

## Response to Editor Comments:

76: Supplemental table S1 has 177 entries, which matches your statement in the abstract, but not what is being said here. Further, entry 196 in the supplemental table lacks results, so is seemingly not included? (I.e. should total number of profiles be 176?)

We thank you for catching this error. The number '196' soil profile has been deleted in the supplemental table. So, the final dataset included 176 soil profiles, and we have corrected this in the abstract (Line 12) and the text (Line 76, 82, 89, 127 and 391).

103-105 Replace “We applied [...] millennial time-scales” by: “In order to calculate the SOM decomposition rate constant, we assumed that input of organic matter to soil and decomposition are in equilibrium with no change in SOM stocks over time (steady state assumption). We acknowledge that this assumption is not valid in most disturbed environments, including agricultural systems, but it provides a reasonable approximation in natural ecosystems, where SOC turnover has equilibrated on century to millennial time-scales.” (This is a suggestion from me, please feel free to rephrase. I think that simply stating “steady state assumption” was not clear enough and that a slightly more elaborate justification was needed.)

Thank you very much. We agree with your suggestion and have replaced the sentence in the revision (Line 106-109).

228-234: This section is important, but it is poorly integrated into the overall discussion. These points reflect the concerns of referee 1 well, but the reader is left not knowing how significant these uncertainties are for your findings. I suggest moving this section up into the main part of the discussion and qualifying whether you think that the patterns you observe in your study are robust despite these limitations. I'm not asking for a lengthy elaboration of implications, but a clearer indication of whether, in your judgement, these limitations are a major limitation to your conclusions.

Thank you for your suggestion. We moved this part up into the method (Line 85-87) and discussion (Line 208-209 and 213-214).

Figure 4: In panel B, the axes are seemingly labelled incorrectly. To match data in panel A,  $k$  seems to be scaled on the y-axis, and  $\ln(-\beta)$  on the x-axis, but your axis labelling suggests the opposite.

Thank you. We have changed the axes.

## 1 Stable isotopic constraints on global soil organic carbon turnover

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9 **Abstract.** Carbon dioxide release during soil organic carbon (SOC) turnover is a pivotal component of atmospheric CO<sub>2</sub>  
10 concentrations and global climate change; however, reliably measuring SOC turnover rates at large spatial and temporal scales  
11 remains challenging. Here we use a natural carbon isotope approach, defined as beta ( $\beta$ ), which was quantified from the  $\delta^{13}\text{C}$  of  
12 vegetation and soil reported in the literature ([176](#) separate soil profiles), to examine large-scale controls of climate, soil physical  
13 properties and nutrients over patterns of SOC turnover across terrestrial biomes worldwide. We report a significant relationship  
14 between  $\beta$  and calculated soil C turnover rates ( $k$ ), which were estimated by dividing soil heterotrophic respiration rates by SOC  
15 pools.  $\ln(-\beta)$  exhibits a significant linear relationship with mean annual temperature, but a more complex polynomial relationship  
16 with mean annual precipitation, implying strong-feedbacks of SOC turnover to climate changes. Soil nitrogen (N) and clay content  
17 correlate strongly and positively with  $\ln(-\beta)$ , revealing the additional influence of nutrients and physical soil properties on SOC  
18 decomposition rates. Furthermore, a strong ( $R^2 = 0.76$ ;  $p < 0.001$ ) linear relationship between  $\ln(-\beta)$  and estimates of litter and root  
19 decomposition rates suggests similar controls over rates of organic matter decay among the generalized soil C stocks. Overall,  
20 these findings demonstrate the utility of soil  $\delta^{13}\text{C}$  for independently benchmarking global models of soil C turnover and thereby  
21 improving predictions of multiple global change influences over terrestrial C-climate feedback.

### 22 1 Introduction

23 Soil contains a large amount of organic carbon (C) and plays a crucial role in regulating Earth's C cycle and climate system  
24 (Schmidt et al., 2011; Reichstein et al., 2013). Approximately 1500 Gt of soil organic carbon (SOC) is stored in the upper meter of  
25 global mineral soil (Scharlemann et al., 2014), which is equivalent to ~160 years-worth of current fossil fuel CO<sub>2</sub> emissions.  
26 Disagreement exists, however, over the residence time of this vulnerable C stock and its relationship to factors of ongoing change,  
27 particularly climate changes and widespread nitrogen pollution (Reay et al., 2008; Reichstein et al., 2013). Biogeochemical models  
28 rely heavily on turnover rates of discrete SOC pools (active, intermediate, and recalcitrant) derived from lab incubation studies  
29 (Davidson and Janssens, 2006; Xu et al., 2016). In practice, however, SOC pools fall along a continuum of characteristic turnover  
30 times (from days to centuries; (Schmidt et al., 2011; Lehmann and Kleber, 2015)), in a given ecosystem site. Furthermore, lab-  
31 derived estimates of SOC turnover disrupts the sensitive balance between plant-soil-microbe interactions in ecosystems, adding  
32 questions on the reliability of such techniques when applied to real-world conditions.

33 The rate of SOC turnover is an important parameter for process-based ecosystem models (Davidson and Janssens,  
34 2006; Schimel et al., 1994) and those used to forecast the global carbon cycle and climate system in the future (Friedlingstein et al.,  
35 2006). Global biogeochemical models often use climatic factors such as precipitation and temperature to predict SOC turnover  
36 rates (Schimel et al., 1994; Nishina et al., 2014). While several studies reported positive relationships between temperature and

37 SOC turnover (Chen et al., 2013;Trumbore et al., 1996;Bird et al., 1996;Trumbore, 1993;Carvalhais et al., 2014), however, others  
38 have called the generality of such relationships into question (Giardina and Ryan, 2000). This discrepancy could be due to  
39 interactions among factors which are difficult to separate in the field, for example, among soil temperature, soil moisture and  
40 nutrient controls over SOC decomposition (Davidson and Janssens, 2006). Nitrogen (N) in particular can affect SOC  
41 decomposition by changing microbial community structure, microbial activity or both (Curiel et al., 2007). Incorporation of factors  
42 besides climate is crucial for improving model performance and predicting the feedback-response of the terrestrial carbon cycle to  
43 climate change (Nishina et al., 2014).

44 In addition, questions remain regarding whether the turnover of different C stocks behaves fundamentally similarly. For  
45 example, climate is considered to be a “master regulator” of leaf litter (Zhang et al., 2008), root (Gill and Jackson, 2000;Silver and  
46 Miya, 2001) and soil organic C pools (Davidson and Janssens, 2006). However, recent findings have pointed out that soil microbial  
47 community composition may play a more important role in litter decomposition rates than climate or litter quality (Bradford et al.,  
48 2016;Keiser and Bradford, 2017). Due to the different microbial communities among leaves, roots and soils, and different chemical  
49 composition of such pools, rates of C turnover have the potential to vary widely across generalized classes of C stocks.

50 Stable carbon isotope composition ( $\delta^{13}\text{C}$ ) provides relatively non-disruptive insights into the turnover of SOC (Garten et al.,  
51 2000;Accoe et al., 2002;Powers and Schlesinger, 2002;Bird et al., 1996). For sites with reasonably stable vegetation stocks,  
52 measures of vertical soil-profile  $\delta^{13}\text{C}$  can provide constraints on SOC turnover rates in ecosystems (Acton et al., 2013;Garten et  
53 al., 2000;Wynn et al., 2006). Soil  $\delta^{13}\text{C}$  generally increases from shallow to deep mineral soils in relatively well-drained systems,  
54 concomitant with decreasing SOC concentrations (Fig. S1). The vertical distribution of the  $\delta^{13}\text{C}$  reflects microbial preferences for  
55  $^{12}\text{C}$  vs.  $^{13}\text{C}$  in decomposing substrates (Garten et al., 2000), which, in turn, increases the  $^{13}\text{C}/^{12}\text{C}$  of residual organic C fractions  
56 with a kinetic isotope effect defined by  $\epsilon$  (Fig. S1). Therefore, SOC  $\delta^{13}\text{C}$  tends to increase with depth along vertical soil profiles  
57 until it reaches a maximum value at which point a steady-state is achieved (Kohl et al., 2015;Accoe et al., 2002;Brunn et al.,  
58 2014;Garten et al., 2000;Wynn et al., 2006;Brunn et al., 2016). These trends result in a negative linear relationship between the  
59 log-transformed SOC concentration and soil  $\delta^{13}\text{C}$  (Acton et al., 2013;Garten et al., 2000;Garten and Hanson, 2006;Powers and  
60 Schlesinger, 2002). The slope of the linear regression between soil  $\delta^{13}\text{C}$  and the log-transformed SOC concentration is defined as  
61 beta ( $\beta$ ), which has been proposed as a proxy for SOC turnover rate in a select number of sites (Acton et al., 2013;Garten et al.,  
62 2000;Powers and Schlesinger, 2002).  $\beta$  has also been assessed in set of regional scale analyses (Acton et al., 2013;Brunn et al.,  
63 2014); however, whether  $\beta$  values can be used to constrain rates and controls on SOC turnover is yet to be explored at the global  
64 scale. Furthermore, the Suess effect (the atmospheric isotopically depleted fossil fuel  $\text{CO}_2$  lowering atmospheric  $\delta^{13}\text{C}\text{-CO}_2$ )  
65 (Boström et al., 2007;Wynn et al., 2006) and the mixing of different C sources (Acton et al., 2013;Diocion and Kellman,  
66 2008;Wynn, 2007) may also influence the profile of soil  $\delta^{13}\text{C}$  with depth. Identifying the relative influence of different factors in  
67 vertical profiles of soil  $\delta^{13}\text{C}$  is essential to applying this proxy to patterns of SOM turnover.

68 Here, we examine the efficacy of  $\beta$  as a proxy for SOC turnover rates by synthesizing soil profile data from sites around the  
69 world (Fig. 1). To understand the overall utility of C isotope composition for constraining SOC turnover rates, we explore the  
70 relationship between  $\beta$  and modeled SOC decomposition constant  $k$  and environmental factors, particularly climate, soil clay  
71 content and nutrient availability. We also compare the variation of  $\beta$  with that of root and litter turnover rates across latitude  
72 (thermal) gradient to examine whether and how the decomposition of generalized C pools varies as a function of likely controls.

## 73 2 Materials and Methods

### 74 2.1 Data compilation

75 Using the key words of ‘carbon isotope & vertical profile’, ‘ $\delta^{13}\text{C}$  & soil depth profile’, or ‘soil carbon turnover & stable isotope’  
76 on the Web of Science source, we assembled a total of 149 soil profiles from 51 journal papers (Fig. 1; A list of the literature  
77 sources is given in Table S1). Only soil profiles under pure  $\text{C}_3$  vegetation without significant human disturbance were selected. For  
78 each profile, we collected carbon isotope ( $\delta^{13}\text{C}$ ), organic carbon (SOC) and N concentration of leaf/litter and mineral soil layers at  
79 different depths if the data is available, and more than four  $\delta^{13}\text{C}$  values should be provided within the top 1 meter. Where data were  
80 not available in tables, Data Thief software (<http://www.datathief.org/>) was used to acquire values from figures. We also noted the  
81 experiment location (latitude and longitude), biome types, mean annual precipitation (MAP), and mean annual temperature (MAT)  
82 for each soil profile. In cases where climate variables were not reported (15 soil profiles out of 176), we used the WorldClim data  
83 (<http://www.worldclim.com/>), which have average monthly temperature and precipitation between 1970 to 2000 with a resolution  
84 of  $\sim 1 \text{ km}^2$  at the global scale, to reconstruct climate values based on latitude and longitude coordinates in ArcGIS version 10.0  
85 using Spatial Analysis tool (ESRI, Redlands, CA). The extracted model data may not precisely match the actual climate data of  
86 these 15 soil profiles. However, because the model has been widely tested and accepted (Harbert and Nixon, 2015) and the  
87 resolution is high (Hijmans et al., 2005), any deviation should be relatively small.

88 In addition, a previous reported arid and semi-arid grassland transect along 3000 km with 27 sampling locations was added  
89 into the dataset (Wang et al., 2017), which results in a total of 176 soil profiles in the compilation. Those sampling sites are  
90 dominated by  $\text{C}_3$  plants and cover approximately  $16^\circ$  longitude ranging from  $104^\circ 52' \text{ E}$  to  $120^\circ 21' \text{ E}$  and  $10^\circ$  latitude ranging from  
91  $40^\circ 41' \text{ N}$  to  $50^\circ 03' \text{ N}$ . The MAP ranges from 90 mm to 420 mm and MAT ranges from  $-2^\circ \text{ C}$  to  $+7^\circ \text{ C}$ . At each location, five  $1 \text{ m}$   
92  $\times 1 \text{ m}$  sub-plots (or one  $5 \text{ m} \times 5 \text{ m}$  sub-plot in areas with shrub as the dominating plants) were setup within a  $50 \text{ m} \times 50 \text{ m}$  plot.  
93 Twenty soil cores (0 - 100 cm) in each  $1 \text{ m} \times 1 \text{ m}$  sub-plot were collected and divided into 0-10 cm, 10-20 cm, 20-40 cm, 40-60  
94 cm and 60-100 cm depth segments and bulked to form one composite sample for each segment per sub-plot. Leaf samples of five  
95 dominating genera (*Stipa*, *Leymus*, *Caragana*, *Reaumuria* and *Nitraria*) were sampled for carbon isotope analysis if these genera  
96 were present in the sub-plots.

97 In laboratory, leaf samples were washed with deionized water to remove dust particles and then dried at  $65^\circ \text{ C}$  for 48 h. Both  
98 soil and leaf samples were ground in a ball mill and stored in a plastic bag. Soil carbonate was removed from soil samples using  
99  $0.5 \text{ M HCl}$ . Organic carbon concentration and isotope composition of soil and leaf were carried out at the Stable Isotope Faculty  
100 of University of California, Davis.

### 101 2.2 Beta calculation

102 A negative linear regression between the  $\log_{10}$ -transformed SOC concentration and  $\delta^{13}\text{C}$  for each soil depth profile was conducted  
103 (Fig. S1). The slope of the this linear regression is defined as beta ( $\beta$ ) value (Acton et al., 2013; Garten et al., 2000; Powers and  
104 Schlesinger, 2002).

### 105 2.3 Soil decomposition rate constant ( $k$ )

106 In order to calculate the SOM decomposition rate constant, we assumed steady-state between organic matter inputs to the soil and  
107 decomposition rates. We acknowledge that this assumption is not valid in most disturbed environments, including agricultural  
108 systems, but it provides a reasonable approximation in natural ecosystems, where SOC turnover does not show significant  
109 deviations on century to millennial time-scales. The carbon decomposition rate constant ( $k$ ) was estimated as the ratio between soil

110 heterotrophic respiration ( $R_H$ ) and soil organic carbon stock (SOC) (Sanderman et al., 2003):  $k = R_H / \text{SOC}$ . The SOC stock for  
111 each soil profile was extracted from a global soil organic carbon map (within 1 m depth), which was created by IGBP-DIS (1998)  
112 with a resolution of 0.5 by 0.5 degree; the mean annual soil total respiration ( $R_S$ ) was extracted from a long-term dataset with a  
113 resolution of 0.5 by 0.5 degree (Raich et al., 2002). We added the two datasets and the coordinate of soil profiles in ArcGIS (version  
114 10.0, ESRI, Redlands, CA) to extract SOC stock and respiration rates for each profile using the Spatial Analysis tool. Then, we  
115 used the linear relationship between soil respiration ( $R_S$ ) and  $R_H$  to calculate  $R_H$  (Bond - Lamberty et al., 2004):  $\ln(R_H) = 1.22 +$   
116  $0.73 \times \ln(R_S)$ .

## 117 2.4 Data analysis

118 Negative  $\beta$  value and decomposition rate constant  $k$  were log-transformed to perform statistical tests. Larger  $\ln(-\beta)$  translated to  
119 faster SOC decomposition rates (Acton et al., 2013; Powers and Schlesinger, 2002). Soil  $\ln(-\beta)$  was analyzed and summarized  
120 across different biome types. Soil  $\ln(-\beta)$  was also compared with litter and root decomposition rate along latitude at the global  
121 scale. Two-variable regression analysis was first performed to explore the relationship between  $\ln(-\beta)$  and  $\ln(k)$ , or  $\ln(-\beta)$  and  
122 climate variables (MAP and MAT) as well as soil edaphic factors (N and clay content). Multiple regression analysis was then used  
123 to examine the relationship between  $\ln(-\beta)$  and these variables (MAP, MAT, soil N and clay content). Akaike information criterion  
124 (AIC) was used to estimate the quality of model when increasing the number of parameters.

## 125 3 Results

### 126 3.1 Worldwide patterns of $\beta$

127 A total of 176 soil profiles from all continents other than Antarctica were encapsulated in our compiled dataset (Fig. 1). Carbon  
128 isotope composition ( $\delta^{13}\text{C}$ ) increased with soil depth in the majority of examined profiles and was strongly correlated with the  
129 logarithm of SOC (Table. S1).  $\ln(-\beta)$  was significantly positively related with site-based estimates of the soil C decomposition  
130 constant,  $\ln(k)$  with  $R^2 = 0.34$  (Fig. 2).

131 The values for  $\ln(-\beta)$  ranged from -0.50 to 2.20 across sites (non-transformed  $\beta$  values ranged from -0.60 to -7.41, Table S1).  
132 Highest mean  $\ln(-\beta)$  was observed in tropical forests (Fig. 3), followed by deserts, temperate forests, and temperate grasslands,  
133 with a mean value of 1.15, 0.70, 0.58 and 0.49, respectively. MAP among those four biomes increased from desert < temperate  
134 grassland < temperate forest < tropical forest and MAT increased from temperate grassland < desert < temperate forest < tropical  
135 forest (Fig. 3).

136 Along the latitude gradient,  $\ln(-\beta)$  decreased from the equator to poles, but was higher at 20-30° N compared to the 10-20° N  
137 latitudinal band (Fig. 4a). The mean decomposition rate of leaf-litter and root C displayed similar latitudinal patterns ( $R^2 = 0.76$ ;  
138  $p < 0.001$ , Fig. 4b).

### 139 3.2 Controls on $\beta$ across ecosystems

140 The  $\ln(-\beta)$  and MAT displayed a strong, positive relationship across the global dataset ( $R^2 = 0.43$ ;  $P < 0.001$ ; Fig. 5a).  $\ln(-\beta)$  did  
141 not show a simple linear correlation with MAP, but instead showed a polynomial relationship with a tipping point at MAP = 3000  
142 mm (Fig. 5b). When MAP was less than 3000 mm,  $\ln(-\beta)$  was positively correlated with MAP ( $R^2 = 0.23$ ,  $P < 0.001$ );  $\ln(-\beta)$   
143 decreased with the increasing of MAP in areas receiving > 3000 mm of MAP. A quadratic equation provided the best fit to the  
144 relationship between  $\ln(-\beta)$  and MAP for all sites ( $R^2 = 0.24$ ,  $P < 0.001$ ; Fig. 5b). Soil N explained 20% of the variations in  $\ln(-\beta)$   
145 ( $P < 0.001$ ; Fig. 5c). Moreover, a quadratic equation best described the relationship between soil clay and  $\ln(-\beta)$ , with  $R^2 = 0.49$  ( $P$

146 < 0.001; Fig. 5d). AIC analysis showed that the full-factors model (i.e., MAT, MAP, soil N and clay) accounted for more of the  
147 variation in  $\ln(-\beta)$  than any other regression model in the global data set (Table 1).

## 148 **4 Discussion**

149 Our global data synthesis reveals significant relationships between  $\ln(-\beta)$  and the turnover of soil, litter and root C pools at  
150 geographically broad scales (Fig. 2 and 4). These findings build on site-based observations and regional assessments (Accoe et al.,  
151 2002; Garten et al., 2000; Powers and Schlesinger, 2002; Brunn et al., 2014; Brunn et al., 2016), and suggest that C isotope  
152 composition is a useful proxy for understanding generalized patterns of SOC turnover and the underlying controls over soil C  
153 metabolism. That our results hold across all major soil C pools implies that SOC, root and litter turnover share common controls,  
154 in particular those related to climate and soil nitrogen contents. These findings suggest that decomposition of belowground and  
155 aboveground soil C may have similar responses to global climate change, such as global warming and increasing atmospheric N  
156 deposition. Furthermore, our results highlight the potential of incorporating natural stable C isotopes in global biogeochemical and  
157 Earth system models to constraint soil and litter decomposition rates that are vital to climate change forecasts.

158 Within the terrestrial biosphere, our findings point to highest mean  $\ln(-\beta)$  in tropical forest ecosystems, indicating a high SOC  
159 decomposition rate in these regions, which is consistent with previous studies (Carvalhais et al., 2014). At the other extreme, our  
160 analysis suggests that slowest mean rates of SOC decomposition occur in temperate grassland (Fig. 3), consistent with results from  
161 previous simulation modeling (Carvalhais et al., 2014; Schimel et al., 1994). Relatively slow decomposition rates have been  
162 observed for plant litter decay in arid grassland sites (Zhang et al., 2008), and largely reflects strong moisture controls on  
163 decomposition. In addition, microbial biomass and microbial activities are much lower in arid/semi-arid vs. mesic or humid sites  
164 (Fierer et al., 2009), thus leading to low rates of SOC and litter decomposition.

### 165 **4.1 Climate and nutrient dependences of $\beta$**

166 The differences of  $\beta$  value among different biomes reflect several controlling variables- especially mean annual temperature, mean  
167 annual precipitation, soil N contents, and clay content. Of particular importance is temperature-driven controls over  $\beta$ , in which  
168 MAT explains 43% of the variation of  $\ln(-\beta)$  in our global data compilation (Table 1; Fig. 5a). A recent meta-analysis, which  
169 included 24 soil profiles across a range of cool temperate to tropical forest sites, reported similarly strong temperature-dependencies  
170 of  $\beta$  (Acton et al., 2013). Our findings broaden this perspective to a global range of terrestrial biomes and climates, and indicate  
171 that, with increasing MAT, SOC turnover is substantially accelerated. This result agrees with previous studies which have identified  
172 temperature as the strongest regulator of soil C decomposition among all known controls (Carvalhais et al., 2014; Schimel et al.,  
173 1994), and is consistent with global C-climate feedback models, which project accelerated rates of CO<sub>2</sub> efflux from the land  
174 biosphere with climate warming (Ciais et al., 2014).

175 Our study also points to significant relationships between  $\beta$  and precipitation-climates, which are more complex than those  
176 observed for MAT. Rather, we find an inflection point in  $\beta$  in our global data set at MAP ~ 3000 mm (Fig. 5b). This relationship  
177 reveals negative effects of moisture on change of soil  $\delta^{13}\text{C}$  in very wet climates. A cross-system compilation of the smaller though  
178 more dynamic litter pool shows a similar pattern of decreasing decay rates in regions with MAP > 3000 mm compared to drier  
179 sites (Zhang et al., 2008). In addition, Schuur (2001) showed that leaf and root decomposition rates declined significantly with  
180 increasing precipitation along a highly constrained rainfall sequence in Hawaiian forest sequence (from 2020 mm < MAP < 5050  
181 mm), thereby resulting in slower rates of nutrient mineralization and declines in net primary production (NPP) in the wettest sites.  
182 The consistencies between our study and past work suggests that precipitation affects the decomposition of SOC and litter in  
183 similar ways, slowing decomposition rates when MAP is very high and anaerobic conditions dominate (i.e. MAP > 3000 mm;

184 Schuur 2001).

185 In addition to climate, nutrients influence the magnitude of  $\ln(-\beta)$  in our compilation, with SOC turnover rates generally  
186 increasing with soil N concentrations across ecosystem sites (Table 1, Fig. 5c). Although soil N has been suggested as an important  
187 control over SOC decomposition in previous work (Schimel et al., 1994), our study is one of the few to confirm the existence of  
188 such a relationship at the global scale. Positive correlations between litter decomposition rates and litter N contents during the early  
189 stages of decay have been reported previously (Berg, 2000). Past work has also suggested that high N availability enhances soil  
190 degrading enzyme activities (Fioretto et al., 2007).

191 Finally, our results suggest that soil physical factors, particularly soil clay content, plays a role in  $\ln(-\beta)$  and soil organic C  
192 turnover (Fig. 5d), consistent with previous expectations (Schimel et al., 1994; Xu et al., 2016). In sites where clay content is < 50%  
193 (i.e., sandy soils), for example,  $\ln(-\beta)$  increases with the soil clay content; however, when clay content is > 50% (loamy or clayey  
194 soils), no clear relationship between  $\ln(-\beta)$  and clay content is observed (Fig. 5d). The change in this relationship could be explained  
195 by the higher “preservation capacity” of clayey soils (Vogel et al., 2014).

196 SOC turnover is an important parameter for process-based models and Earth system models (Schimel et al., 1994; Davidson  
197 and Janssens, 2006), and models used to forecast the carbon cycle and climate system into the future (Friedlingstein et al., 2006).  
198 Global biogeochemical models commonly use climatic factors as predictors of SOC turnover rates (Carvalhais et al., 2014). In  
199 contrast, our results point to factors beyond climate singly, soil N content and soil texture, in altering organic C turnover across the  
200 terrestrial biosphere. Taken together, for instance, our multiple regression analysis considering all factors (i.e., MAT, MAP, soil  
201 N and clay) explains nearly 70% of variation of  $\ln(-\beta)$  ( $R^2= 0.66$ ,  $P<0.001$ ; Table 1), suggesting the high dependence of SOC  
202 turnover on these factors. We therefore suggest the need for models that include all of these factors when forecasting global C  
203 cycle response to change.

204 In addition, our findings suggest that the C isotope composition of the soil can help to improve global C model performance.  
205 A common problem in global C research is finding consistent and sufficiently integrated metrics against which the performance of  
206 different biogeochemical models can be quantitatively analyzed (Tian et al., 2015). The strong relationships we observe between  
207  $\beta$  and SOC turnover ( $k$ ) suggest that this natural-isotope proxy can be used to ground-truth large-scale patterns of model-simulated  
208 soil C dynamics. It should be noted that  $k$  values were based on multiple data sources of soil carbon storage and respiration, which  
209 might add uncertainty to the regression statistics between  $\ln(-\beta)$  and  $\ln(k)$ .

210 Future work to collect and analyze C isotope data in vertical soil profiles, which is a relatively inexpensive process, can further  
211 extend the regional coverage of  $\beta$  and help benchmark SOC turnover estimates among global model simulations. This is important  
212 given the potential for SOC turnover to respond to multiple global changes and produce significant feedbacks on climate at the  
213 global scale (Carvalhais et al., 2014; Lehmann and Kleber, 2015). Further, application of our results to ecosystems that are far from  
214 steady-state should be approached with caution.

#### 215 4.2 Alternative controls over soil $\delta^{13}\text{C}$ with depth

216 Several processes have been proposed to explain the widely observed pattern of increasing  $\delta^{13}\text{C}$  from shallow to deep soils beyond  
217 those related to kinetic isotope fractionation during decomposition. For example, atmospheric  $\delta^{13}\text{C}$ -CO<sub>2</sub> has been decreasing since  
218 the industrial revolution owing to the combustion of  $^{13}\text{C}$ -depleted fossil fuels, which could lead to lower  $\delta^{13}\text{C}$  in surface soils vs.  
219 deeper horizons (Friedli et al., 1987). However, the magnitude of this effect is small (i.e., 1.4 - 1.5‰) compared to the substantial  
220 variation of soil  $\delta^{13}\text{C}$  along depth profiles (~3.5‰) in our dataset. Based on a 100-year-old soil archive (i.e. soil collected before  
221 extensive fossil fuel CO<sub>2</sub> emissions) and modern samples collected from a common site in the Russian steppe, Torn *et al.*(2002)  
222 demonstrated that  $\delta^{13}\text{C}$  profiles of modern and pre-industrial soils were similar. Thus, the  $\delta^{13}\text{C}$  values of SOM in soil profiles that

223 can be attributed to the changes in the  $\delta^{13}\text{C}$  of atmospheric  $\text{CO}_2$  should be small.

224 In addition, bioturbation and consequent mixing of C from different sources has the potential to alter soil  $\delta^{13}\text{C}$  profiles (Acton  
225 et al., 2013; Ehleringer et al., 2000). The  $\delta^{13}\text{C}$  of root material is generally higher than that of above ground biomass, such as leaves  
226 (Powers and Schlesinger, 2002), and so the  $\delta^{13}\text{C}$  of SOC at the soil surface may be lower than deep soils. Because microbes,  
227 invertebrates, and other soil fauna are typically enriched in  $\delta^{13}\text{C}$  compared to source-substrates, biological migration and physical  
228 mixing of soils may alter relationships between soil C concentrations and  $\delta^{13}\text{C}$  (Wynn et al., 2006). Kohl et al. (2015) suggested  
229 that increased proportions of soil bacteria ( $^{13}\text{C}$  enriched) relative to fungi ( $^{13}\text{C}$  depleted) biomass might also contribute to increasing  
230  $\delta^{13}\text{C}$  with depth; however the process-based modeling predicts the opposite pattern (Acton et al., 2013).

231 Moreover, in extremely wet sites, it is likely that leaching of dissolved organic carbon (DOC) from soils to streams affects the  
232 relationship between decomposition and isotope effect expression (Powers and Schlesinger, 2002). Previous studies have shown  
233 that DOC increases with increasing soil depth (Kaiser et al., 2001). Because DOC is generally  $^{13}\text{C}$ -enriched (Kaiser et al., 2001),  
234 increasing DOC leaching into very wet sites would be expected to induce a larger change in soil  $\delta^{13}\text{C}$  with depth, and hence,  
235 increasing  $\ln(-\beta)$ .

### 236 **4.3 Uncertainty on carbon isotope method**

237 ~~It is important to stress that we applied steady state assumptions in estimating turnover, which would not hold for all sites,~~  
238 ~~especially highly disturbed or human altered environments, such as agricultural soils. Application of our results to ecosystems that~~  
239 ~~are far from steady state should be approached with caution. Further, we used multiple data sources to estimate soil carbon store~~  
240 ~~and respiration for profiles in our dataset and then calculated the  $k$  values, which might add uncertainty to the comparison between~~  
241  ~~$\ln(-\beta)$  and  $\ln(k)$ . Finally, the coordinates that we used to extract climate data for some soil profiles (15 soil profiles out of ) from a~~  
242 ~~world climate dataset may not match the exact locations of these soil profiles.~~

## 243 **5 Conclusion**

244 Our analysis provides a globally integrative tool for understanding variations of SOC turnover rate, which can be applied spatially  
245 based on estimates of factors such as climate and soil properties. Compared with other methods, utilization of C isotope  
246 composition ratios in soil profile provides an independent approach that does not rely on disruption of plant-soil-microbe  
247 interactions. It has the added benefit of integrating over longer time scales (decade to centuries), and thus provides a common  
248 measurement for model-based benchmarking and calibration schemes.

249 **Author contribution.** C.W. and E.B. conceived and wrote the paper with contributions from B.Z.H. C. W., W. C., D. L., and J.  
250 H. conducted the field and laboratory works. C.W. E.B. and D.W.L. compiled data from peer-reviewed publications and conducted  
251 the modelling. All co-authors interpreted the results.

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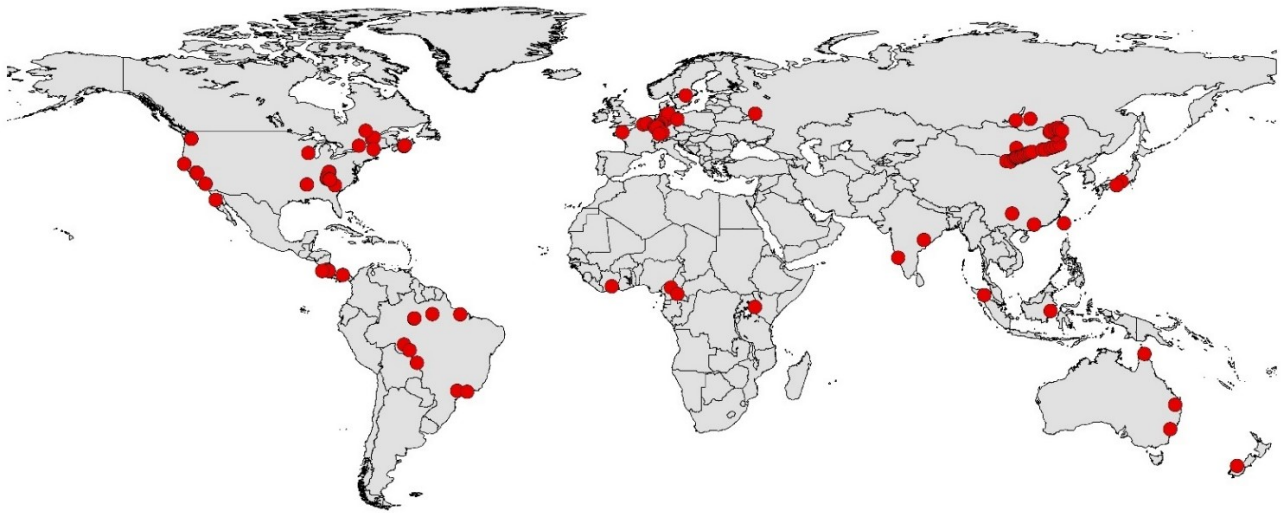
386 **Table 1:** Multiple regressions between  $\ln(-\beta)$  and climate and other edaphic factors at global scale.

Variables	$R^2$	$n$	AIC
$\ln(-\beta) = 0.046 \text{ MAT} - 0.058 \text{ MAP} + 0.225$	$0.43^{***}$	176	167.30
$\ln(-\beta) = 0.053 \text{ MAT} - 0.137 \text{ MAP} + 0.384 \text{ N} + 0.150$	$0.55^{***}$	104	64.71
$\ln(-\beta) = 0.046 \text{ MAT} - 0.222 \text{ MAP} + 0.849 \text{ N} + 0.006 \text{ Clay} + 0.069$	$0.66^{***}$	70	28.95

387 MAT: Mean Annual Temperature ( $^{\circ}\text{C}$ ); MAP: Mean Annual Precipitation (m); N: Soil nitrogen concentration (%) in topsoil. Clay:

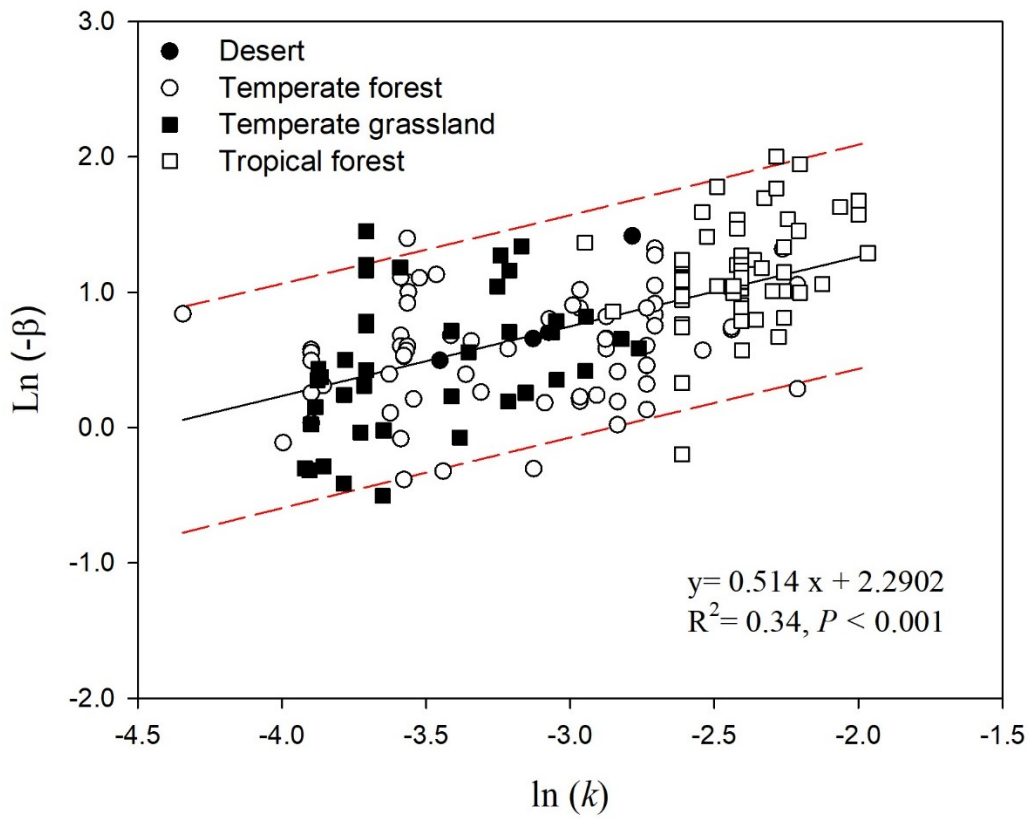
388 Soil clay concentration (%) in topsoil.  $n$  is the number of data, and  $R^2$  is the coefficient of determination for the regression line.

389 AIC: Akaike information criterion.  $^{***}$  represents significant at  $p$  less than 0.001.



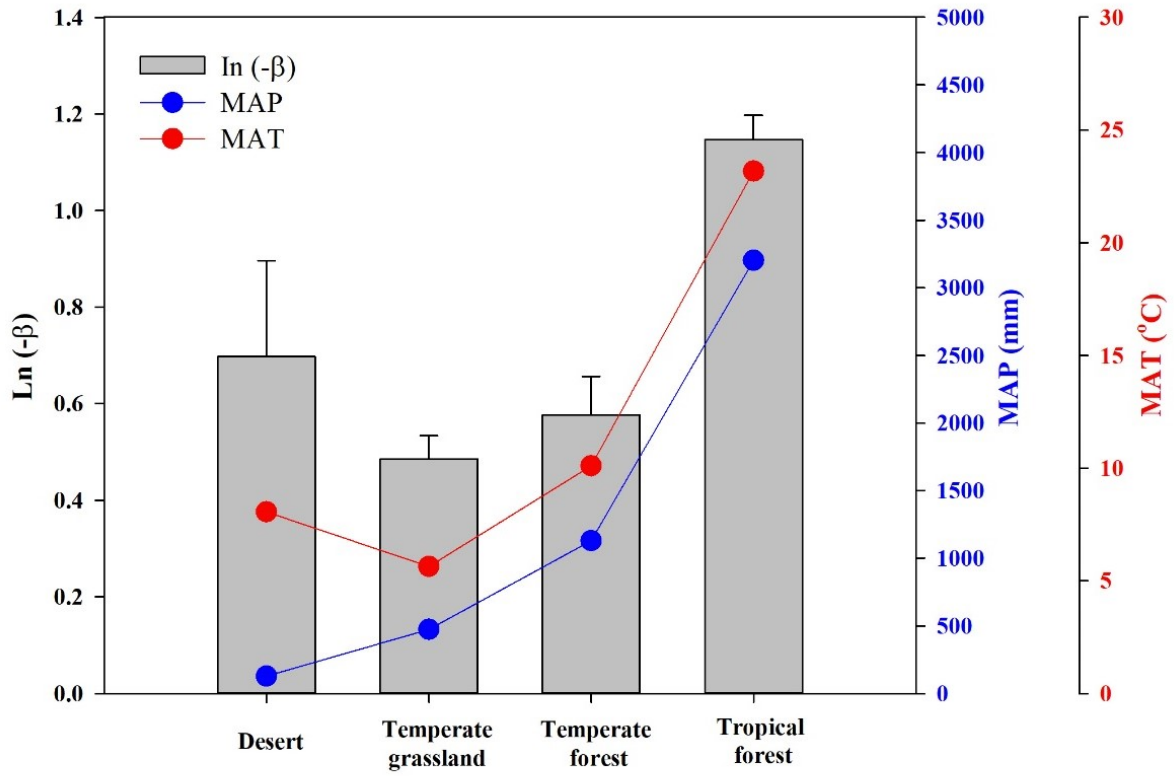
390

391 **Figure 1.** Locations of the 176 soil profiles used to calculate  $\beta$  values in this study.



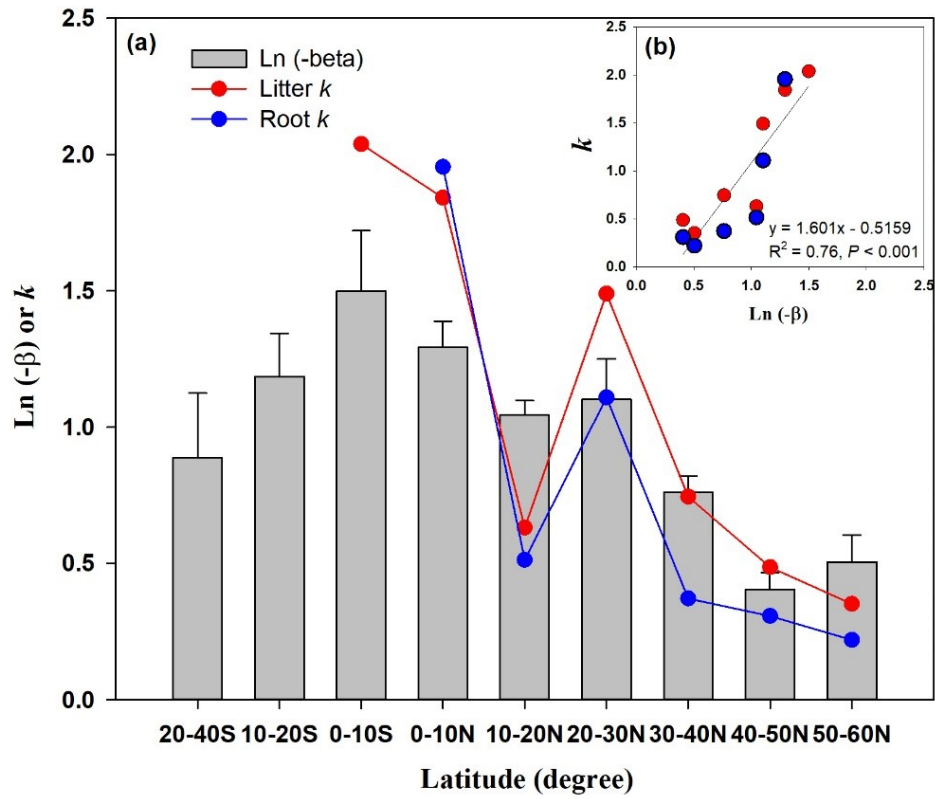
392  
 393 **Figure 2.** Link between  $\beta$  value and modeled soil carbon turnover rate ( $k$ ), which was estimated as the ratio between  
 394 soil heterotrophic respiration and soil carbon stocks. Solid line is regression line and dashed lines denote 95%  
 395 prediction interval.





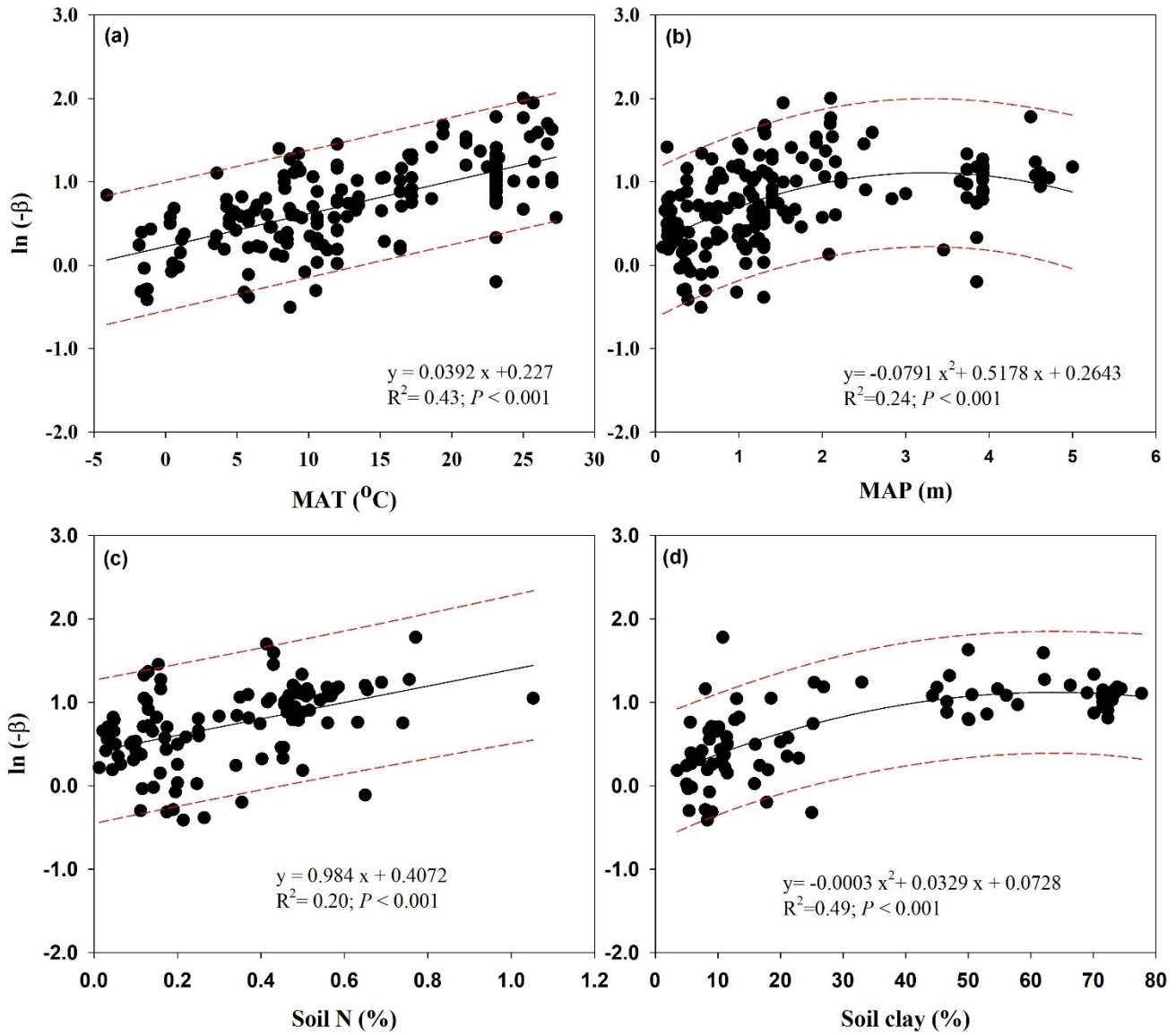
396

397 **Figure 3.** Variations of mean  $\beta$  with biome types. Blue and red points present mean annual precipitation (MAP) and  
 398 mean annual temperature (MAT) for each biome, respectively.



399

400 **Figure 4.** Variation of mean  $\ln(-\beta)$  value across latitude (bar chart), litter decomposition rate  $k$  ( $\text{yr}^{-1}$ , red dots, Zhang et  
 401 al., 2008) and root decomposition rate  $k$  ( $\text{yr}^{-1}$ , blue dots, Silver and Miya, 2001) at the global scale. The inner panel is  
 402 the regression between soil  $\ln(-\beta)$  value and litter and root decomposition rate  $k$ .



403

404 **Figure 5.** Beta varied with climatic and edaphic factors. Relationships between  $\ln(-\beta)$  and MAT (a), MAP (b), soil N  
 405 (c), and clay concentration (d) for global dataset. Solid line is regression line and dashed lines denote 95% prediction  
 406 interval.