlab="",ylab="",ylim=c(0,9),
  type="l",lwd=1)
par(new=TRUE)
plot(rowSums(out_rothC_C0$C),axes=FALSE, col=2, cex.lab=2,xlab="",ylab="",ylim=c(0,90),
  type="l",lwd=1)
par(new=TRUE)
plot(x=meas_data_ex[,1],y=meas_data_ex[,3],axes=FALSE, col=1, cex.lab=2,xlab="",ylab="",
  xlim=c(0,length(rowSums(out_rothC_C0$N))),ylim=c(0,9),pch=4,cex=3)
par(new=TRUE)
plot(x=meas_data_ex[,1],y=meas_data_ex[,2],axes=FALSE, col=2, cex.lab=2,xlab="",ylab="",
  xlim=c(0,length(rowSums(out_rothC_C0$N))),ylim=c(0,90),pch=4,cex=3)
par(new=TRUE)
axis(side=2, pos=0,
  labels=(0:8)*1, at=(0:8)*10, hadj=1, padj=0.5, cex.axis=2,las=1,col.axis=1)
axis(side=4, pos=60,
  labels=(0:8)*10, at=(0:8)*10, hadj=0, padj=0.5, cex.axis=2, las=1,col.axis=2)
axis(side=1, pos=0,
  labels= (0:8)*10 , at=(0:8)*10, hadj=0.5, padj=0, cex.axis=2)
title(ylab=expression("SON [t ha"^-1*"]"), line=2, cex.lab=2)
mtext(expression("SOC [t ha"^-1*"]"), side=4, line=3, cex=2,col=2)
title(xlab="time", line=2, cex.lab=2)
legend(x=30,y=30,legend=c("model result","measurement"),lwd=c(1,0))
legend(x=31,y=30,legend=c("",""),pch=4,pt.cex=c(0,3),bty="n")
par(oldpar) #back to old par
```
#4 Yasso15 application using multiple sites and #input values of different wood diameters which take uncertainties into account #4.1 Input data(Yasso_Cin_ex_wood_u_sl, Yasso_Nin_ex_wood_u_sl, Yasso_C0_ex_sl, Yasso_N0_ex_sl, RothC_env_in_ex) #fictional data #show last entries of C input for 3rd site, 2nd wood layer, 4th uncertainty layer tail(Yasso_Cin_ex_wood_u_sl[[3]][[2]][[4]]) #diameter of wood input: 2 classes of 0 cm and 10 cm for each of the 3 sites wood_diam_ex_sl<-list(c(0,10),c(0,10),c(0,10)) #environmental variables Yasso_env_in_ex<-RothC_env_in_ex[,1:2] #4.2 Simulation out_multi_yasso_wood_unc <- sorcering(model="Yasso15", C0_sl=Yasso_C0_ex_sl, env_in_sl=rep(list(Yasso_env_in_ex),3), wood_diam_sl=wood_diam_ex_sl, Cin_wood_sl=Yasso_Cin_ex_wood_u_sl,Nin_wood_sl=Yasso_Nin_ex_wood_u_sl,

N0_sl=Yasso_N0_ex_sl, calcN=TRUE, tsteps="monthly", multisite=TRUE, sitelist=list("a","b","c"))

#4.3 Results

#show the last C results for 3rd site, 4th uncertainty layer tail(out_multi_yasso_wood_unc[[3]][[4]]\$C)

```
#5 RothC application using stochastically varying parameters
#and multiple sites
#5.1 fictional data
data(RothC_Cin_ex_sl, RothC_Nin_ex_sl, RothC_C0_ex, RothC_N0_ex,
  RothC_site_ex, RothC_env_in_ex)
#standard deviations [%] used for each of the 7 RothC theta parameters
RothC_{th} = \text{Area\_unc} < - \text{c}(0, 0, 1, 1, 1, 1, 2)#5.2 Simulation
out_sl <- sorcering( model="RothC", site_sl=rep(list(RothC_site_ex),3),
  env_in_sl=rep(list(RothC_env_in_ex),3), Cin_sl=RothC_Cin_ex_sl,
  Nin_sl=RothC_Nin_ex_sl, C0_sl=rep(list(RothC_C0_ex),3),
  N0_sl=rep(list(RothC_N0_ex),3),calcN=TRUE,theta_n_unc=10,
  theta_unc=RothC_theta_unc, multisite=TRUE,
  sitelist=list("normal","half_input","double_Cin"))
#5.3 Means and standard deviation
#60 time steps, 5 pools, 9 output types, 10 theta_n_unc, 3 sites
out_sl_arr <- array(unlist(out_sl),c(60,5,9,10,3))
out_sl_arr_N <- out_sl_arr[,,2,,] #only output type 2: N
#mean over all uncerts
out_sl_arr_N_mean <- apply( out_sl_arr_N , c(1,2,4), na.rm=TRUE, FUN=mean )
#standard deviation
out_sl_arr_N_sd<-
array(0, dim=c(dim(out_sl_arr_N)[1],dim(out_sl_arr_N)[2],dim(out_sl_arr_N)[4]))
for (dim3 in c(1:dim(out_sl_arr_N)[4]))
 out_sl_arr_N_sd[,,dim3]<-apply(out_sl_arr_N[,,,dim3],c(1:2),sd)
#5.4 Results
#show the last N means for stand 1
tail(out_sl_arr_N_mean[,,1])
#show the last N standard deviations for stand 1
tail(out_sl_arr_N_sd[,,1])
```

```
#6 How to create input lists for a RothC application using stochastically
#varying inputs and input scenarios
#6.1 Input
#fictional data
data(RothC_Cin_ex_sl, RothC_C0_ex, RothC_site_ex, RothC_env_in_ex)
#create input list of 3 scenarios, 100 uncertainties each
set.seed(17) #to make 'random' results reproducible
f1<-1for (no in c(1:3)) #loop over 3 input scenarios
{
    #normal, half and double input
    Cin <- switch (no, RothC_Cin_ex, RothC_Cin_ex/2, RothC_Cin_ex*2)
    f2 < -1#create fictional uncertainties
    for (unc in c(1:100)) #loop over 100 uncertainties
    {
        randnum<-max(0,rnorm(1,1,0.5)) #out of normal dist. with 50% sd.
        if (f2==1) Cin_u <- list(Cin*randnum) else
        Cin_u[[length(Cin_u)+1]] <- Cin*randnum
       f2 < -0}
    if (f1==1) Cin_u_sl <- list(Cin_u) else
    Cin_u_sl[[length(Cin_u_sl)+1]] <- Cin_u
    f1 < -0}
#show input of scenario 3, uncertainty 51
head(Cin_u_sl[[3]][[51]])
#6.2 Simulation
out_sl <- sorcering( model="RothC", site_sl=rep(list(RothC_site_ex),3),
  env_in_sl=rep(list(RothC_env_in_ex),3),Cin_sl=Cin_u_sl,
  C0_sl=list(RothC_C0_ex,RothC_C0_ex,RothC_C0_ex), tsteps="monthly",
  multisite=TRUE, sitelist=list("normal","half_input","double_Cin"))
#6.3 Means and standard deviation
#60 time steps, 5 pools, 1000 uncertainties, 3 sites
out_sl_arr <- array(unlist(out_sl),c(60,5,100,3))
#means
out_sl_arr_mean <- apply( out_sl_arr , c(1,2,4), na.rm=TRUE, FUN=mean )
#standard deviation
out_sl_arr_sd<-
  array(0, dim=c(dim(out_sl_arr)[1],dim(out_sl_arr)[2],dim(out_sl_arr)[4]))
for (dim3 in c(1:dim(out_sl_arr)[4]))
  out_sl_arr_sd[,,dim3]<-apply(out_sl_arr[,,,dim3],c(1:2),sd)
```
#6.4 Results

```
#C-pool sums of means for the 3 scenarios
totalC_m1<-rowSums(out_sl_arr_mean[,,1])
totalC_m2<-rowSums(out_sl_arr_mean[,,2])
totalC_m3<-rowSums(out_sl_arr_mean[,,3])
#C-pool sums of standard deviations for the 3 scenarios
totalC_s1<-rowSums(out_sl_arr_sd[,,1])
totalC_s2<-rowSums(out_sl_arr_sd[,,2])
totalC_s3<-rowSums(out_sl_arr_sd[,,3])
#example plot
oldpar <- par(no.readonly=TRUE) #save old par
par(mfrow=c(1,1),mar=c(4,4,1,4))
plot(totalC_m1,axes=FALSE, col=2, cex.lab=2,xlab="",ylab="",ylim=c(0,100),
  type="l",lwd=1)
par(new=TRUE)
plot(totalC_m2,axes=FALSE, col=3, cex.lab=2,xlab="",ylab="",ylim=c(0,100),
  type="l",lwd=1)
par(new=TRUE)
plot(totalC_m3,axes=FALSE, col=4, cex.lab=2,xlab="",ylab="",ylim=c(0,100),
  type="l",lwd=1)
par(new=TRUE)
polygon(c(1:60,60:1),c(totalC_m1+totalC_s1, rev(totalC_m1-totalC_s1)),
  border=NA,col=rgb(1,0,0,0.27),density=40,angle=180,xlab="",ylab="")
par(new=TRUE)
polygon(c(1:60,60:1),c(totalC_m2+totalC_s2, rev(totalC_m2-totalC_s2)),
 border=NA,col=rgb(0,1,0,0.27),density=30,xlab="",ylab="")
par(new=TRUE)
polygon(c(1:60,60:1),c(totalC_m3+totalC_s3, rev(totalC_m3-totalC_s3)),
 border=NA,col=rgb(0,0,1,0.27),density=25,angle=90,xlab="",ylab="")
par(new=TRUE)
axis(side=2, pos=0,
    labels=(0:10)*1, at=(0:10)*10, hadj=1, padj=0.5, cex.axis=2,las=1,col.axis=1)
axis(side=1, pos=0,
    labels= (0:6)*10 , at=(0:6)*10, hadj=0.5, padj=0, cex.axis=2)
title(ylab=expression("SOC [t ha"^-1*"]"), line=2, cex.lab=2)
title(xlab="time", line=2, cex.lab=2)
legend(x=20,y=30,fill=c(0,0,0,4,2,3),density=c(0,0,0,25,40,30),angle=c(0,0,0,90,0,45),
  border=c(0,0,0,1,1,1),legend=c("mean double input scenario",
  "mean regular input scenario", "mean half input scneario",
  "uncertainty range double input scenario", "uncertainty range regular input scenario",
  "uncertainty range half input scenario"))
legend(x=20,y=30,lty=c(1,1,1,0,0,0),seg.len=c(1,1,1,0,0,0), col=c(4,2,3,0,0,0),
 legend=c("","","","","",""),bty="n")
par(oldpar) #back to old par
```

```
#7 RothC application with fictional input for a spin-up application
#7.1 Input
#fictional data
data(RothC_Cin_ex_sl_spin, RothC_Nin_ex_sl_spin, RothC_site_ex, RothC_env_in_ex)
#7.2. Simulation
out_multi_rothC <- sorcering( model="RothC", site_sl=rep(list(RothC_site_ex),3),
  env_in_sl=rep(list(RothC_env_in_ex[1:12,]),3), Cin_sl=RothC_Cin_ex_sl_spin,
  Nin_sl=RothC_Nin_ex_sl_spin, calcN=TRUE, tsteps="monthly", multisite=TRUE,
  sitelist=list("normal","half_input","double_Cin"), spinup=TRUE, t_spin_sl=36000,
  C0 = C(0, 0, 0, 0, 20), N0 = C(0, 0, 0, 0, 2), CN\_spin = C(100, 100, 50, 50, 10)#7.3 Results
#example plot
oldpar <- par(no.readonly=TRUE) #save old par
par(mfrow=c(1,1),mar=c(4,4,1,4))
for (listelement in c(1:3))
{
  lwidth<-1
  if (listelement==2)lwidth<-3
  printN<-rowSums(out_multi_rothC[[listelement]]$N)
  printseq<-seq.int(1L,length(printN),100L)
  printC<-rowSums(out_multi_rothC[[listelement]]$C)
  plot(printN[printseq],axes=FALSE, col=1,type="l", lwd=lwidth,
      lty=listelement+2,cex.lab=2,xlab="",ylab="",ylim=c(0,30))
  par(new=TRUE)
  plot(printC[printseq],axes=FALSE, col=2,type="l", lwd=lwidth,
      lty=listelement+2,cex.lab=2,xlab="",ylab="",ylim=c(0,180))
  par(new=TRUE)
}
axis(side=2, pos=0,
  labels=(0:6)*5, at=(0:6)*30, hadj=0.7, padj=0.5, cex.axis=2,las=1,col.axis=1)
axis(side=4, pos=360,
  labels=(0:6)*30, at=(0:6)*30, hadj=0, padj=0.5, cex.axis=2, las=1,col.axis=2)
axis(side=1, pos=0,
  labels= (0:6)*6000 , at=(0:6)*60, hadj=0.5, padj=0, cex.axis=2)
title(ylab=expression("total N [t ha"^-1*"]"), line=2, cex.lab=2)
mtext(expression("total C [t ha"^-1*"]"), side=4, line=2, cex=2,col=2)
title(xlab="time", line=2, cex.lab=2)
legend(x=120,y=140,legend=c("normal","half_input","double_Cin"),lty=c(3,4,5),
  lwd=c(1,3,1))
```

```
par(oldpar) #back to old par
```
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