

# Probability distributions of radiocarbon in open compartmental systems

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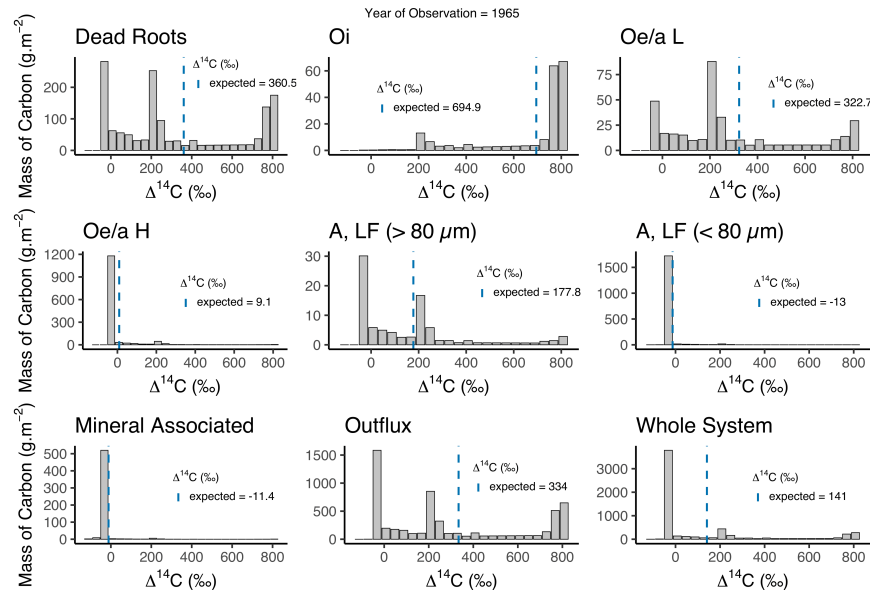
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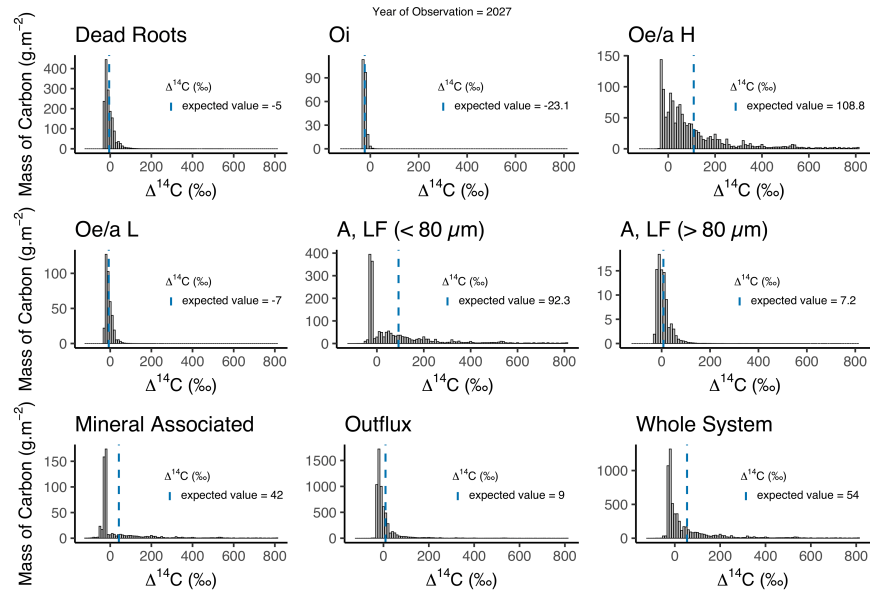
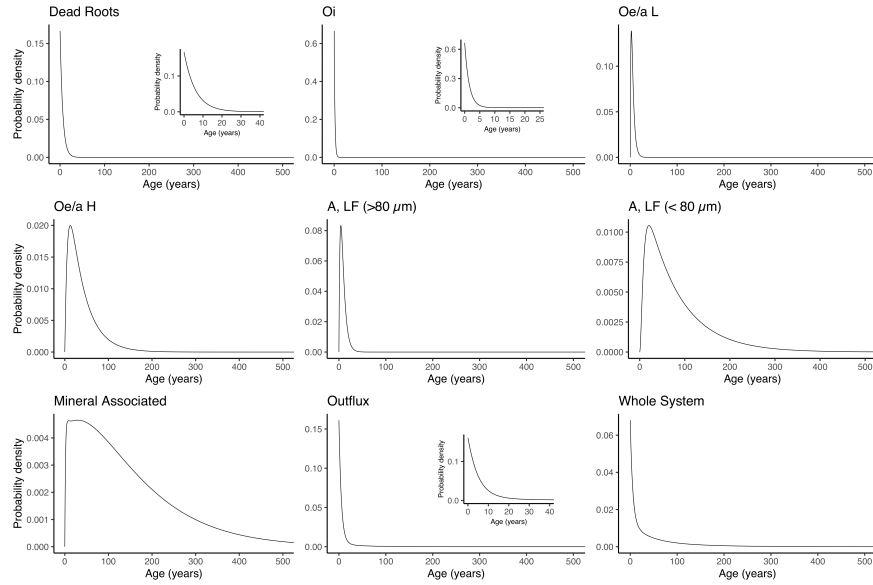
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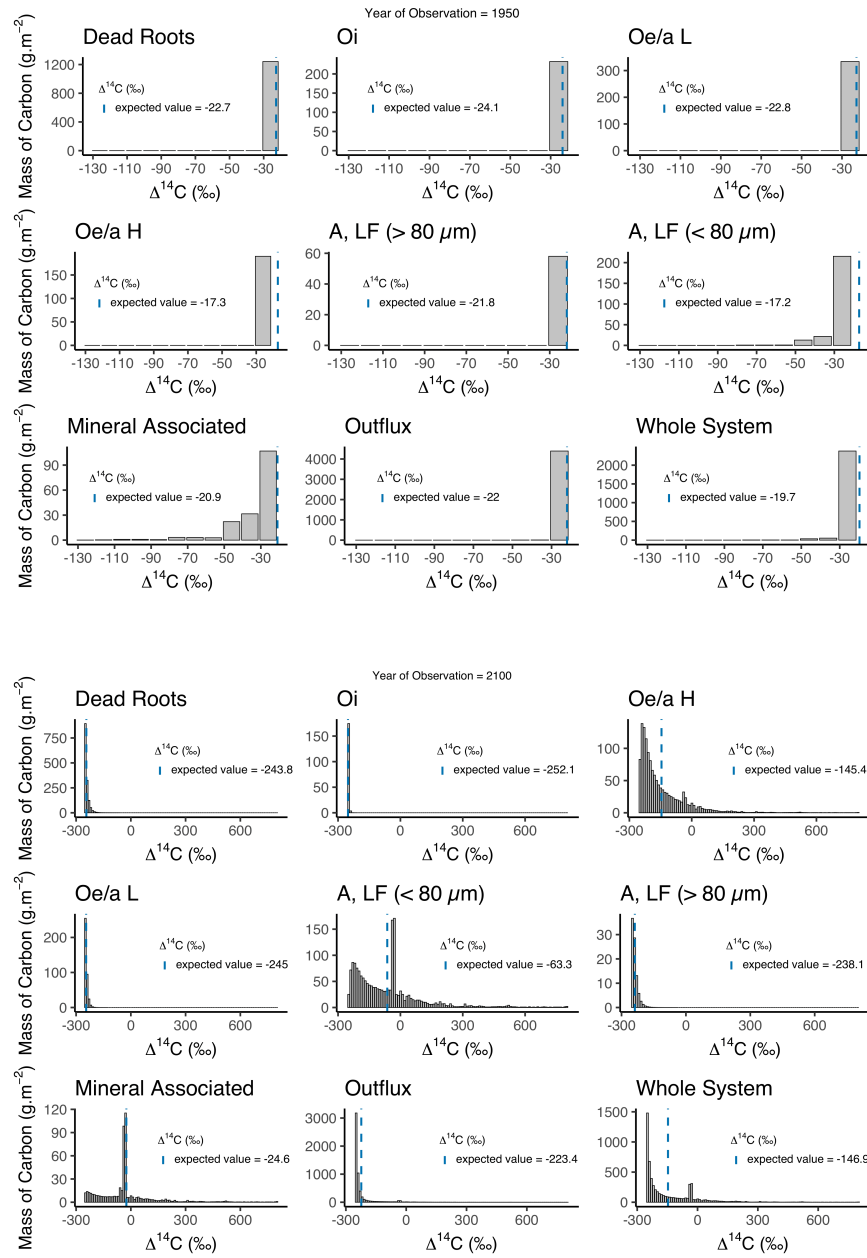
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## Abstract

Radiocarbon ( $^{14}\text{C}$ ) is commonly used as a tracer of the carbon cycle to determine how fast carbon moves between different reservoirs such as plants, soils, rivers or oceans. However such studies mostly emphasize the mean value (as  $\Delta^{14}\text{C}$ ) of an unknown probability distribution. We introduce a novel algorithm to compute  $\Delta^{14}\text{C}$  distributions from knowledge of the age distribution of carbon in compartmental systems at equilibrium. Our results demonstrate that the shape of the distributions might differ according to the speed of cycling of ecosystem compartments and their connectivity within the system, and are mostly non-normal. The distributions are also sensitive to the variations of  $\Delta^{14}\text{C}$  in the atmosphere over time, as influenced by the counteracting anthropogenic effects of fossil-fuel emissions ( $^{14}\text{C}$ -free) and nuclear weapons testing (bomb  $^{14}\text{C}$ ). Lastly, we discuss insights that such distributions can offer for sampling and design of experiments aiming to capture the precise variability of  $\Delta^{14}\text{C}$  values in ecosystems.







# Probability distribution of radiocarbon

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- Predicted radiocarbon distributions in open compartment are according to the  
gasolubility and model data
- Expected  $\Delta^{14}\text{C}$  of ecosystem respiration are in accordance with empirical  $\Delta^{14}\text{C}$   
data
- Probability distributions of radiocarbon in open compartment provide insights  
into ecosystem dynamics

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## A

Radiocarbon ( $^{14}\text{C}$ ) is commonly used as a tracer of the carbon cycle to determine how fast carbon moves between different reservoirs such as plants, soils, rivers, and oceans. However, the distribution of  $^{14}\text{C}$  is not uniform, and the mean value (as  $\Delta^{14}\text{C}$ ) of an unknown probability distribution. Without a novel algorithm to compute  $\Delta^{14}\text{C}$  distributions from knowledge of the age distribution of carbon in compartmental systems, the distribution of  $^{14}\text{C}$  in the atmosphere has the shape of the distribution might differ according to the speed of cycling of ecosystem compartments and their connectivity within the system, and are mostly non-normal. The distributions are also sensitive to the variations of  $\Delta^{14}\text{C}$  in the atmosphere over time, as influenced by the contrasting anthropogenic effects of fossil-fuel emissions ( $^{14}\text{C}$ -free) and nuclear weapons testing (bomb  $^{14}\text{C}$ ). Laboratory studies show that distributions can offer formal sampling and design of experiments aiming to capture the peculiar variability of  $\Delta^{14}\text{C}$  values in ecosystems.

Radiocarbon is a radioactive isotope of carbon prominent in environmental sciences for tracing the dynamics of ecosystems especially as recent changes in atmospheric radiocarbon allow tracking excess  $^{14}\text{C}$  created by weapons testing in the atmosphere on timescales that can be determined using radioactive decay. For climate change mitigation, a critical uncertainty is the time carbon captured through the photosynthesis process in ecosystems before being released. For this purpose, radiocarbon can be valuable as a biological tracer, however, it is necessary to accurately link the real age of carbon and its radiocarbon age, as they usually differ. Forests and soils are open systems connecting compartments with intrinsically different cycling timescales, so that the mean age is representing an age distribution that is not normally distributed. Here we developed an algorithm to compute the  $^{14}\text{C}$  content from modeling of multiple interconnected carbon pools. Our approach, offering more accurate estimation of the mean  $^{14}\text{C}$  content of the system and computation of the distribution of  $^{14}\text{C}$  within the system at different positions in time. From the results, we can have more insight into the dynamics of the carbon cycle and how to better design experiments to improve model-observations comparisons.

## 1

Radiocarbon ( $^{14}\text{C}$ ) is a valuable tool for studying dynamical processes in living systems. In particular, radiocarbon produced by nuclear bomb testing in the 1960s has been used in many contexts as a tracer for the dynamics of carbon in different compartments of the global carbon cycle, including the atmosphere, the terrestrial biosphere, and the oceans (Godfrain, 1992; Jain et al., 1997; Randerson et al., 2002; Negler et al., 2006; Levin et al., 2010). As a biological tracer, radiocarbon can be used to infer rates of carbon cycling in specific compartments and to infer timescales among interconnected compartments. Therefore, radiocarbon is used as a diagnostic metric to assess the performance of models of the carbon cycle (Garn et al., 2017), and new data are now being incorporated into radiocarbon in model benchmarking (Lawrence et al., 2020).

Carbon cycling in biological systems can be represented using a patchwork of mathematical models scaled compartmental systems (Sien et al., 2018). As carbon enters a system such as the terrestrial biosphere, it is stored and transferred among a network of interconnected compartments such as foliage age, wood, soils, and other organisms. Compartmental systems represent the dynamics of carbon as it flows along the network of compartments (Rasmussen et al., 2016; Sien et al., 2018), and provides information about the time carbon spends in particular compartments and the entire system (Rasmussen et al., 2016; Sien et al., 2017). Although these seem to be a direct relation between the time carbon spends in a compartmental system and its radiocarbon dynamics, several caveats both concepts

An open compartmental  $\delta^{13}\text{C}$  contains flows of different forms (Jacobs & Simon, 1993). Timescales in open compartmental  $\delta^{13}\text{C}$  are all characterized by the concept of a *grand transit time* (Bolin & Rodhe, 1973; Rasmussen et al., 2016; Si et al., 2017). In open  $\delta^{13}\text{C}$  systems, the incorporation and release of carbon occur continuously, but it is possible to define the concept of a *grand time elapsed* since carbon enters the compartmental  $\delta^{13}\text{C}$  until a generic time. The *transit time* can be defined as the time the carbon needs to travel through the entire  $\delta^{13}\text{C}$ , i.e., the time elapsed between carbon entry into the system.

In order to estimate the time metrics from  $^{14}\text{C}$  measurements, a model linking both carbon and radiocarbon dynamics is required. Thompson and Rasmussen (1999) have developed a response function from compartmental model to obtain ages and times and time-dependent radiocarbon dynamics. However, his approach is computationally expensive and can introduce numerical errors if simulations are not long enough to cover the dynamics of low-lying pools.

Explicit form has for age and time metrics in compartmental  $\delta^{13}\text{C}$  have been recently developed (Meyer & Si et al., 2017). These forms have no numerical errors and can describe the age distribution of carbon for specific pools and for the entire compartmental  $\delta^{13}\text{C}$ . These age distributions suggest a radiocarbon in compartmental  $\delta^{13}\text{C}$  may consist of a mix of different ages, i.e., compartmental  $\delta^{13}\text{C}$  can be described in terms of radiocarbon distributions at the relative proportion of carbon in a patch radiocarbon  $\delta^{13}\text{C}$ . However, until now radiocarbon is reported and modeled as a single quantity rather than the mean of an underlying distribution.

Knowledge of the distribution of  $^{14}\text{C}$  obtained on the  $^{12}\text{C}$  distribution (Cm) in a compartmental  $\delta^{13}\text{C}$  might give important insight on the model that has been used in existing data. For example, by comparing the signal of radiocarbon in the pool and the relative vegetation signal in the pool model that describes the ecosystem. Consequently, empirical knowledge of the radiocarbon distribution of a patch  $\delta^{13}\text{C}$ , can play a significant role in determining the most appropriate model to describe a  $\delta^{13}\text{C}$ .

Model-data comparisons using radiocarbon are made more complex by the fact that atmospheric  $^{14}\text{C}$  is continuously changing. This is particularly important after the 1960s when the nuclear bomb test began to change the amount of hemispheric  $^{14}\text{C}$ , contributing to the formation of radiocarbon (bomb  $^{14}\text{C}$ ). In addition, large quantities of fossil-fuel derived carbon ( $^{14}\text{C}$ -free) have been emitted to the atmosphere, diluting the atmospheric radiocarbon signal and producing a false decline of radiocarbon  $\delta^{13}\text{C}$  in recent years (Garn et al., 2017). Therefore, we expect different radiocarbon distribution for every compartmental  $\delta^{13}\text{C}$ .

Obtaining a simple and accurate method to estimate radiocarbon distributions as a function of the carbon observation is therefore, of great interest for experimental and modeling studies.

The main objective of this manuscript is to develop a method to obtain distributions of radiocarbon in compartmental  $\delta^{13}\text{C}$  systems. In patchwork, we follow three steps: (i) How do distributions of radiocarbon change over time as a consequence of changes in atmospheric radiocarbon? (ii) How do empirical data compare to these conceptual radiocarbon distributions? (iii) What insights can these distributions provide for experimental and sampling design for improving model-data comparisons by capturing the entire variability of  $\Delta^{14}\text{C}$   $\delta^{13}\text{C}$ ?

The manuscript is organized as follows. First, we provide the necessary theoretical background to obtain age and time metrics from compartmental  $\delta^{13}\text{C}$  systems. Second, we describe an algorithm that computes radiocarbon distributions for patchwork systems using an age or a time distribution and an atmospheric radiocarbon  $\delta^{13}\text{C}$ . Third, we present an application of our algorithm to a simple compartmental  $\delta^{13}\text{C}$  adding the

each of those above. Finally, we discuss in the context of other applications and potential new insights from our approach.

## A

### 1

Compartmental models describe the temporal dynamics of a system through a network of compartments and transitions between them. A set of compartmental models is said to be mathematically a set of linear or non-linear ordinary differential equations (ODE), whose solutions are the amount of material in each compartment at a certain time.

We will consider here linear autonomous compartmental models characterized by the mass of carbon at time  $t$  in compartment  $i$  as the vector  $x(t)$ . The mass of carbon in the compartment changes over time according to the following equation

$$\frac{dx(t)}{dt} = \dot{x}(t) = u + Ax(t) \quad x(0) = x_0 \quad (1)$$

where the vector  $u$  represents the input of carbon into the system, and the compartmental matrix  $A$  contains the diagonal entries representing the loss of carbon from the compartment while the off-diagonal entries represent the transfer of carbon among compartments. In particular, the compartmental matrix in the carbon model has a diagonal entry  $-k_i$  representing the loss of carbon from compartment  $i$  to the atmosphere, and off-diagonal entries  $k_{ij}$  representing the transfer of carbon from compartment  $j$  to compartment  $i$ . The vector  $x_0$  represents the initial condition of the system.

$$A = \begin{pmatrix} -k_1 & k_{12} & \dots & k_{1n} \\ k_{21} & -k_2 & \dots & k_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ k_{n1} & k_{n2} & \dots & -k_n \end{pmatrix} \quad (2)$$

This matrix contains information on the dynamics of the system, and is of a compartmental model. The amount of carbon from the system can also be obtained from this matrix by summing all column elements, i.e., the output of a pool is the sum of the input and the output of the compartment.

The information of the amount of carbon entering the system to be partitioned among the compartments is contained in the input vector

$$u = \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix} \quad (3)$$

Linear autonomous systems of the form of equation (1) have an equilibrium point for each solution  $x^*$  given by

$$x^* = -A^{-1}u \quad (4)$$

where the mass of the compartments do not change over time, and inputs are equal to outputs of all compartments.

## A

We define age in a compartment as the time elapsed between the time of carbon entry into the generic time (Sien et al., 2017). For a time-independent system, a probability distribution of ages of carbon in the compartment can be obtained using stochastic methods. According to Merand Sien (2017), the vector of age densities for the compartments can be obtained as

$$f_a(\mathbf{x}) = (\mathbf{A}^T)^{-1} \cdot \mathbf{A} \cdot \mathbf{u} \quad (5)$$

where  $\mathbf{A} = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$  is the diagonal matrix with the negative vector of carbon stocks as components and  $\mathbf{A}^T$  is the matrix exponential.

For the whole system, the age distribution is given by

$$f_a(\mathbf{x}) = -\mathbf{1}^T \cdot \mathbf{A} \cdot \mathbf{A}^{-1} \cdot \frac{\mathbf{x}}{\|\mathbf{x}\|} \quad (6)$$

where the symbol  $\|\cdot\|$  represents the norm of the mass in a vector

We define an instantaneous time as the time elapsed since carbon enters the compartment until it leaves the boundaries of the system (Sien et al., 2017). The instantaneous is equivalent hereof, to the age of the system. Merand Sien (2017) also provide an explicit formula to obtain the instantaneous density distribution for a time-independent system at steady state as

$$f_a(\mathbf{x}) = -\mathbf{1}^T \cdot \mathbf{A} \cdot \mathbf{A}^{-1} \cdot \frac{\mathbf{u}}{\|\mathbf{u}\|} \quad (7)$$

The distributions are densities so they integrate to 1

$$\int_0^\infty f_a(\mathbf{x}) d\mathbf{x} = \int_0^\infty f_a(\mathbf{x}) d\mathbf{x} = 1 \quad (8)$$

## 1

We developed an algorithm to compute age and instantaneous distributions in  $\Delta^{14}\text{C}$  distributions for any given carbon observation.

The algorithm consists in three main steps: 1) homogenization, 2) discretization, and 3) aggregation (Figure 1). We describe here the steps in detail in the sections below: in the mathematical notation for the system age distribution, but computations are similar for the instantaneous distribution, and the age distribution of individual compartments.

### 1.1

The main inputs for the algorithm are an age distribution  $f_a(\mathbf{x})$ , and an atmospheric radiocarbon concentration  $\Delta^{14}\text{C}$  that provides the  $\Delta^{14}\text{C}$  value of atmospheric  $\text{CO}_2$  for a calendar year. To homogenize the time scales of both  $f_a(\mathbf{x})$  and  $\Delta^{14}\text{C}$ , we define the year of observation  $t_0$ , as the year of interest to probe the radiocarbon distribution.

Since we are interested in determining the radiocarbon value of material observed in the system at time  $t_0$ , we will look in the radiocarbon concentration  $\Delta^{14}\text{C}$  in the past to obtain



the radiocarbon  $\lambda$  is in the form with an age  $t$ . Therefore, atmospheric radiocarbon can be expressed as a function of age, i. e.,  $(\lambda_0 - \lambda) = \lambda_0 (1 - e^{-\lambda t})$  (Figure 1). By both the form age distribution  $\lambda(t)$  and the atmospheric radiocarbon  $\lambda(t)$  are functions of the continuous variable  $t$  at present age.

Several atmospheric radiocarbon datasets can be found in the literature (Reimer et al., 2013, 2020; Hogg et al., 2013, 2020; Hua et al., 2013; Levin et al., 1980; Levin & Komar, 1997; Levin et al., 2010; Gao et al., 2017). Also for cases of radiocarbon content in the atmosphere can be found in the recent literature (Gao, 2015; Shen, 2018). However, these atmospheric radiocarbon datasets do not necessarily have the same resolution in time. Some of them provide predictions or data at an annual or form only time step, while in other datasets some ages are spaced by decades. To homogenize the resolution of the  $\Delta^{14}\text{C}$  and to transform these radiocarbon datasets into a continuous function of  $t$ , we use a cubic spline interpolation to obtain  $\Delta^{14}\text{C}$  for any value of  $t$ . After this step,  $\lambda(t)$  can be computed for any value of  $t \in [0, \infty)$ , and  $\lambda(t)$  will be a available data in the chosen radiocarbon atmospheric dataset.

Although we have now the age distribution and the radiocarbon data as continuous functions of age, we need to discretize these functions in intervals of size  $\Delta t$ . The reason for this discretization is that the probability density function of age  $\lambda(t)$  is a measure of the relative likelihood of an infinitesimal amount of mass having an age. But ultimately we are interested in the probability that a small mass has a certain radiocarbon distribution. Therefore, we need to discretize the probability density function to a probability mass function along a discrete variable  $t \in [0, \infty]$ . The new discrete probability function of ages can be defined as

$$\lambda(t) = \lambda(t) \Delta t + \lambda(t) \Delta t = \lambda(t) \Delta t + \lambda(t) \Delta t \quad (9)$$

From this probability function, we can compute the population of total mass in the form with an age  $t$  as

$$\lambda(t) = \|\mathbf{x}^*\| \quad (10)$$

where

$$\lambda(t) \approx 1 \quad (11)$$

Equation (11) implies that there is an approximation error by discretizing the continuous density function to a finite set of discrete intervals. This approximation error can be minimized by decreasing the size of the intervals and extending  $\infty$  as far as possible.

Once we discretize  $\lambda(t)$  to  $\lambda(t)$  and obtain discrete populations of mass with certain age  $t$ , we proceed to discretize the atmospheric radiocarbon  $\lambda(t)$  with respect to the same discrete interval of ages  $t \in [0, \infty]$ . This is simply done by computing  $\lambda(t) = \lambda(t)$ , which makes the assumption that in each interval  $[t, t + \Delta t]$ , the atmospheric radiocarbon  $\lambda(t)$  is equal to  $\lambda(t)$ .

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Now we are ready to combine the distribution of mass in the  $\delta m$  at discrete age intervals with the atmospheric radiocarbon  $\Delta^{14}C$ . To do so, we find for each  $\delta t$  of  $\delta t \in [0, \delta t_{max}]$  the corresponding  $\delta m$  of mass  $\delta m(\delta t)$  and radiocarbon  $\Delta^{14}C(\delta t)$ . Then, we sum all the mass with similar  $\Delta^{14}C$  values. The result can be organized as the amount of mass in discrete intervals of  $\Delta^{14}C$ ; i. e.  $(\Delta^{14}C) = (\delta t)$ .

This step can also be validated through the graphs in Figure 1.

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We implemented these steps in the R programming language, and the package SoilR (Sien, Mer et al., 2012) to obtain the age distribution of the pools the whole  $\delta m$ , and the output equivalent to the half-time based on equations (5), (6), and (7). The version of the R version 4.0.3 and SoilR version 1.1 (Sien et al., 2014).

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Since atmospheric  $^{14}C$  concentration for the past 55,000 years is principally known from the radiocarbon  $\Delta^{14}C$  we could easily construct age in atmospheric  $\Delta^{14}C$ . By matching the  $\Delta^{14}C$ -based-on-age  $\delta m$  with the previous mass and densities we build a plot of gain in  $\delta m$  in  $\delta t$  with the radiocarbon distributions from the model defined in his work. In the algorithm we defined four functions: *PoolRID*, *SystemRID*, *TIRID*, and *ClHist*. The first three functions take the densities  $\rho$ ; i. e., the carbon content defined by age, from built-in SoilR functions such as *transitTime* and *systemAge*. The densities are used to build bins through the *ClHist* function. The logical elements to construct the bins are based on the atmospheric  $\Delta^{14}C$  data and according to the defined bins. This is all so one to plot the  $\delta m$ -like graphs with the height of the base represent the amount of mass corresponding  $\Delta^{14}C$  values. The total algorithm initial is from a compatible matrix in input and a radiocarbon calibration  $\Delta^{14}C$ , and then an object containing mass of  $^{14}C$  and the remaining decay corrected  $\Delta^{14}C$  values estimated for any given observation year. The math is done by assuming the year of observation as equivalent to the age of the pool or the  $\delta m$  equal zero ( $t_0 - t = 0$ ). This means that the  $\delta m$  of the pool or the  $\delta m$  ages are equivalent to the  $^{14}C$  signal of the atmosphere of the year corrected by the radiocarbon decay of  $^{14}C$  (average lifetime of 8,267 years; i. e., half-life of 5,730 years).

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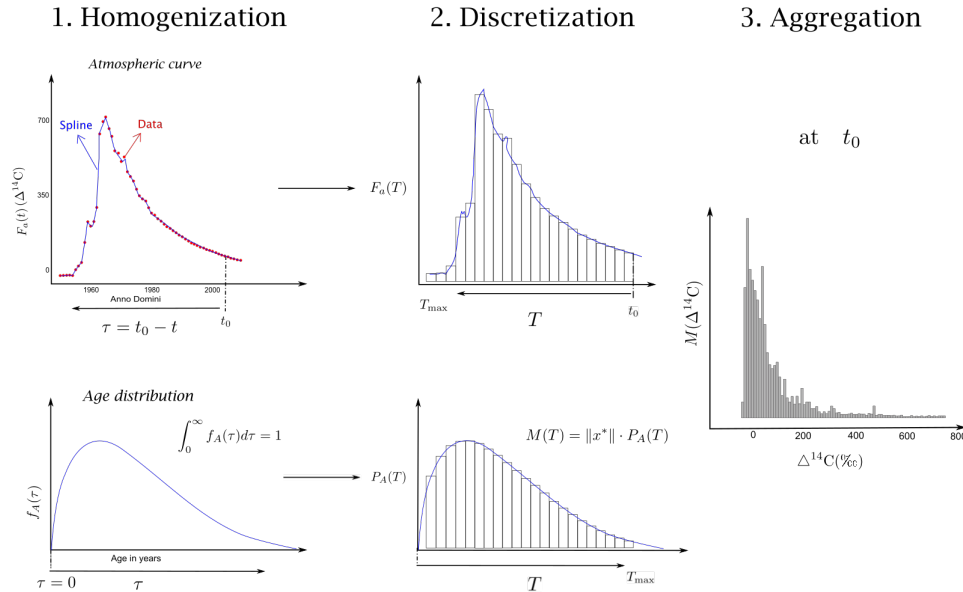
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Besides the radiocarbon distributions for pools the whole  $\delta m$  and output one can also compute the expected value of  $\Delta^{14}C$  from the distributions in any given observation year. This is done by computing the mean of  $\Delta^{14}C$  weighted by the amount of carbon in  $\Delta^{14}C$  bins of  $\delta t$ . The standard deviation of the distribution is obtained as the square root of the difference between the square of the expected value and the expected value of the square of  $\Delta^{14}C$  values.



Graphical visualization of the three main steps for the computation of radiocarbon distributions in a compartmental system using an atmospheric radiocarbon curve of the carbon inputs to the systems, and the age distribution of carbon in a compartmental system. Details about each step are provided in the main text.

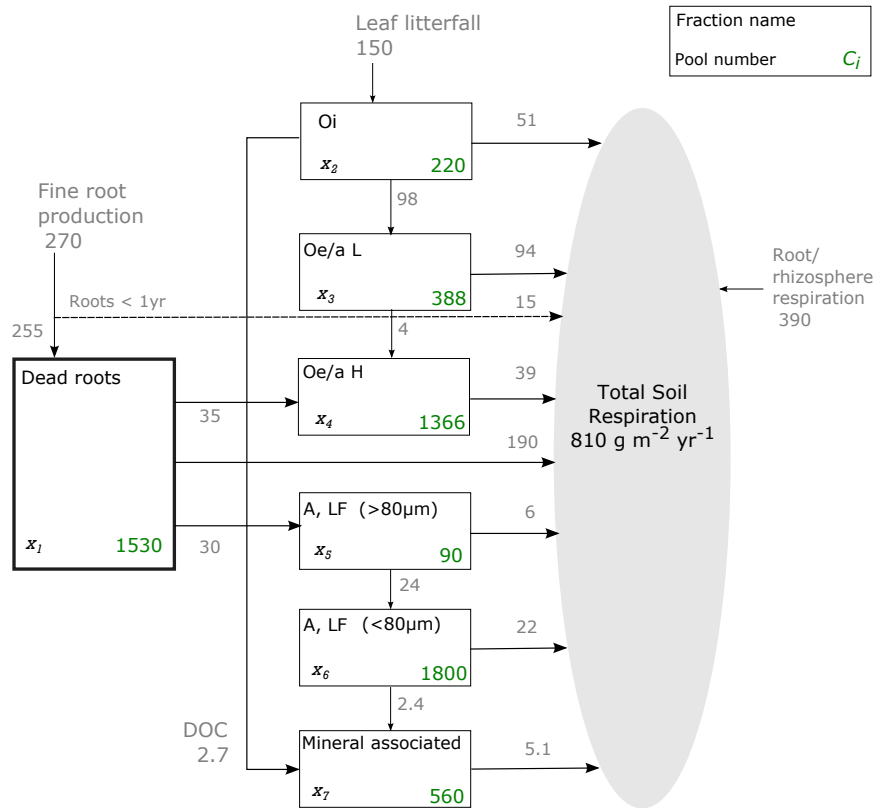
Our approach can be used to obtain radiocarbon distributions for a near compartmental model of any size representing carbon cycling processes at different scales and for different biological systems.

We will focus here on a model that represents the dynamics of soil organic carbon at a temperate forest, which we call here in the Harvard Forest Soil (HFS) model. The model is based on measurements conducted at the Harvard Forest in Massachusetts, USA (Gardner et al., 2000; Si et al., 2012). Soil samples collected in Ohio, corresponding to 0–8 cm depth, and A-horizon (8–15 cm depth) were fractionated into seven soil fractions called: Dead Root Q, Oe/a L, Oe/a H, A, IF (< 80 m), A, IF (> 80 m), and Mineral Associated. They were obtained as follows: The Ohio samples were divided after hand-picking into leaf litter (Oe/a L fraction), recognizable root litter (Oe/a H fraction) and humified, i.e., organic matter that has been transformed by microbial action, corresponding to the fraction Oe/a H. Samples from the A-horizon were fractionated by density into low-density and high-density portions. The high-density portion corresponds to the Mineral Associated fraction. The low-density portion is further divided by sieving into recognizable leaf litter greater than 80 m (A, LF(> 80 m) fraction) and smaller than 80 m (A, LF(< 80 m) fraction). Details about the methods employed to fractionate the samples can be found in Gardner et al. (2000).

The compartmental model consists of seven pools (Fig. 2); one pool corresponds to dead roots, and the other pool corresponds to the different types of organic matter in the surface layer (O) called Q, Oe/a L and Oe/a H, which correspond to pools 1, 2, 3, and 4 in the model. Two additional pools called A, IF (< 80 m), representing material from the A-horizon that floats in a dense (1 g cm<sup>-3</sup>) liquid and does not pass through an 80 m sieve and A, IF (> 80 m) (low-density fraction passing the sieve), represent the dynamics

of  $\Delta^{14}\text{C}$  fractions in the soil A horizon with different ages from 0 to 5 and 6, respectively. The soil pool 7 represents the dynamics of the mineral associated fraction (Sierra, Trumbore, et al., 2012).

The HFS model is built by fitting of empirical radiocarbon data from the above described samples. Details about the data to build the compartmental model are presented in Sierra, Trumbore, et al. (2012). For the same sites there are independent data (i. e., data not used for fitting the compartmental model) available. The independent data are in hisok consists of  $\Delta^{14}\text{C}$  measurements on total soil  $\text{CO}_2$  efflux collected in the years 1996, 1998, 2002, and 2008. The number of samples measured corresponding to the respective years is  $n = 12$ ,  $n = 28$ ,  $n = 23$ , and  $n = 10$ . With these data to compare the representative of the mean  $\Delta^{14}\text{C}$  measurements to the expected  $\Delta^{14}\text{C}$  values obtained through our model.



Scheme of HFS model stocks ( ) and fluxes among compartments (adapted from Sierra, Trumbore, et al. (2012)).

The form of ODE for the HFS model can then be expressed in compartmental form as

$$\begin{pmatrix} \dot{1} \\ \dot{2} \\ \dot{3} \\ \dot{4} \\ \dot{5} \\ \dot{6} \\ \dot{7} \end{pmatrix} = \begin{pmatrix} 255 & -255 & 1530 & 0 & 0 & 0 & 0 & 0 \\ 156 & 0 & -150220 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 98152 & -98388 & 0 & 0 & 0 & 0 \\ 0 & 35255 & 0 & 48 & -391366 & 0 & 0 & 0 \\ 0 & 30255 & 0 & 0 & 0 & -3090 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2430 & -241800 & 0 \\ 0 & 0 & 3152 & 0 & 0 & 0 & 35 & -5560 \end{pmatrix} \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \end{pmatrix} \quad (12)$$

As described before, in order to estimate the radiocarbon distributions and expected values of  $\Delta^{14}\text{C}$ , the algorithm needs the following arguments: a compartmental matrix  $\mathbf{A}$ , containing the decomposition and transfer within the pools; an input vector  $\mathbf{u}$  containing the input to be partitioned among the compartments; the gas of observation (equal to gas of sampling in an experimental framework); the number of gas in the past one aims to compute the distributions for and a set of radiocarbon values in the atmosphere, comprising the gas of observation and the number of gas chosen. An additional argument is, the distribution is described above, which has a default value of 0.1 gas but could be modified according to preferences.

For the HFS model,  $\mathbf{A}$  is the matrix in equation (12), with the form of equation (2), and  $\mathbf{u}$  is the numeric vector in the same equation, with similar form as equation (3). We estimate the radiocarbon distributions for different years of observation, in order to address different research questions in this work. In the following, we present the distributions for the individual pools total flux and volume, for the years 1965, 2027 and 2100. Additionally, in the *Supplementary Material* we provide the non-lagged radiocarbon distributions of individual pools total flux and volume for the years 1950, 1965, 2027, and 2100. Radiocarbon distributions of the outflux are presented for the years 1996, 1998, 2002, and 2008, as for those years we have independent  $\Delta^{14}\text{C}$  data from oil  $\text{CO}_2$  efflux compared to our estimations. For all those estimations the number of gas of computation was 1,000 gas. The bin size (‰) for plotting the histogram was 10‰ for most of the radiocarbon distributions except for the year 1965, where it was 20‰.

## 1.1

The radiocarbon values for gas in the past e.g., AD 1965, were obtained by merging the recently released INCal20 calibration curve (Reimer et al., 2020), which combines radiocarbon data and Bayesian statistical interpolation for the range 55,000–0 cal BP (BP = before present = AD 1950), and the records of atmospheric radiocarbon data compiled by Gaudin et al. (2017), from 1950 to 2015. Gaudin et al. (2017) also provides radiocarbon data in one-gas resolution on the range 1850 to 1949. However, since in this range the estimations were partially based on the previous Northern Hemisphere calibration curve (INCal13, Reimer et al., 2013), we decided to best Gaudin et al. (2017)'s data starting in AD 1950.

For the gas in the future, as AD 2027 and 2100, we made a set of the forecast estimations computed by Gaudin (2015), who simulated  $\Delta^{14}\text{C}$  values in the atmosphere for four Representative Concentration Pathways of fossil fuel emissions RCP2.6, RCP4.5, RCP6.0 and RCP8.5. In this work we use the predictions based on the high emissions scenario (RCP8.5), starting in AD 2016.

The  $\Delta^{14}\text{C}$  values in all datasets in this work are given as deviations from the standard representing the pre-industrial atmospheric  $^{14}\text{C}$  concentration. The published values are already corrected for fractionation and decay with respect to the standard. It is equivalent to  $\Delta$  in Sher and Blach (1977). The equation it follows

$$\Delta^{14} = \left( \frac{^{14}\text{C}}{^{12}\text{C}} - 1 \right) \times 1000 [\text{‰}] \quad (13)$$

where  $F^{14}\text{C}$  is the Fraction Modern ( ), i. e., the sample normalized to  $^{13}\text{C}$  by a linear acid standard (OxI), is the predated  $^{14}\text{C}$  decay constant (eq. 18.267 [yr]), and  $y$  is the year of measurement.

## 4

### 4

Overall, our results show that the age and time distributions for his contemporaneous marine (Figure 3), the radiocarbon distributions are highly dynamic. They change dramatically over time as the atmospheric  $\text{CO}_2$  source is affected by the bomb spike and the Suess effect (Suess 1955), i. e., the effect of the dilution of radiocarbon in the atmosphere due to the emission of fossil fuels ( $^{14}\text{C}$ -free). Bolshatov et al. (2015), pool size and age distributions peaks such as *Dead Roots* and *Oi*, followed most closely the radiocarbon dynamics in the atmosphere, while pool size and age distributions are a wide range of values. Consequently the expected  $\Delta^{14}\text{C}$  values are largely

The distributions obtained for the components of the HFS model show different shapes for the different components (Figures 4, 5, and 6, and Figures S2, S3, S4 and S5 in Supplemental Material). In 1965, just after the peak of bomb  $^{14}\text{C}$  in the atmosphere due to nuclear weapons pool size and age distributions had a wide  $\Delta^{14}\text{C}$  range with high probability due to the incorporation of radiocarbon which had changed rapidly over the period AD 1950–1965. Component age distributions are narrower than the radiocarbon age distributions corresponding to negative  $\Delta^{14}\text{C}$  values as expected for bomb atmospheric signal shape and lags.

For the whole system in AD 1965 (Figure 7), the distribution of radiocarbon aggregates the contributions of the different pools which exist in different peaks in the overall distribution. The mode (i. e., the  $^{14}\text{C}$  with highest density) is below 0 ‰ because a large portion of the total amount of carbon is contributed by the mineral associated pool that is predominantly pre-bomb carbon with little contribution from carbon fixed after 1964. In addition, other pool size and age distributions contribute to all amounts of bomb  $^{14}\text{C}$  to the overall distribution.

The radiocarbon distribution in the optimum AD 1965 (Figure 7), i. e., the radiocarbon distribution that corresponds to the time distribution for the system has the distribution peaks in the distribution. This distribution is similar to that of the *Dead Roots* pool (Figure S3), which is the main contributor to the total respiration flux. However, other pool sizes contribute to the respiration flux with the radiocarbon signature and emphasize the flux from the fast cycling pool (O) and respiration of carbon that is present in other pool size before the bomb peak.

The shapes of the distributions change dramatically only shortly after the bomb spike (Figure 5). For AD 2027, the expected  $\Delta^{14}\text{C}$  values of fast pool size considerably in parallel with atmospheric  $^{14}\text{C}$ , compared to AD 1965. The fast pool size is noted much radiocarbon from the bomb period, and the radiocarbon signature reflects recent carbon from the atmosphere. In contrast, slow cycling pool size in AD 2027 had relatively high  $\Delta^{14}\text{C}$  values mostly because they still contain radiocarbon from the bomb period. In the optimum expected, since the respiration flux is dominated by the fast cycling pool size

as *Dead Roots* and *Oi*, most of the radiocarbon is nearly fixed around the recent atmospheric  $\Delta^{14}\text{C}$  value in 2027, with almost no contributions from bomb  $^{14}\text{C}$ .

By the year 2100, the atmospheric  $\Delta^{14}\text{C}$  will have dropped to  $-254 \pm 5$  ‰ (Garn, 2015), reflecting the Suess effect. The distribution of most pools are less variable. For cycling pools have dropped to effect negative  $\Delta^{14}\text{C}$  in the atmosphere over the 73 years since 2027, while the slow pools (*Mineral Associated*, *LF* ( $> 80 \mu\text{m}$ ) and *Organic* pool) still have a wide range of  $\Delta^{14}\text{C}$  values at inclusion during the bomb period (now  $\sim 150$  ‰) as previously.

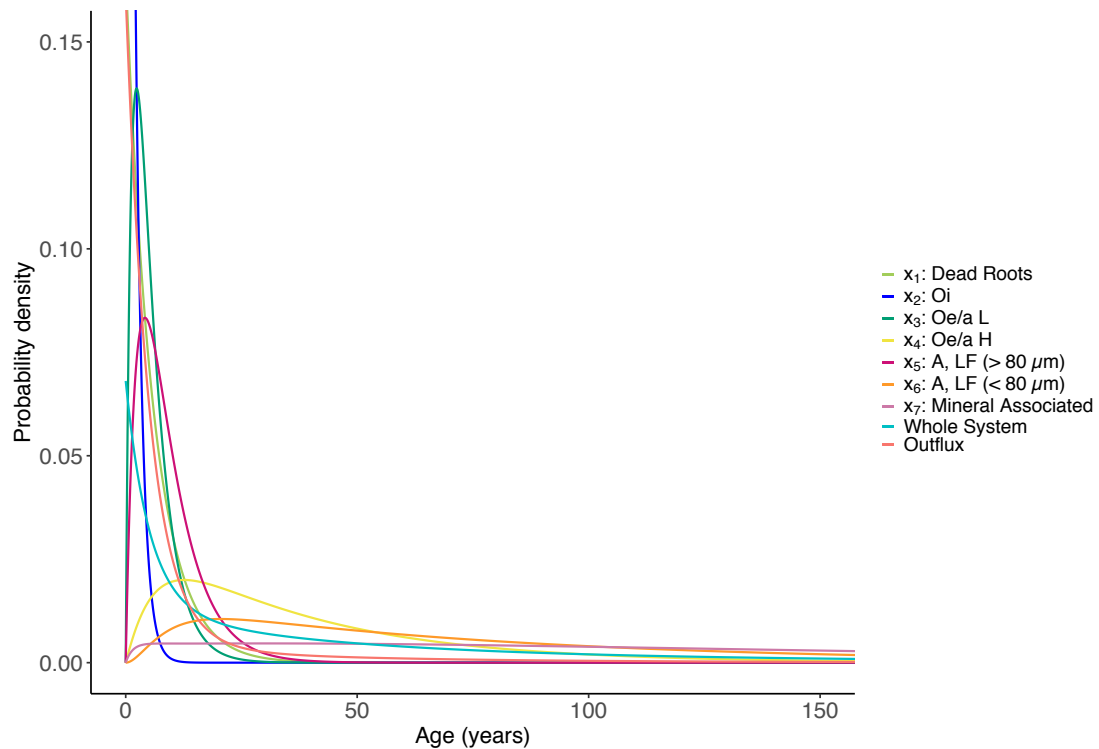
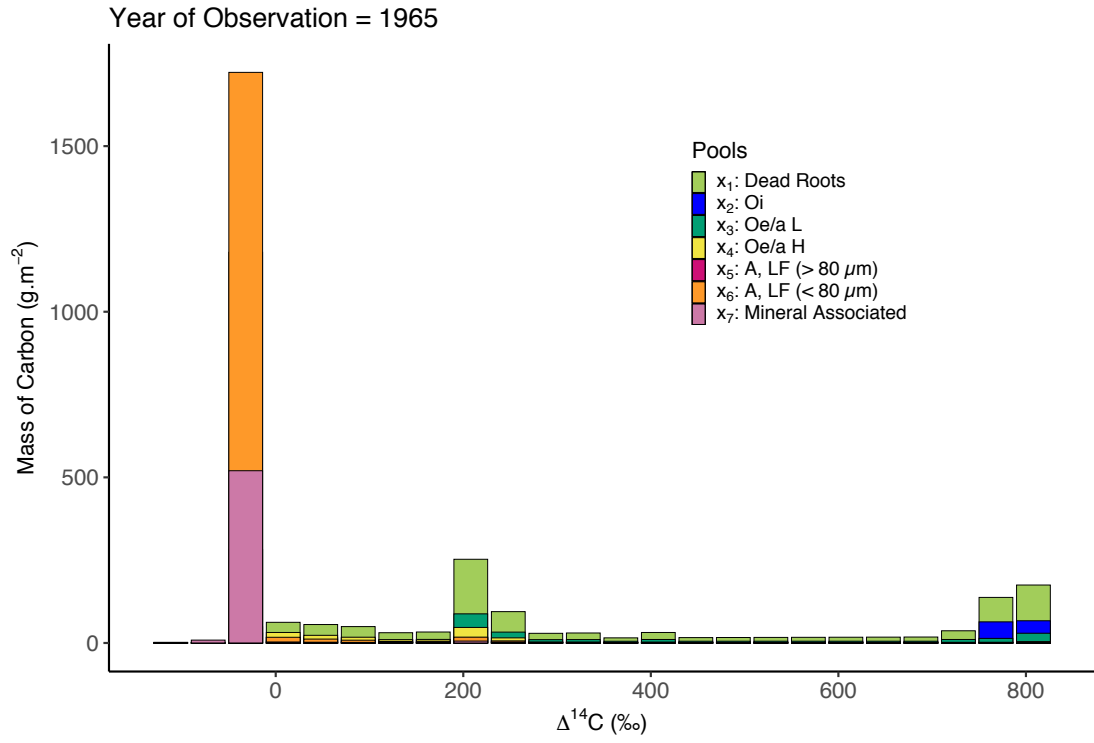
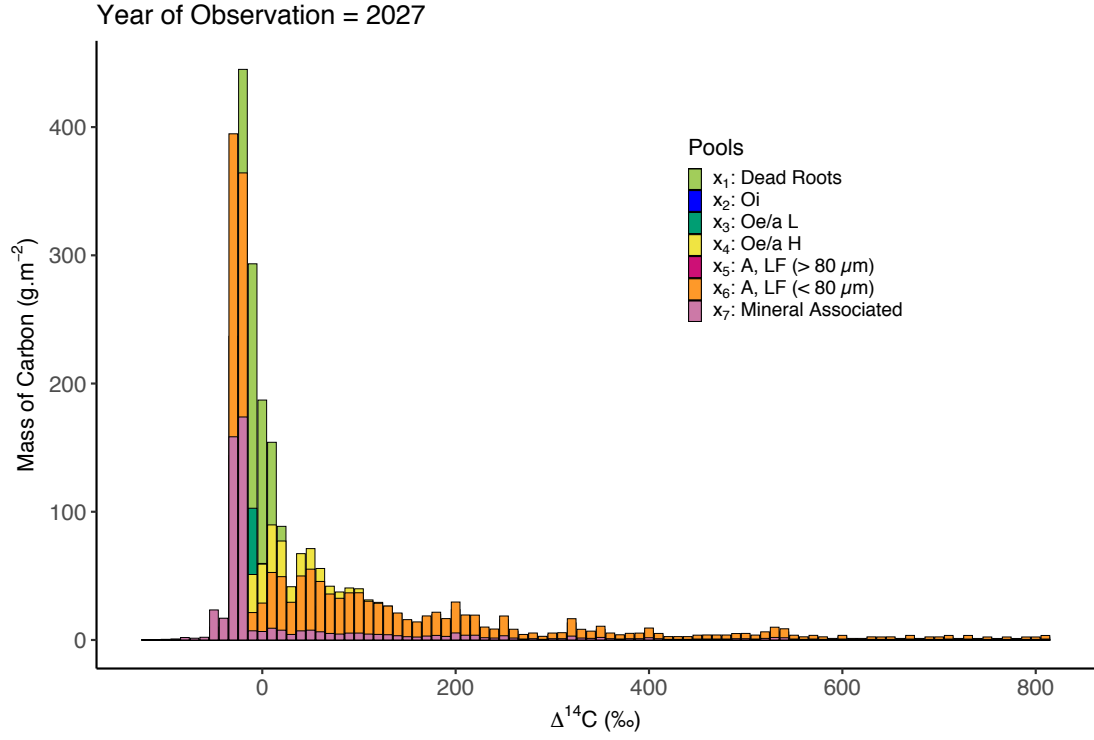


Figure 1: Age distributions for the Harvard Forest Soil model computed in a span of 1,000 years with a resolution of 0.1 year. The x-axis is limited to 150 years and the y-axis is limited to 0.15 for better visualization of the data.

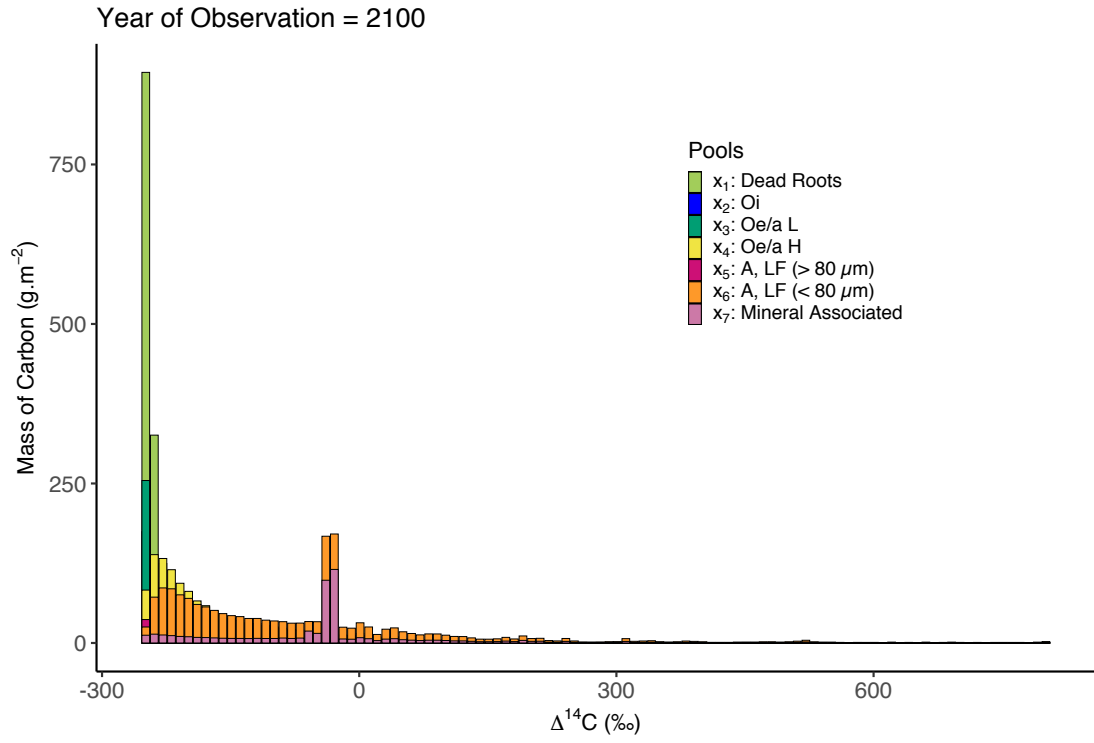


$\Delta^{14}\text{C}$  distributions of each of the seven pools of the HFS model through the algorithm described above. The year of observation is 1965 – just after the bomb peak in 1964 – and the distributions are computed over 1,000 years. The bin size is equal to 40 ‰. The expected value and standard deviation of this distribution is  $141 \pm 280$ .





$\Delta^{14}\text{C}$  distributions of each of the seven pools of the above-mentioned HFS model through the algorithm described above. The year of observation is 2027 and the distributions are computed over 1,000 years. The bin size is equal to 10 ‰. The expected value and standard deviation of this distribution is  $54 \pm 144$ .



$\Delta^{14}\text{C}$  distributions of each of the seven pools of the above-mentioned HFS model through the algorithm described above. The year of observation is 2100 and the distributions are computed over 1,000 years. The bin size is equal to 10 ‰. The expected value and standard deviation of this distribution is  $-147 \pm 146$ .

**Figure 7.**  $\Delta^{14}\text{C}$  distributions of *Outflux* and *Whole System* of the HFS model for the years 1965, 2027 and 2100. The bin size **b** for all the three years is equal to 40 **h** .

**Figure 8.** Evolution of the expected  $\Delta^{14}\text{C}$  values of *Outflux* and *Whole System* for the HFS model between the years 1900 and 2100.

Table 1.  $^{14}\text{C}$  ranges with the highest masses of radiocarbon according to our estimations;  $^{14}\text{C}$  expected values according to weighted mean of mass distribution of radiocarbon; and observed  $^{14}\text{C}$  mean values of soil  $\text{CO}_2$  e ux.

$^{14}\text{C}$ [h ]					
Year	Primary Peaks <sup>a</sup>	Secondary Peaks <sup>b</sup>	Expected value <sup>c</sup>	Mean value <sup>d</sup>	
1996	(112, 122]	(-28, -18], (102, 112], (122, 212]	153 107.6	129.5	17.3
1998	(-37, -17], (93, 153]	(153, 273], (323, 333], (493, 503]	139.4103.3	117.6	26.2
2002	(82, 102]	(-28,-18], (72, 82], (102, 152]	115.9 96.3	100.8	8.4
2008	(51,61]	(41, 51], (61, 121], (-29, -19]	85 89.7	74.8	13.6

a For 1996, 2002 and 2008, masses  $10^3 \text{ g m}^{-2}$ ; For 1998, masses  $10^2 \text{ g m}^{-2}$ ;

b For 1996, 2002 and 2008, masses  $10^2 \text{ g m}^{-2}$ ; For 1998, masses  $10 \text{ g m}^{-2}$ ;

c Expected value of theoretical radiocarbon distribution of the Out ux (weighted mean);

d Mean value of the  $^{14}\text{C}$  values measured on soil  $\text{CO}_2$  e ux from the Harvard Forest.

Figure 9. Comparison between theoretical radiocarbon distribution and independent empirical data. a: Year of observation equals to AD 1996; b: Year of observation equals to AD 1998; c: Year of observation equals to AD 2002; d: Year of observation equals to AD 2008.

time distributions from compartmental systems one should be able to establish at least one combination of atmospheric compartmental mathematical estimates

Moreover, as pointed out by Gadnik et al. (2000), limited information about the cycling rates obtained by  $^{14}\text{C}$  measurements of bulk SOM made at a single point in time. Therefore, being able to compartmental carbon distributions for different gases of observation could improve the interpretation of siladiocarbon in atmospheric carbon dynamics

Compartmental models are a common approach to describe the dynamics of open systems partially when modeling the carbon cycle in ecosystems. The mathematical equations developed to obtain age and distribution estimates are a standard approach already used in several contexts, and therefore, using these distributions to obtain radiocarbon distributions in the same system is a powerful method. The algorithm presented, besides being simple, demonstrated the potential power of the method. It also showed how for a specific model, predictions can be compared with experimental data.

Radiocarbon distributions can be obtained with the known changes in atmospheric  $\Delta^{14}\text{C}_{\text{CO}_2}$  to evaluate how model predictions of the changing distributions of radiocarbon in each compartment and isotopes over at least decades. This provides a powerful method to estimate model sagas observations and to refine model representations of C dynamics in soils and ecosystems.

Overall, we have shown that the heterogeneity of the ecosystem described through the mixing of material in the pool is related to the heterogeneity of the radiocarbon distributions. As opposed to age and distribution of systems in each case, radiocarbon distributions are expected to vary in time, largely depending on the rate of observation as a consequence of the dependence on the atmospheric  $^{14}\text{C}$  input in the system. Thus, not only the distributions are a simple change according to the rate of observation, but also the expected values, modes and variance.

Overall, fast cycling pools with less heterogeneity present a wide spread of all the gases of observations, whereas slow cycling pools with less heterogeneity compartmentalize present a wide spread of multiple peaks of  $\Delta^{14}\text{C}$  for high labeled gases (e.g., 1965, when the concentration of  $^{14}\text{C}$  in the atmosphere was almost twice as high as the natural level).

The theoretical distributions can be estimated for specific time points, however, it is not always feasible in experiments. That means the estimations through the algorithm have to be taken carefully when one aims to compare them to empirical data. It is also important to be aware of the radiocarbon atmospheric levels to estimate the distributions as the variation of atmospheric  $\Delta^{14}\text{C}$  can influence the heterogeneity and mean values of the distributions. In this sense, having accurate data on the  $^{14}\text{C}$  content in the atmosphere is key for the determination of the radiocarbon distributions in multiple interconnected compartmental systems.

## A

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The atmospheric  $\Delta^{14}\text{CO}_2$  datasets in this research are available through Gaillardet (2015), Gaillardet et al. (2017), and Reimer et al. (2020). Data on the compartmental model presented in this research, including the independent  $\Delta^{14}\text{C}$  data and for comparisons with observations are available through Si et al., Töpel, et al. (2012).

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