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Soil organic carbon dynamics jointly controlled by climate, carbon inputs, soil properties and soil carbon fractions

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Abstract

Soil organic carbon (SOC) dynamics are regulated by the complex interplay of climatic, edaphic and biotic conditions. However, the interrelation of SOC and these drivers and their potential connection networks are rarely assessed quantitatively. Using observations of SOC dynamics with detailed soil properties from 90 field trials at 28 sites under different agroecosystems across the Australian cropping regions, we investigated the direct and indirect effects of climate, soil properties, carbon (C) inputs and soil C pools (a total of 17 variables) on SOC change rate (r_C, Mg C ha^{-1} yr^{-1}). Among these variables, we found that the most influential variables on r_C were the average C input amount and annual precipitation, and the total SOC stock at the beginning of the trials. Overall, C inputs (including C input amount and pasture frequency in the crop rotation system) accounted for 27% of the relative influence on r_C, followed by climate 25% (including precipitation and temperature), soil C pools 24% (including pool size and composition) and soil properties (such as cation exchange capacity, clay content, bulk density) 24%. Path analysis identified a network of intercorrelations of climate, soil properties, C inputs and soil C pools in determining r_C. The direct correlation of r_C with climate was significantly weakened if removing the effects of soil properties and C pools, and *vice versa*. These results reveal the relative importance of climate, soil properties, C inputs and C pools and their complex interconnections in regulating SOC dynamics. Ignorance of the impact of changes in soil properties, C pool composition and C input (quantity and quality) on SOC dynamics is likely one of the main sources of uncertainty in SOC predictions from the process-based SOC models.

KEYWORDS
agricultural soil, carbon sequestration, measured carbon fractions, physical protection, soil geochemistry, soil organic carbon

1 | INTRODUCTION

Soil is the largest reservoir of carbon (C) in the terrestrial biosphere. How this soil C pool responds to environmental and management changes is vital for climate change mitigation and sustainable soil management (Davidson & Janssens, 2006; Lal 2004, Paustian et al., 2016). A series of mechanisms have been proposed to explain soil organic carbon (SOC) dynamics over space and time (Davidson, Savage, & Finzi, 2014; Dungait, Hopkins, Gregory, & Whitmore, 2012; Lehmann & Kleber, 2015; Schmidt et al., 2011). Involved in these mechanisms are mainly three groups of factors including (1) climatic variables such as precipitation and temperature, (2) soil conditions including various physico-chemical properties, and (3) biotic properties consisting mainly of the quantity and quality of C inputs into soil. These factors work together to regulate SOC dynamics. Therefore, any studies focusing on single effects of these factors to predict SOC change would lead to great uncertainties (Bradford et al., 2016; Luo, Keenan, & Smith, 2015). Any observed effect of a particular factor may be the combined consequences of direct and indirect (via affecting other soil processes) effects of the factor on SOC dynamics. A big challenge is to elucidate how these various forces work together to directly and/or indirectly regulate SOC dynamics, and thus provide robust mechanistic understanding towards reliable predictions.

Climate is generally regarded as the dominant control over soil C dynamics and often explains the largest proportion of variations in SOC decomposition at global and regional scales (Carvalhais et al., 2014; Mahecha et al., 2010). This climate–SOC relationship has been adopted in ecosystem C cycle and Earth system models (ESMs), and SOC decay is usually simulated as a first-order decay process modified by soil moisture and temperature (McGuire and Treseder, 2010, Xu et al., 2014). As a result, modelled soil C dynamics are very sensitive to precipitation and temperature changes, and ESMs predict that soil is a significant source of atmospheric CO_2, particularly under global warming. However, large uncertainties remain in ESMs' predictions of soil C dynamics (Carvalhais et al., 2014; Luo, Ahlstrom et al., 2016; Negron-Juarez, Koven, Riley, Knox, & Chambers, 2015; Todd-Brown et al., 2013). Both current experimental observations (Doetterl et al., 2015; Hamdi, Moyano, Sall, Bernoux, & Chevallier, 2013) and modelling exercises (Sulman, Phillips, Oishi, Shevliakova, & Pacala, 2014; Tang & Riley, 2015) suggest that the effect of climate on SOC dynamics should be assessed with the consideration of physical protection of SOC from decomposition. In the context of global change, fertilization effect of atmospheric CO_2 enrichment may also result in another indirect effect on SOC dynamics through its regulation on the quantity and quality of C inputs into soil (Guo & Gifford, 2002; Hyvönen et al., 2007; Magnani et al., 2007; Norby & Luo, 2004).

The quantity and quality of C inputs into soil indeed exert significant direct impacts on SOC dynamics (Bardgett & Wardle, 2010; De Deyn, Cornelissen, & Bardgett, 2008; Luo, Wang, & Smith, 2015). The importance of the quantity of C input is straightforward as C influx to soil directly determines soil C balance. The quality of C inputs (e.g., the ratio of lignin or C to nitrogen) influences the utilization by microbes, microbial community structure and substrate utilization strategies, and finally the composition and distribution of SOC pools and their decomposability as a cohort (Bending, Turner, & Jones, 2002; Cotrufo, Wallenstein, Boot, Denef, & Paul, 2013; Prescott, 2010; Raich & Tufekciogul, 2000). In general, the quantity and quality of C inputs associate with vegetation type, which is predominantly controlled by climatic conditions and interacts with soil environment (Beer et al., 2010; Finzi, Van Breemen, & Canham, 1998; Raich & Schlesinger, 1992).

Besides climate and C inputs, there is growing evidence that soil conditions reflected by geochemistry and physical structure also have significant direct effects on SOC stability through physico-chemical barriers from microorganisms to access C sources (Delgado-Baquerizo, Garcia-Palacios, Milla, Gallardo, & Maestre, 2015, Doetterl et al., 2015). For instance, SOC can be occulated into soil aggregates and/or adsorbed to mineral surfaces, and thus is protected from decomposition. The protective capacity of different soils would vary significantly depending on soil type and physico-chemical conditions (Feng, Plante, & Six, 2013; Krull, Baldock, & Skjemstad, 2003; Six, Conant, Paul, & Paustian, 2002). In mineral soils, Schimel and Schaeffer (2012) argued that soil physical protection of SOC from decomposition is the dominant mechanism controlling SOC stability. Constraining a theoretical model that considers protected and unprotected SOC using incubation data sets also suggested that the protected SOC accounts for more than 95% of total SOC, and SOC dynamics depend on the dynamics of the protected SOC (Luo, Baldock, & Wang, 2017). Other than the physical protection of SOC itself, soil physical (e.g., bulk density) and chemical properties (e.g., pH) also directly determine the microbial processes involved in decomposition. Under similar climate and C inputs, microbial decomposition processes would be significantly different among soils because distinct microbial enzyme activities (Derrien et al., 2014) and community structure (Bernard et al., 2012, Foesel et al., 2014) as a result of specific soil conditions, leading to soil-dependent stabilization/destabilization of SOC (Keiluweit et al., 2015; Waldrop & Firestone, 2004).

It is apparent that complex interconnections exist among climatic, biotic and edaphic controls over SOC dynamics. While most studies focus on the overall effect of one or several typical factors, few studies have quantitatively partitioned the direct from indirect effects directly based on observational data. Such quantitative analysis can provide new insights into mechanisms underpinning SOC dynamics and are critical for robust SOC predictions under global and environmental changes. Path analysis (also known as "structural equation modelling") is a powerful approach designed for the study of multivariate interacting systems (Grace & Kelley, 2006). It has been widely used in ecological studies and can effectively distinguish between direct and indirect effects (Grace & Kelley, 2006; Jonsson & Wardle, 2010). In this study, we applied a hypothesis-oriented path analysis to a large-scale observational data set collected from 90 trials at 28 sites across the Australian cropping areas. The data set includes temporal measurements of SOC stocks with detailed measurements and records of climatic, edaphic and biotic variables. Combining with path analysis, the data set provides us a good opportunity to identify the potential direct and indirect effects of these variables and quantify their relative contributions to the observed SOC dynamics. Specifically, we ask and try to answer the following questions: (1) What is the relative importance (i.e., which factor is more important) of climatic, edaphic and biotic controls over SOC dynamics? (2) Whether and how do these controls directly and/or indirectly affect overall SOC dynamics? (3) Whether and how are the effects of climatic, edaphic and biotic variables on SOC dynamics dependent upon each other?

2 | MATERIALS AND METHODS

2.1 | Study sites

Legacy data from 90 trials located at 28 sites (Figure 1) were used in this study. These trials were initially selected to collect data to

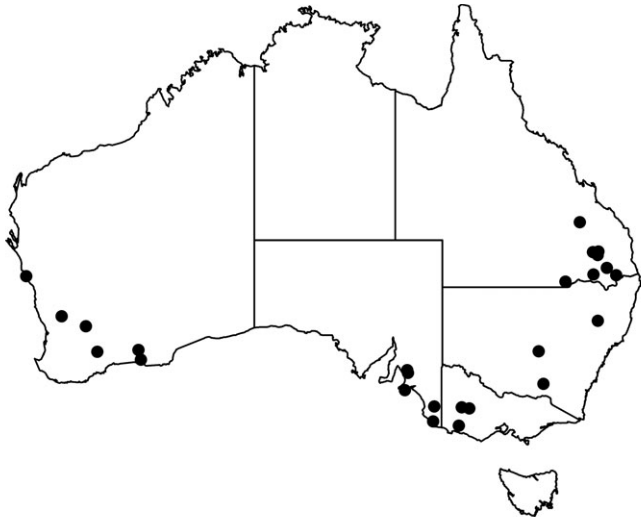

FIGURE 1 The location of the studied 28 sites across Australian cropping areas. Some sites are very close to each other, and thus, the corresponding symbols are overlapped to some extent

estimate changes in soil C resulting from land use changes (Skjemstad & Spouncer, 2003). Most of the trials were conducted during the period from 1970–2000 (Table S1). The 28 sites span the Australian cereal-cropping areas, covering diverse climate, soil and agricultural management conditions. The duration of the 90 trials ranged from 5–82 years with an average duration of 26 years (Table S1). Crop sequence, annual crop yield and residue production (estimated according to harvest index), and agricultural practices such as residue management (removal or retention) were recorded each year, enabling the calculation of aboveground residue C input (Mg C ha^{-1} yr^{-1}) into the soil. The meteorological records for each site include total monthly precipitation and pan evaporation, and mean monthly temperature. This climatic data can be obtained from the SILO Patched Point Dataset (https://www.longpaddock.qld.gov.au/silo/ppd/). On average, the annual rainfall across the sites ranges from 221–892 mm, and annual mean temperature from 12.8–21.9°C. More details about the sites, trial design and measurements were described by Skjemstad and Spouncer (2003).

2.2 | SOC measurements, fractionation and other soil properties

SOC stock was determined for representative samples in the 0–30 cm soil at the beginning and end of each trial at least (Table S1). At each time point of measurements, soil cores (up to 80 cores depending on trials) were randomly sampled from the experimental field. Then, a composite bulk sample was produced by thoroughly mixing all the cores and was sieved as <2 mm materials. Total SOC stock (Mg C ha^{-1} in the top 30 cm soil) was determined using a Leco combustion furnace (Merry & Spouncer, 1988) taking into account the bulk density and gravel content. Soils were fractionated, and the allocation of total SOC to its component fractions was determined (Janik, Skjemstad, Shepherd, & Spouncer, 2007; Skjemstad, Spouncer, Cowie, & Swift, 2004). The fractions of SOC quantified include the following: (1) charcoal C, particle size <2 mm with a poly-aromatic chemical structure, which is recalcitrant to decomposition; (2) particulate organic C (POC), organic carbon contained in particulate organic matter with particle size of 53 μm–2 mm; and (3) mineral-associated organic C (MOC), organic C contained in organic matter particles <53 μm excluding charcoal C. The detailed procedures for SOC measurements and pool fractionation were reported elsewhere (see the section 1.6 Analytical Methods in the report by Skjemstad & Spouncer, 2003). As only charcoal C and POC were directly determined, the amount of MOC was calculated as: *MOC = TOC – POC – charcoal C*. These measurements of SOC fractions represent three C pools with different decomposability (POC > MOC > charcoal C). The temporal data of total SOC stock and its fractions at each site were presented in Table S1.

Along with the measurements of total SOC and its fractions, key soil geochemical characteristics were also estimated including calcium carbonate ($CaCO_3$), pH in water (pH), electric conductivity (EC), cation exchange capacity (CEC), total content of silicon (Si), aluminium (Al) and iron (Fe), bulk density (BD), total nitrogen (TN) and percentage clay content. These estimations used the prediction algorithm coupled with spectral analyses developed by Haaland and Thomas (1988) and had been described by Skjemstad and Spouncer (2003). In brief, the algorithm predicts soil properties using soil spectral data, which was obtained for the soil by a mid-infrared spectrometer. Viscarra Rossel, Walvoort, McBratney, Janik, and Skjemstad (2006) have demonstrated the suitability of this approach for predicting various soil properties (explaining >80% of the variance in most soil properties tested in their study). All the data sets used in this study were from the calibration and enhanced paired sites reported by Skjemstad and Spouncer (2003) and are available for public on: http://www.fullcam.com/FullCAMServer/Help/reps/ (TR 36 Soils Modelling for NCAS).

Here, we want to emphasize that no information about the variability of the data in individual trials is available; thus, it is impossible for us to assess uncertainties induced by measurement/estimation errors. However, the 90 trials cover a wide range of spatial variability (e.g., SOC ranges from 13.7–106 Mg ha^{-1}), and the uncertainty at the trial level would be negligible compared to the large spatial variability. In addition, most of the studied sites were newly cleared from natural grassland or forest. These newly cultivated soils may rarely stay at the equilibrium state, and may experience soil weathering, erosion and other soil physiochemical changes. However, the estimated temporal soil properties may quantitatively reflect the soil status of the studied systems, which have been explicitly assessed in the following data assessment.

2.3 | Calculation of SOC change rate

We calculated the SOC change rate (r_C, Mg C ha^{-1} yr^{-1}) as:

$$r_C = \frac{C_{t+\Delta t} - C_t}{\Delta t} \quad (1)$$

where C_t and $C_{t+\Delta t}$ are the SOC stocks (Mg ha^{-1}) in the 0–30 cm soil at time t and t+Δt, respectively. As all other soil geochemical variables were measured with the SOC measurement and to exploit and amplify available information, we calculated r_C for all combinations of measurement time points. For example, if SOC is measured in years 1, 2 and 3, there are three combinations: r_C from year 1 (i.e., t = 1) to 2 (Δt = 1) and 3 (Δt = 2), and from year 2 (t = 2) to 3 (Δt = 1). As a result, a total of 509 r_C were estimated, with the corresponding C input, soil properties, climate calculated as the average of all measurements between t and $t+\Delta t$. For POC, MOC and charcoal C, we used their estimations at time t to calculate the variables indicating C pool composition in the following path analysis, acknowledging that initial pool size and composition would have significant effect on the following SOC dynamics.

2.4 | Path analysis

We used a path model (i.e., structural equation model) with four latent variables, that is, climate, soil (i.e., various soil physical and chemical properties), C input (both quantity and quality) and soil C pools, to assess their direct and indirect effects on r_C. The latent variables were reflected by observed variables (i.e., indicators). For the latent variable "climate," we considered three indicators: temperature, precipitation and evaporation. All measurements of soil geochemical properties including pH, clay, EC, CEC, Si, Al, Fe, $CaCO_3$, TN and BD were considered as potential indicators for the latent variable "soil". For "C input", we considered two indicators: the absolute amount of C input (e.g., residue C input amount per year) and the relative frequency of pasture in the crop-pasture system. For example, the relative frequency was assigned to be 0 if there is no pasture in the system (i.e., continuous cropping), 0.5 if half of the time from t to $t+\Delta t$ was pasture and 1 if it is a pure pasture system. In the data sets, pasture is mostly dominated by legumes which have lower *C:N* ratio than that of cereal crops. The frequency of pasture can therefore reflect the quality of retained residue. For soil C pools, we estimated the ratio of POC to MOC, the fraction of charcoal C in total SOC and the total C pool size (i.e., the total SOC stock) as indicators.

We considered the following potential paths in a hypothesis-oriented path model. First, we hypothesized that all the four latent variables have direct effect on r_C. Second, climate may also indirectly affect r_C through its effect on soil geochemical properties, C input, and soil C pools. Third, soil may indirectly affect r_C through its effect on C input and soil C pools. At last, C input may indirectly affect r_C through its effect on soil C pools.

Prior to the path analysis, we screened the indicators by conducting a boosted regression trees (BRT) to identify the influential factors controlling SOC stocks (Elith, Leathwick, & Hastie, 2008). The BRT involves a type of data-mining (machine-learning) algorithm that combines the advantages of a regression tree (decision tree) algorithm and boosting. It can analyse different types of variables and interaction effects between variables and are applicable to non-linear relationships. The BRT analyses also can identify the relative importance (percentage of influence or contribution) of a predictor variable (explanatory variable) compared with other variables considered (Elith et al., 2008). The significant variables (i.e., indicators) identified by the BRT were used in the path model. The predicted r_C by the BRT driven by the identified variables was compared with observed r_C calculated based on Equation (1). This comparison allows us to judge the overall predictive power of all considered variables.

The partial least squares (PLS) approach was used for the path analysis. The PLS path analysis is different from the conventional covariance-based path analysis, and does not impose any distributional assumptions on the data which is usually difficult to meet (Sanchez, 2013). So, the criteria (e.g., chi-square estimates to judge model fit) used in covariance-based approaches is invalid for PLS path analysis. In the PLS path analysis, the loading of each indicator variable is the key to estimate latent variable scores and calculated as the correlation between a latent variable and its indicators. An iterative algorithm is used to estimate the loadings until the convergence of the loadings is reached to maximize the explained variance of the dependent variables (both latent and observed indicator variables). A non-parametric bootstrapping (200 resamples in this study) was used to estimate the precision of the PLS parameter estimates. The 95% bootstrap confidence interval was used to judge that whether the estimated path coefficients are significant. To ease interpretation, if an indicator has a negative loading, its opposite was used in the model to ensure a positive loading, and all indicators were standardized. The BRT and PLS path analyses were performed using the package *gbm* and *plspm*, respectively, in R 3.3.1 (R Core Team 2016).

2.5 | Testing inter-correlations among soil, climate, C input and soil C pools

The PLS path analysis quantified the potential cause–effect relationships involved in r_c. Another interesting question is that whether and how the effect of a particular variable is dependent upon other variable(s). In the PLS path analysis, latent variable scores are calculated as weighted sums of their indicators (i.e., different indicators have different loadings). These scores are quantitative representations of the latent variable. Using the latent variable scores, we assessed the bivariate correlations between the latent variable scores of climate, soil, C input, soil C pools and r_C using zero-order correlations and partial correlations (Pearson correlation) by controlling for one variable (Doetterl et al., 2015). Partial correlations control the effect of a given variable on the correlation between other variables and response variables (r_C in this study), and estimate the strength of the linear associations between two variables (e.g., r_C with climate) that cannot be accounted by the variability in other variables (e.g., C input). For example, if the correlation between a latent variable and r_C is increased/decreased by controlling another variable, it means that the effect of the former variable depends on the latter variable. The estimated mean and standard error (SE) of the correlation coefficient were used to calculate the 95% confidence interval (mean $\pm$ 1.96SE). If the 95% confidence intervals of the coefficients of the zero-order and partial correlations do not overlap, it indicates the controlled variable in the partial correlation has significant effect. The partial correlation was performed using functions in the package *ppcor* in R 3.3.1 (R Core Team 2016).

3 | RESULTS

The result of boosted regression trees suggested that C input amount, total SOC content at the beginning of trials and precipitation were the three most influential variables on r_C (>20%, Figure 2) among the studied 17 variables. The three variables together accounted for 63% of the overall influence of all assessed variables (Figure 2). The relative individual influence of soil properties was small, but the overall contribution of soil properties to observed r_C was 24%, while it was 27%, 24% and 25% from C inputs, soil C pools and climate, respectively (Figure 2). Some variables had little contributions and were dropped from the boosted regression trees. Overall, the boosted regression tree model driven by the variables showed in Figure 2 explained 79% of the variance in observed r_C (Figure 3).

The variables identified by the boosted regression trees were grouped to indicate four latent variables (i.e., climate, soil, C input and soil C pools) in the PLS path analysis. Figure 4 shows the standardized loading of each indicator to the corresponding latent variable. The loading scores suggested that precipitation, C input amount and total SOC stock were more powerful indicators of climate, C input and soil C pools, respectively, compared with other indicators of that latent variable (Figure 4). This result verified the results of the boosted regression trees on the relative important of these variables in the related variable groups (Figure 2).

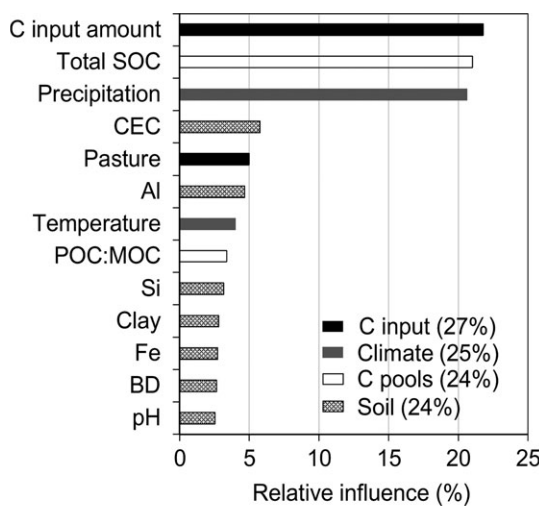

FIGURE 2 The relative contributions (%) of predictor variables for the boosted regression tree model of soil organic carbon change rates. POC:MOC, the ratio of POC (particulate organic carbon) to MOC (mineral-associated organic carbon); Fe, Si and Al, contents of total iron, silicon and aluminium; BD, bulk density; CEC, cation exchange capacity; Clay, soil clay content; pH, soil pH

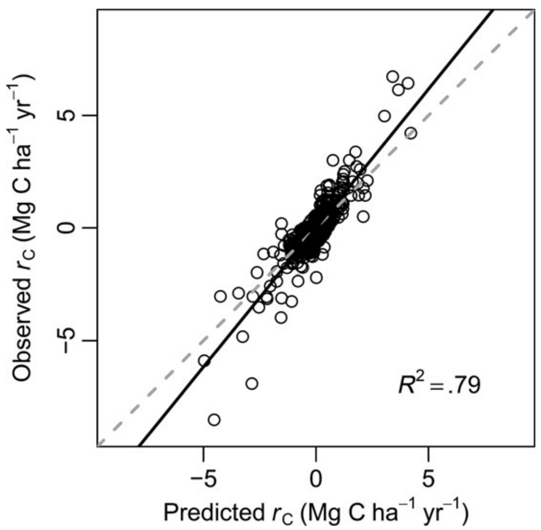

FIGURE 3 Observed and predicted SOC change rates (r_C) by the boosted regression tree model using predictors showed in Figure 2. The dashed line shows the 1:1 line

The PLS path analysis could explain 57% of the variance in r_C (R^2 = .57, Figure 5). Climate had direct and indirect significant associations with r_C via all hypothesized pathways in the study, including that involving soil, C inputs and composition of soil C pools, and a direct path (Figure 5). Climate (i.e., precipitation and temperature as indicated in Figure 4a) significantly and negatively associated with r_C, while its association with the studied soil properties, C input and C pool size were significantly positive. Soil properties (i.e., CEC, –Si, –BD, clay, Al and Fe as indicated in Figure 4b) significantly and positively but only indirectly associated with r_C via negatively associating with C pool size and composition (i.e., the ratio of POC to MOC as indicated in Figure 4d), which negatively associated with r_C. C input (i.e., the C input amount and pasture frequency in the system as indicated in Figure 4c) not only had direct positive effect on r_C, but also indirectly affected r_C via its positive effect on C pools, which negatively associated with r_C (Figure 5).

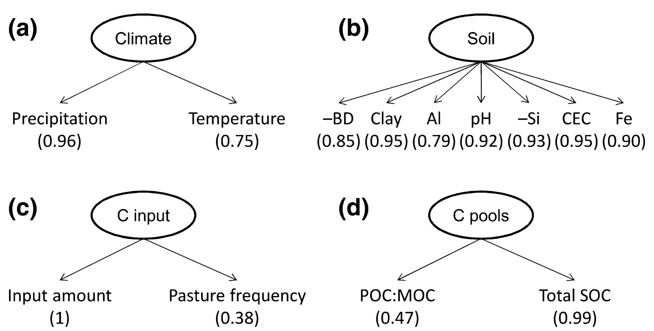

FIGURE 4 Latent variables with their indicators considered in the path analysis. Numbers in the parentheses show the loading scores (i.e., the correlation coefficient between the latent variable and its indicators). Si and BD have been transferred to their opposite to ensure positive loading. All symbols are as that in Figure 2

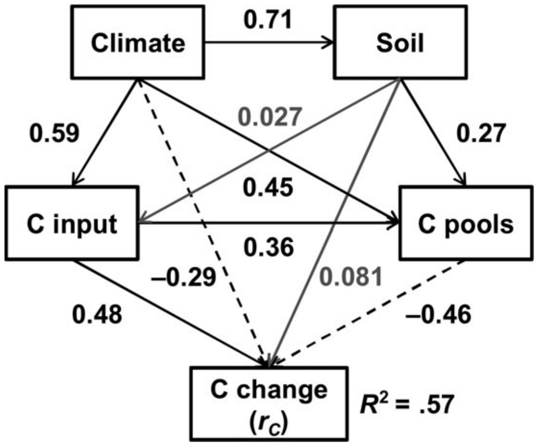

FIGURE 5 Path analysis results on the direct and indirect effects of soil, climate, C input and C pools on soil organic carbon change rates. Numbers show the path coefficients. Grey path and number indicate that the effect is insignificant, and dashed paths and the associated numbers indicate the effect is negative. See Figure 4 for the indicators of the four latent variables

	Zero-order	Climate	Soil	C input	C pools
Climate	**−0.45**	–	***−0.25***	***−0.64***	*−0.079*
Soil	**−0.42**	***−0.20***	–	**−0.52**	*−0.039*
C input	0.17	***0.49***	***0.35***	–	***0.57***
C pools	**−0.50**	***−0.24***	**−0.28**	***−0.73***	–
	Partial correlation controls				

FIGURE 6 Partial correlations (Pearson's r) between SOC change rates and the four latent variables in the path analysis. Changes of correlation between SOC change rates and climate, C input, soil and C pools, controlled for one variable. Difference between zero-order and partial correlations indicates the level of dependency of the correlation between a given variable and the SOC change rates. The colour and numbers indicate the sign (red and green colours indicate negative and positive correlations, respectively) and strength (the intensity of the colour) of the correlation. No change in colour between controlled variable and zero-order = no dependency; decrease/increase of colour intensity = loss/gain of correlation. Bold values indicate that the correlation is significant at $p < .05$. Italic numbers indicate that the coefficients are significantly changed (increased or decreased) compared with the coefficient of zero-order correlation (the first column). See Figure 4 for the indicators of the four latent variables

The importance of the interconnections was further evidenced by the partial correlation analysis (Figure 6). The negative correlation between climate and r_C (i.e., the zero-order correlation with Pearson's r = –.45) significantly enhanced after removing the effect of C input (r = –.64). As demonstrated by the PLS path analysis, this result was due to the fact that the indirect effect of climate on r_C via C input (positive) was opposite to the direct effect of climate (negative, Figure 5). In contrast, the correlation between climate and r_C significantly decreased if removing the effect of soil (r = –.25) and C pools (r = –.079). Meanwhile, if the climate was controlled, the correlation between soil and r_C also significantly decreased (Figure 6). With the results of the PLS path analysis (the path coefficient from climate to soil was 0.69 in Figure 5), these results highlighted the close interrelation of climate and soil in determining SOC dynamics. Although the zero-order correlation between r_C and C input was much weaker than the correlations of r_C with climate, soil and C pools (Figure 6), the correlation of r_C with C input was significantly increased if removing the effect of climate, soil or C pools (Figure 6). C pools showed the strongest zero-order correlation with r_C (r = –.50), and this correlation could be significantly weakened (r = –.24) and strengthened (r = –.73) by removing the effect of climate and C input, respectively (Figure 6).

4 | DISCUSSION

A great number of observational and modelling studies have acknowledged the general importance of climatic, edaphic and biotic factors in controlling SOC dynamics in different context (Carvalhais et al., 2014; Luo et al., 2013; Schimel et al., 1994; Wynn et al., 2006). Our results identified that C input amount, total SOC content, and precipitation are the three most important variables controlling SOC dynamics and could explain the majority of the variances in observed SOC change rates for the environments included in this study. Moreover, the results provided quantitative analyses of the direct and indirect contributions of soil, climate and C input in regulating SOC dynamics (Figure 5).

As expected, climate has significant direct effect on SOC change rate r_C. However, its overall direct contribution for explaining the variance of observed SOC change rates was comparable to other variables including soil C pools, C inputs and soil properties in our studied agricultural systems (Figure 2). Climate mainly plays a key role in regulating plant growth thus potential C input to the soil and microbial decomposition activity. This role can be largely mediated by land use types and intensive agricultural practices including the selection of cropping systems, fertilizer and residue management, and tillage, which have strong impact on final C inputs and soil environment. Even in natural systems, the effect of climate is subject to great uncertainties (Bradford et al., 2016). A recent study focusing on the wood decomposition on soil surface suggested that the effect of climate was only secondary compared with that of the soil geochemistry (Bradford et al., 2014). These results may imply that the direct impact of climate in controlling SOC decomposition dynamics may be overestimated. Nevertheless, climate represented by precipitation and temperature are the mostly widely considered controls over SOC decomposition dynamics. The uncertainties in SOC predictions from the Earth system models are likely due to incorrectly accounting for the indirect impact of climate (e.g., its impact on soil property [CEC, texture, minerals, etc.] and on C input quantity and quality) together with inaccurate simulations of SOC decomposition in response to moisture and temperature changes (Todd-Brown et al., 2013), which may be mediated by variations in microbial community. Among the climate variables, our results further suggested that precipitation is more important than temperature in the studied environments. This result may attribute to the fact that Australian agro-ecosystems are mainly water- rather than temperature-limited, resulting in the greater response of SOC change to precipitation than to temperature. This result is also consistent with our previous modelling study assessing drivers of SOC change across the Australian cropping regions (Luo et al., 2013).

The impact of climate on soil properties and the subsequent effect on SOC dynamics are well-documented, but rarely quantified. A direct evidence is that the same volcanic soil has evolved distinct soil properties (e.g., reactive-phase minerals, the content of major elements and soil nutrient conditions) after only 20,000 years (this is a very short time in terms of soil weathering) of weathering across an altitude climate gradient on Mauna Kea, Hawaii (Kramer & Chadwick, 2016). These distinctions in soil geochemical properties further lead to different capacity of retaining soil C and SOC dynamics (Doetterl et al., 2015; Kramer & Chadwick, 2016). Bradford et al. (2014) found that local-scale variables explained 73% of the variance in wood decomposition, while climate only 28%. Although they did not identify the specific local-scale variables, soil properties may account for a large part as their great spatial variability even at a plot scale (Zhou et al., 2008). Our results showed that soil structure (BD and clay content) and soil chemistry (CEC, Fe, Si and Al) all have significant direct effect on soil C pools (the path from soil to soil C pools in Figure 5), which directly affect SOC dynamics. Another noteworthy point is that the positive association between climate variables and soil properties. As a result, the direct negative association of climate with r_C will be further enhanced by the indirect effect of climate through affecting soil properties. This is proved by the partial correlation analysis. The correlation of r_C with climate was changed from –0.45 to –0.25 if the effect of soil was controlled, while the correlation with soil was changed from –0.42 to –0.20 if the effect of climate was controlled (Figure 6). These results demonstrated that climate–soil intercorrelations must be considered simultaneously to reliably predict SOC dynamics.

Climate (i.e., temperature and, particularly, precipitation in this study) has significant positive effect on C input and soil C pool size and composition, leading to positive and negative effects on r_C, respectively. The positive correlation between climate and C input is straightforward. For example, high precipitation and temperature usually couple with high plant productivity (Beer et al., 2010) and thus high amount of C inputs to soil. In terms of pasture frequency, under Australian conditions, the high rainfall and warmer areas are characterized by the high-value grazing land use, and perennial pasture like lucerne is grown more often during wetter periods to control drainage. The effect of climate on the soil C pools may attribute to the direct linkage between climate and microbial processes. It will be of interest to empirically and directly test that how climate regulates the transfer of new fresh C substrates to different SOC pools, given soil and C input. Similar to the intercorrelation between climate and soil, both C input and C pool size were intercorrelated with climate to affect SOC dynamics (Figure 6), with the positive effect of C input on r_C was increased from 0.17–0.49 and 0.35 if the effect of climate and soil was controlled, respectively. However, the corresponding negative association of r_C with soil C pools was decreased from –0.50 to –0.24 and –0.28, respectively. These results suggested that the effect of C input and C pool size on soil C dynamics was largely weakened by the effects of climate and soil. As such, the consequences of changes in C input and soil C pools induced by potential environmental and management changes on soil C dynamics will significantly depend upon local soil and climatic conditions.

Besides the direct effect of C inputs on r_C, it also indirectly affects r_C via its influence on C pools. The two indicators of C input here were the amount of C input and pasture frequency (Figure 3). In Australian pasture systems, legumes such as lucerne and clover are common species. The residues of these nitrogen-fixing species have lower *C:N* ratio than cereal crops such as wheat—the dominant crop in our data set, resulting in high quality of C inputs to soil in systems with high pasture frequency. Thus, the two indicators reflect the quantity and quality of C inputs to soil, respectively, which directly affect the size and composition of soil C pools (POC:MOC and the total C pool size in this study).

While the effects of soil properties on SOC storage and dynamics have received much attention in recent years (e.g., Doetterl et al., 2015; Hoyle, O'Leary, & Murphy, 2016; Rabbi et al., 2015; Sollins et al., 2009), less quantitative relationships have been developed to describe such effects. Our results provide such quantitative analyses to describe the importance of soil properties. Comparing to the impacts of climate, C inputs, and soil C pools, however, the relative influences of individual soil properties are very limited, implying the difficult to quantify the specific role of a particular soil physico-chemical properties in SOC dynamics. We need a novel approach to work out a metric representing soil heterogeneity that can generally describe the effects of various soil properties on SOC dynamics across space and time. It also should be noted that the complexity of soil physico-chemical environment inhibits the identification of the typical role of individual soil properties in regulating SOC dynamics. We also know much little about which soil properties and how they respond to environmental and management changes. This is certainly a knowledge gap.

The results in this study provide useful mechanistic insights into process-based soil C modelling. While some SOC models take addition of new C into the system as model input, most soil C models take into account the effect of climate on the quantity and quality of C inputs and the impact of soil moisture, temperature (and some clay content) on SOC decomposition. However, the changes in soil properties and soil C pool composition in response to climate and management changes are largely ignored. This is likely one of the main sources of uncertainty in SOC predictions. For example, climate may have direct effects on soil texture, mineralogy and chemical properties, which also closely link with SOC turnover (Figure 5).

Another point should be highlighted was the importance of soil C fractions represented by POC:MOC, their contributions to explain the variability in SOC change was relative small. The C fractions in this study were currently measured based on soil particle size, they may not match the conceptual C pools in models, which are usually estimated based on model-fitting. It is unsurprising that these models may generate great uncertainties in their predictions (Todd-Brown et al., 2013; Luo, Wang *et al*., 2015) because of unrealistic estimation of C pools even at model initialization stage (Luo, Wang, & Sun, 2017). These results demonstrate the requirement to better understand the composition and decomposability of SOC. While the measurable fractions of SOC can be a step forward to initialize C pools in models and thus reduce model uncertainties (Luo et al., 2017), the association of climate, soil properties and C inputs with the distribution of those C pools also should be considered (Figure 5). Another point is that the path modelling (Figures 4 and 5) and partial correlation (Figure 6) suggest that POC:MOC negatively associates with r_C; that is, the higher POC:MOC is, the lower the r_C is. This is reasonable as POC (particulate organic carbon) is more vulnerable than MOC (mineral-associated organic carbon) to decomposition. The SOC content is a key indicator of soil productivity and health, particularly in agroecosystems. Our results highlight that the soil C pool composition is also important. Sequestering more C as MOC or reducing the disturbance on MOC will reduce the vulnerability of SOC to potential management and climate changes.

We acknowledge that there are uncertainties also associated with our data and assessment approach, but believe that such uncertainties do not change our main results. Firstly, most of the soil properties are not directly measured but estimated based on prediction algorithms, and the data set were mainly from cultivated soils in Australia. Although the algorithm approach is cost-efficient and easy to operate, more precise measurements *in situ* would enhance the data quality and reduce the uncertainties in the results. In other land uses and/or ecosystems rather than agroecosystems, the relative importance of climate, soil properties, C inputs and soil C pools may be different among ecosystem types. More comprehensive data set covering more land uses and management with detailed monitoring of various soil properties will be valuable for further identifying primary controls over SOC dynamics. Secondly, the path model did not consider the potential interactions between the indicators for a particular latent variable. This would also be one of the reasons that the path model explained less variance (57%, Figure 5) of the SOC change than the boosted regression model (79%, Figure 3) which does consider the interactions of variables. Thirdly, the results of boosted regression trees indicated that SOC change rates were relatively poorly estimated when SOC is experiencing large changes (decrease or increase, Figure 3). Land management such as land use transitions and tillage, which usually result in sharp changes in SOC stocks, may explain such discrepancies, while it was not well represented in the statistical model. Long-term monitoring of SOC and C input changes, together climate conditions, and soil properties, would help to identify site-specific sensitive controls and develop mathematic solutions to improve process-based models.

Using the large-scale observational data sets from 90 trials under diverse soil, climate and management conditions, our analyses provide quantitative evidences on the relative importance of climatic, edaphic, and biotic variables as they impact on SOC dynamics through direct and indirect pathways. We found that antecedent SOC stocks, C input amount and precipitation are the three most influential variables to influence SOC dynamics under the studied environments. Climate impacts on SOC dynamics through its direct influence on SOC decomposition/formation processes and its indirect impact on C input (via primary productivity) and soil properties. Our results demonstrate that the indirect impact can be larger than the direct impact, reflecting the importance of the interactions between climate, soil and C input amount and quality. This implies that the effect of climate largely depends on its correlation with pathways that have different or opposite effects on SOC dynamics, suggesting that the sensitivity of SOC dynamics to climate variability may be buffered by changes in primary productivity and soil properties. These results have important implications for climate-smart soil management and reliable model predictions. While current Earth system models consider the direct impact of climate on SOC decomposition processes (e.g., in response to soil moisture and temperature over space and time), they ignore, to large extent, the changes in soil properties and the subsequent impact on SOC dynamics, and to less extent, the potential impact of climate on C input quality and quantity. These shortcomings have to be overcome in order to reduce the uncertainty in SOC productions in response to climate, soil and vegetation conditions. Novel approaches are required to specifically target the indirect effects and interactions, and develop mechanistic understanding to improve next generation models.

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SUPPORTING INFORMATION

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