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On the use of air temperature and precipitation as surrogate predictors in soil respiration modelling

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Abstract

Soil respiration (R_S), the soil-to-atmosphere CO_2 flux that is a major component of the global carbon cycle, is strongly influenced by local soil temperature (T_{soil}) and water content (SWC). Regional to global-scale R_S modelling thus requires this information at local scales, but few high-quality, wall-to-wall (global) T_{soil} and SWC data exist. As a result, such modelling efforts commonly use air temperature (T_{air}) and monthly precipitation (P_m) as surrogate predictors, but their site-scale accuracy and potential bias are unknown. Here, we used monthly data from 880 sites across a wide variety of different environmental conditions (i.e., climate, ecosystem type, elevation, vegetation leaf habit and drainage conditions) to determine the suitability of T_{air} as a surrogate for T_{soil}, and data from 507 sites to examine the suitability of P_m as a surrogate for SWC. Site-specific linear and second-order exponential non-linear models were compared using model evaluation metrics (i.e., slope, *p*-value of slope, root mean square error [RMSE], index of agreement and model efficiency). We found that T_{soil} and T_{air} are highly correlated and explain similar R_S variability. In contrast, P_m is not a good surrogate for SWC, even though P_m explains a similar amount of R_S variability to SWC. The wide variability in the site-specific relationships between R_S and SWC means that no single relationship can be used for large-scale modelling. The results from this study support the use of T_{air} in continental-to-global scale R_S models, and highlight the urgent need for continental-to-global scale SWC datasets for the modelling and evaluation of future soil carbon dynamics under global climate change.

Highlights

- The accuracy of air temperature and precipitation as surrogates in global soil respiration modelling is unknown.

- Monthly air temperature and soil temperature are strongly correlated and explained similar amounts of variability in soil respiration.
- Relationships between precipitation and soil water content are extremely variable by region, thus precipitation is a poor surrogate in global modelling.
- There is a need for accurate multiscale soil moisture datasets to evaluate future soil carbon dynamics.

KEYWORDS

modelling, moisture surrogate, soil respiration, temperature surrogate

1 | INTRODUCTION

The soil-to-atmosphere CO_2 flux, also known as soil respiration (R_S), is a major component of the global carbon cycle and it is typically driven by many biotic (e.g., microbial biomass, plant root biomass and plant coverage) and abiotic (e.g., temperature, soil organic carbon and soil moisture) factors (Bond-Lamberty & Thomson, 2010; Jensen et al., 1996; Kursar, 1989; Luo & Zhou, 2006; Raich & Schlesinger, 1992; Reichstein et al., 2003). It is difficult to directly measure R_S at scales larger than ~1 m^2, but statistical upscaling from site-scale R_S measurements can be performed based on the relationship between R_S and its driving factors (Bond-Lamberty & Thomson, 2010; Jian, Steele, Day, & Thomas, 2018; Jian, Steele, Thomas, Day, & Hodges, 2018; Raich & Schlesinger, 1992). The two most widely used factors in statistical upscaling are temperature and moisture.

Temperature is one of the most important environmental factors in continental-to-global scale R_S fluxes and modelling (Hashimoto et al., 2015; Reichstein et al., 2003; Rodeghiero & Cescatti, 2005) because it influences critical biological, physical and chemical processes mediating R_S rates. For example, soil temperature (T_{soil}) influences soil microbial activities (Awe, Reichert, & Wendroth, 2015; Gehrig-Fasel, Guisan, & Zimmermann, 2008; Mackiewicz, 2012; Yazaki et al., 2013), the rates of chemical reactions (Davidson, Belk, & Boone, 1998; Fang, Moncrieff, Gholz, & Clark, 1998; Jensen et al., 1996; Luo & Zhou, 2006) and the formation of dew (Li & Dong, 2003). It is believed that T_{soil}, where soil microbes and roots act, is the controlling temperature Hamdi et al., (2013); however, there are few long-term, high-frequency and high quality T_{soil} 'wall to wall' (i.e., across the entire terrestrial domain) data available to support robust R_S modelling.

Existing global R_S statistical models thus typically use site- to grid-cell-scale air temperature (T_{air}) as a surrogate for T_{soil} (Bond-Lamberty & Thomson, 2010; Chen et al., 2010; Raich & Potter, 1995; Raich, Potter, & Bhagawati, 2002; Raich & Schlesinger, 1992; Wang, Chen, & Wang, 2010; Wang & Fang, 2009). Site-scale studies show that T_{soil} is closely related to T_{air}, suggesting that T_{air} may be a good surrogate for T_{soil} in R_S modelling at daily to monthly timescales (Kang, Kim, & Lee, 2000; Mariko et al., 2000; Thunholm, 1990; Zhang, Chen, & Cihlar, 2003; Zheng, Hunt, & Running, 1993). Using data from six climates (seven sites) across the United States, Zheng et al. (1993) found that 11-day running average T_{air} and precipitation explained 85 to 96% of the daily T_{soil} variation. In Switzerland, daily T_{soil} at the treeline can be accurately estimated by T_{air} using a time series regression model (Gehrig-Fasel et al., 2008). But the error introduced by this practice is uncertain, as the relationship between T_{soil} and T_{air} weakens at regional, continental or global scales (Kang et al., 2000; Liang, Riveros-Iregui, Emanuel, & McGlynn, 2014). Additional environmental factors may alter the relationship, including surface global radiation, surface albedo and water content, and soil texture, elevation, slope and aspect, leaf area index and ground litter are related to T_{soil} variation (Kang et al., 2000; Liang et al., 2014). Other factors, such as the presence of snowpack, can also significantly affect the relationship between T_{soil} and T_{air} (Brooks, McKnight, & Elder, 2005; Mariko et al., 2000; Rango & Martinec, 1995; Tatariw, Patel, MacRae, & Fernandez, 2017; Wang, Yang, & Zhang, 2006).

Soil water content (SWC) is another key factor that controls belowground ecological and biogeochemical processes and affects R_S (Jensen et al., 1996; Kursar, 1989; Luo & Zhou, 2006; Patel et al., 2021; Reichstein et al., 2005; Tang & Baldocchi, 2005; Wang et al., 2010). SWC at regional scales is strongly coupled with precipitation and T_{air} (Hohenegger, Brockhaus, Bretherton, & Schär, 2009; Holsten, Vetter, Vohland, & Krysanova, 2009; Koster et al., 2004). Even though global soil moisture data derived from remote sensing images now exist (Guevara, Taufer, & Vargas, 2019), high-resolution and long-term global field-measured SWC data are still lacking (Scipal, Wagner, Trommler, & Naumann, 2002), and R_S studies have heavily relied on SWC simulations from indirect measurements such as precipitation.

The relationship between SWC and precipitation is highly variable, however. Soil physical characteristics exercise strong controls on SWC, and the soil moisture–respiration relationship is soil texture/structure dependent (Thomsen, Schjonning, Jensen, Kristensen, & Christensen, 1999). Based on 90 soils from 42 sites covering a wide range of soil properties, Moyano et al. (2012) showed that the relationship between soil heterotrophic respiration and soil moisture is consistently affected by soil texture and other properties (e.g., soil bulk density and soil organic carbon). The relationship between SWC and R_S is also strongly related to soil texture. Many studies have shown that no single factor can fully explain SWC variation (Gaur & Mohanty, 2013; Holsten et al., 2009; Wohl et al., 2012). For instance, Sterling, Ducharne, and Polcher (2012) and Yang, Wei, Chen, and Mo (2012) found that land cover is the most important factor influencing SWC. Other studies reported that the relationship between SWC and precipitation varies with land cover conditions (Haddeland et al., 2014; Li, Liu, Zhang, & Zheng, 2009). A study in the Poyang Lake Basin, China, demonstrated that SWC responds positively to precipitation, but negatively to T_{air} change, and that T_{air} explained more SWC variation than did precipitation (Feng & Liu, 2015).

Therefore, the use of T_{air} as a surrogate for T_{soil}, and precipitation for SWC, has to be evaluated carefully. In this study, we used monthly R_S, T_{soil}, T_{air}, SWC and monthly precipitation (P_m) data from almost 900 sites across the globe to: (a) evaluate whether T_{air} and P_m are good surrogates of T_{soil} and SWC in R_S modelling; (b) compare the relationship between R_S and T_{soil}, R_S and T_{air}, T_{soil} and T_{air}, R_S and SWC, R_S and P_m, and SWC and P_m from multiple sites across the globe, and compare the strength and bias of those relationships; and (c) determine what environmental factors cause heterogeneity in these relationships. We chose monthly data as our temporal focus, as it offers a good trade-off between capturing seasonal dynamics important in, for example, Mediterranean ecosystems, while not being overly burdensome in terms of data volume. R_S modelling can also be substantially improved by using monthly data rather than annual means (Jian, Steele, Thomas, et al., 2018). We evaluated the usage of T_{air} and P_m in site-to-continental-to-global scale R_S models, and provide insights for evaluating soil carbon dynamics under global temperature and precipitation change in the future.

2 | METHODS AND MATERIALS

We used site-specific linear regression (LR) and second-order exponential non-linear regressions (NLR) between R_S and T_{air}, precipitation, soil temperature (T_{soil}) and SWC to test whether T_{soil} and P_m could serve as robust surrogates for T_{air} and SWC in modelling R_S. A variety of model metrics were evaluated over hundreds of separate observational sites for factors such as bias, skew and variability to assess whether using global air and precipitation data affect estimates of monthly to annual R_S.

2.1 | Data sources and processing

We used data from a daily global soil respiration database (DGR_SD), aggregated to a monthly timescale (Jian, Steele, Day, & Thomas, 2018; Steele & Jian, 2018), to compare relationships between driving factors (T_{soil} and SWC) and potential surrogates for these factors (T_{air} and P_m) and R_S. As noted above, monthly details offer a good trade-off in temporal resolution, capturing seasonal variability while remaining reasonable in terms of data volume and inter-annual variability (Jian, Steele, Thomas, et al., 2018). DGR_SD records detailed daily time series of R_S, T_{soil} and SWC from the original publication, and also metadata such as latitude, longitude, day, month and year of measurements, etc. Detailed information about DGR_SD can be found in Jian, Steele, Day, & Thomas (2018) and Jian, Steele, Thomas, et al., (2018) and the dataset itself is available at http://doi.org/10.5281/zenodo.4745953. We made the following updates to DGR_SD to support analyses in this study. (a) Whereas the previous DGRsD included only publications before 2011, new papers after 2011 were identified from SRDB_V4 (downloaded from https://github.com/bpbond/srdb; also available at the Oak Ridge National Laboratory DAAC, https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1578), and the corresponding data digitized and compiled with the DGRsD, resulting in an increase in the total number of R_S samples from 13,482 to 28,178. (b) We searched publications to obtain background information on the T_{soil} and SWC-measure metrics: T_{soil} measurement depth, SWC measurement depth and SWC type (e.g., whether SWC was measured as gravimetric SWC, volumetric SWC or water filled porosity). (c) For the temperature surrogates, only sites with R_S, T_{soil}, latitude, longitude, and day and year of measurements all available were used. (d) For the soil moisture surrogates, only sites with R_S, SWC, latitude, longitude, and day and year of measurements all available were used. (e) R_S, T_{soil}, T_{air}, SWC and P_m data in this study are all standardized to a monthly timescale; only those sites with more than 6 months of data were used. With these criteria, 880 sites for temperature surrogates and 507 sites for soil moisture surrogates were used in this study. The sites we used have a good temperature coverage compared to the global temperature, although we lacked sites from high-precipitation

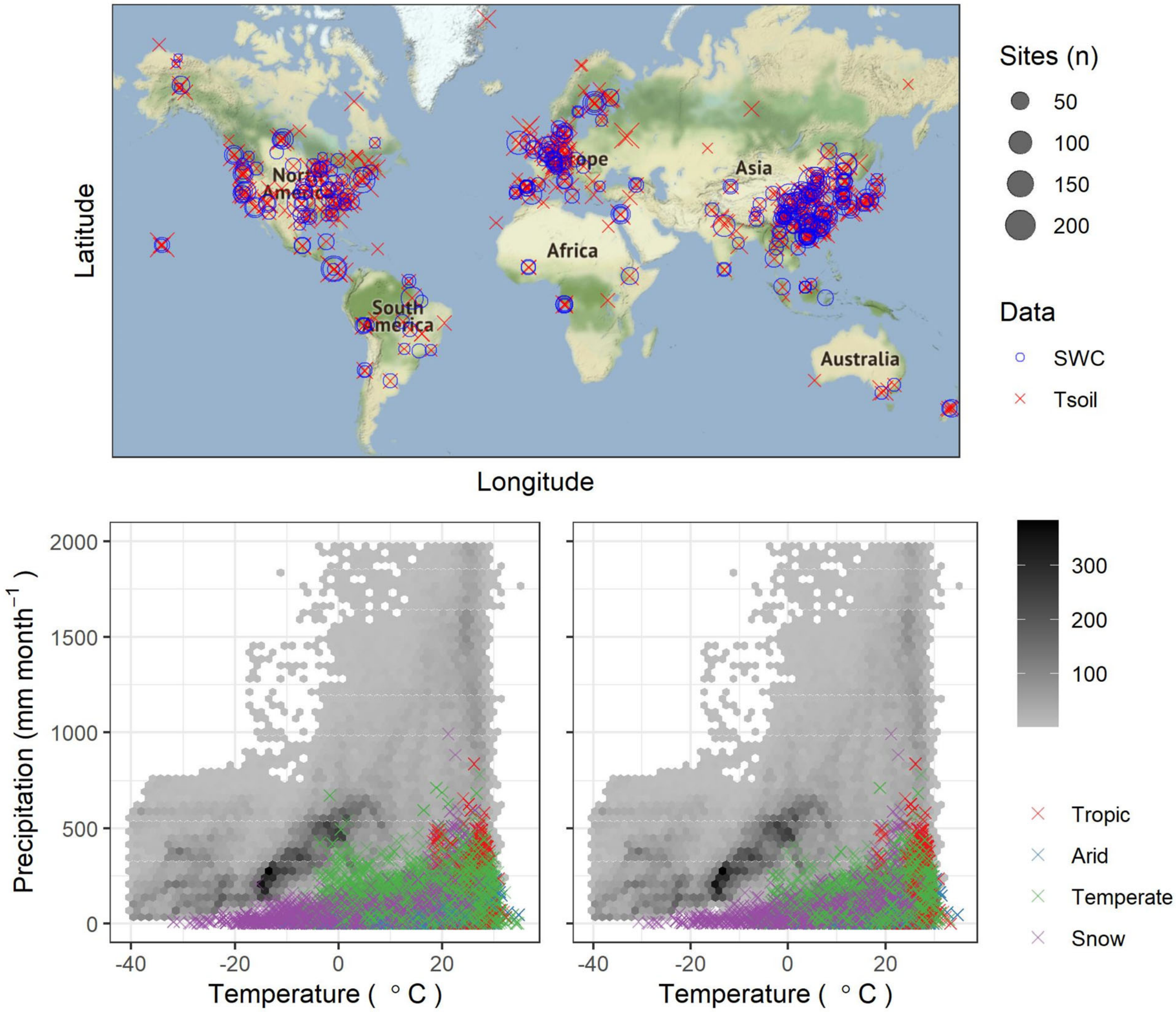

FIGURE 1 Sites' monthly air temperature and precipitation coverage in this study (coloured dots) compared with global measurements (grey plot background). Sites with information on soil temperature reported (points in panel a, coloured by climate type) and sites with information on soil water content reported (points in panel b, coloured by climate type). The sites used in this study have a similar temperature range to the global temperature (panel a), but we lack sites from high-precipitation regions (panel b). SWC, soil water content; Tsoil, soil temperature

regions compared with the global distribution (Figure 1). Monthly T_{air} and precipitation were obtained from the Centre for Climate Research at the University of Delaware (Willmott, Matsuura, & Legates, 2001), and climate-type information from the Köppen climate classification (Kottek, Grieser, Beck, Rudolf, & Rubel, 2006), R_S and SWC data were grouped into four climate groups according to the first level of climate classification (i.e., Tropic, Arid, Temperate and Snow).

We plotted the LR (Equation (1)) and NLR (Equation (2)) trends (Supplemental information) to identify any potential data input errors. Specifically, we checked those sites with negative slope of LR (i.e., $\beta_1 < 0$ in LR). In general, we found that those negative LR trends were due to either outlier effects or higher temperature (or SWC) rather than data input error. Therefore, regression models from all sites were used in this study.

2.2 | R_S response to temperature, soil water content and precipitation

We analysed the relationship between R_S and T_{soil}, T_{air}, SWC and P_m in each site. Different SWC metrics are not comparable to each other, and as soil bulk density was not reported in most studies, only gravimetric and volumetric SWC data were used in this study. Even for the same SWC metrics (e.g., volumetric SWC), data from different studies may not be comparable to each other due to the effects of pedological factors such as soil texture and pore structure. As a result, the analysis of T_{air} and P_m as surrogates for T_{soil} and SWC was conducted within each site, and not across sites. For each site, we used an LR (Equation (1)) and an NLR (Equation (2)) to characterize the nature of the T_{soil}, T_{air}, SWC and P_m relationships with R_S (Supplemental information):

$$y = \beta_0 + \beta_1 x + \varepsilon, \tag{1}$$

$$y = \beta_0 \times e^{(\beta_1 x - \beta_2 x^2)} + \varepsilon, \tag{2}$$

where y is the response value (R_S, g C m^{-2} day^{-1}), x is the predictor (T_{soil}, (°C), T_{air}, (°C), SWC (%) or P_m (mm)), β_0 is the intercept, β_1 in Equation (1) is the regression slope, and ε represents residual error. For the NLR, β_1 and β_2 determine the shape of the regression curve, with $\beta_2 > 0$ an accelerating curve, but $\beta_2 < 0$ a decelerating curve with a threshold that can be detected (i.e., below this threshold, R_S increases as temperature or SWC increases, but R_S decreases as temperature or SWC increases when over this threshold). A significance level (α-level) of 0.05 was used as a threshold to determine statistical significance of the linear regression. All analysis were performed in R (version 3.5.2, R Core Team, 2019).

Previous studies have used a variety of model types to describe the relationship between R_S and temperature (e.g., linear, polynomial, exponential and Arrhenius) and the relationship between R_S and SWC/P_m (linear, polynomial and exponential). We chose to use the LR and NLR models because they are commonly used at a wide range of sites and at global scales (Hashimoto et al., 2015; Jian, Steele, Thomas, et al., 2018; Lloyd & Taylor, 1994; McCarron, Knapp, & Blair, 2003; Schwendenmann, Veldkamp, Brenes, Brie, & Mackensen, 2003; Wang et al., 2010; Wang & Fang, 2009), and their flexibility means that they are relatively robust across all sites (Supplemental information). We acknowledge they are purely empirical formulations, but site-specific mechanistic insight was not a goal of the current study.

For sites with a significant relationship between temperature or SWC and R_S ($p < 0.05$) we compared a variety of model metrics (e.g., slope, RMSE) for LR/NLR(R_S-vs.-T_{soil}) (simple linear/or non-linear regression between R_S and T_{soil}) with the metrics for LR/NLR (RS-vs.-Tair) (simple linear/non-linear regression between Rs and Tair). The same process was used to test the P_m surrogate. If the model evaluation metrics (i.e., slope, RMSE, index of agreement (d) and model efficiency (EF)) of LR/NLR (R_S-vs.-T_{air}) models show a clear linear relationship with the model evaluation metrics of LR/NLR(R_S-vs.-T_{soil}) models and the slope is close to 1, T_{air} should be a good surrogate for T_{soil} in R_S modelling and vice versa (Figure S1). The index of agreement d was calculated as:

$$d = 1 - \frac{\sum_{i=1}^{n} (S_i - M_i)^2}{\sum_{i=1}^{n} \left(|S_i - \overline{M}| + |M_i - \overline{M}| \right)^2}, \tag{3}$$

where n is the number of observations, S_i is the i_{th} predicted R_S and M_i is i_{th} measured R_S, and $\overline{M}$ represents the average of all measured R_S. For interpretation of d, ≥ 0.90 means *excellent* agreement between measured and predicted values, $0.8 \leq d < 0.9$ is *good* agreement, $0.7 \leq d < 0.8$ denotes *moderate* agreement and $d < 0.7$ means *poor* agreement (Yang, Yang, Liu, & Hoogenboom, 2014). Model efficiency *EF* was defined as:

$$EF = 1 - \frac{\sum_{i=1}^{n} (S_i - M_i)^2}{\sum_{i=1}^{n} (M_i - \overline{M})^2}, \tag{4}$$

where S_i, M_i and $\overline{M}$ are the same as Equation (3). For interpretation of EF, <0 means the model predicted values are worse than simply using the observed mean to replace the predicted values, whereas $EF > 0$ is a critical condition to conclude 'goodness of match' between the predicted and the observed values (Yang et al., 2014).

We used LR of T_{soil} versus R_S and T_{air} versus R_S to quantify the proportion of sites where T_{air} can be used as a surrogate for T_{soil} in R_S modelling. For each of the LR relationships, we grouped the results into three groups: positive correlation (+), negative correlation (−) or no correlation (na). Thus, combining the two LRs, we grouped the sites into 3 × 3 = 9 classes (Table 1). Where both T_{soil} and T_{air} are strongly positively (or negatively) correlated with R_S (i.e., combinations +/+ and −/− in Table 1), this suggests that T_{air} was an acceptable surrogate for T_{soil} in R_S calculations. The same process can be used to quantify the proportion of sites where P_m is a good surrogate for SWC.

All codes and data to reproduce our results are available in Jian (2021, May 10): jinshijian/Surrogates: Surrogates version 2.0 (Version v2.0.0). Zenodo. http://doi.org/10.5281/zenodo.4745953.

3 | RESULTS

3.1 | Air temperature as a surrogate for soil temperature

For most of the 880 sites, T_{air} and T_{soil} were significantly correlated with R_S and explained similar amounts of

TABLE 1 Summary of sites in different groups when using air temperature (T_{air}) or precipitation (P_m) as surrogate for soil temperature (T_{soil}) and soil water content (SWC) in soil respiration (R_S) modelling

LR(R_S-vs.-T_{air})				
LR(R_S-vs.-T_{soil})		+	−	na
	+	**682 (77.50%)***	2 (0.23%)	40 (4.55%)
	−	0 (0%)	**11 (1.25%)***	4 (0.45%)
	na	16 (1.82%)	5 (0.57%)	120 (13.64%)
LR(R_S-vs.-P_m)				
LR(R_S-vs.-SWC)		+	−	na
	+	**66 (13.02%)***	35 (6.90%)	0 (0%)
	−	30 (5.92%)	**9 (1.78%)***	50 (9.86%)
	na	118 (23.27%)	4 (0.79%)	195 (38.46%)

Note: Explaining distribution of sites where R_S is strongly correlated (positive or negative) with (a) T_{soil} and/or T_{air}, and (b) SWC and/or P_m. * Denotes sites where T_{air} or P_m can be considered strong surrogates in R_S modelling, and 'na' means sites where R_S does not show significant relationship with T_{soil}, T_{air}, SWC or P_m. LR, linear regression. Bold values means Tair or Pm are good surrogates for Tsoil and SWC in these scenarios

variation in R_S. More than 80% of sites exhibited a significant first-order linear regression between R_S and T_{soil} or T_{air} (p value of $x < 0.05$; Figure S2b,c), whereas ~45% had NLR relationships between R_S and T_{soil} or T_{air} (p value of β_1; Figure S2e,f), and approximately 14% of the sites had no significant relationship between R_S and temperature (Table 1). In the LR, T_{air} explained a similar amount of variability as T_{soil} for approximately 57% of sites (R^2 difference within 0.10; Figure S2a), whereas for 30% of sites T_{soil} explained more R_S variability (R^2 difference ≥ 0.1; Figure S2a). For the remaining 13% of the sites, T_{air} actually explained more R_S variability than T_{soil} (R^2 difference ≤ -0.1) (Figure S2a).

We compared a set of model evaluation metrics (i.e., slope, d, EF and RMSE), excluding the 14% of sites with overall model p-value ≥ 0.05. At first, we tested whether the model evaluation metric comparisons were affected by outliers (whenever Cook's distance >0.1 or standardized residual >2); we found that the model slope comparison was affected by outliers, but other model evaluation comparisons were not (Figure S3). We then removed all the outliers, and found that all four model evaluation metrics from the LR and NLR for R_S-vs.-T_{air} were highly correlated with the model evaluation metrics from the LR and NLR for R_S-vs.-T_{soil} models, and the slopes were all close to 1:1 line (Figure 2). This evidence supports the use of T_{air} as a surrogate for T_{soil} in R_S modelling.

3.2 | Precipitation as a surrogate for soil water content

R_S was not well correlated with SWC or P_m, and P_m was not a good surrogate for SWC in R_S modelling. Across 507 sites, less than half of the sites' R_S exhibited a simple linear relationship with SWC and P_m (37% and 45%, respectively; Figure S4b,c), whereas only 15% and 24% sites' R_S showed NLR with SWC and precipitation, respectively (Figure S4e,f). For 26% of sites, SWC explained similar amount of R_S variability to precipitation using linear regression (Figure S4a, 14% if using non-linear regression, Figure S4d). For the rest, either SWC explained 10% more R_S variability than P_m, or vice versa (Figure S4a,d).

For sites at which R_S was significantly correlated with SWC or P_m ($p < 0.05$ of x or x^2 for LR/NLR), we compared a set of model evaluation metrics (i.e., d, EF, RMSE and slope). The comparison showed that all four model evaluation metrics from the LR/NLR(R_S-vs.-P_m) (simple linear/non-linear regression between R_S and P_m) models are weakly correlated with the evaluation metrics from the LR/NLR(R_S-vs.-SWC) (simple linear/non-linear regression between R_S and SWC) models. The slopes are all far away from the 1:1 line (except RMSE), indicating that the P_m is not a good surrogate for SWC in R_S modelling (Figure 3). The weak correlation between model evaluation metrics was unlikely to be caused by outlier effects, as we found similar results whether outliers were excluded or not (Figure 3 and Figure S5).

All sites in this study can be grouped into one of nine groups according to LR(R_S-vs.-T_{air}) and LR(R_S-vs.-T_{soil}), and we found that for ~79% of sites, T_{air} is a good surrogate for T_{soil} in R_S modelling (Table 1a). However, P_m is a good surrogate for SWC for only ~15% of sites (Table 1b).

The relationship between T_{air} and T_{soil}, SWC and P_m (Figure 4) further confirmed that T_{air} is a good surrogate for T_{soil}, whereas P_m was not a good surrogate for SWC in R_S modelling. Generally, T_{air} was highly correlated with T_{soil} in all climate regions (Figure 4, left panels), although

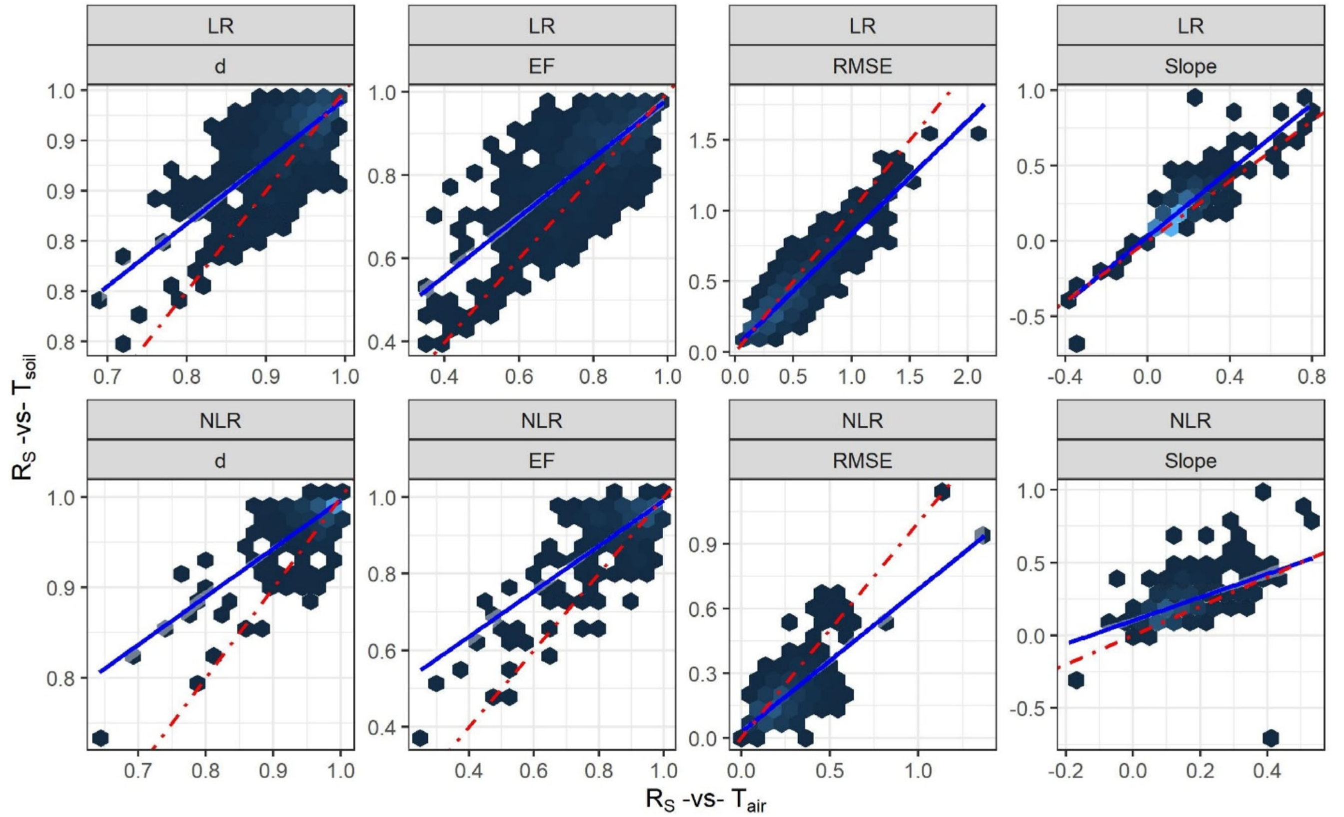

FIGURE 2 Relationship between model evaluation metrics (i.e., index of agreement [d], model efficiency [EF], root mean square error [RMSE] and slope) of regression between soil respiration and air temperature (LR/NLR(R_S-vs.-T_{air})), and between linear regression of soil respiration and soil temperature (LR/NLR(R_S-vs.-T_{soil})), with outliers (whenever Cooks distance <0.1 or standardized residual >2) excluded. The relationships showed a clear linear trend, with trend lines close to the dashed 1:1 line, indicating T_{air} is a good surrogate for T_{soil} when predicting R_S. The top panels are simple linear regression (LR) and the bottom panels non-linear regression (NLR); each dot represents a model result from a site. The red dashed lines are the 1:1 line and the solid blue lines are the regression trend

in tropical regions T_{air} explained only 25% of T_{soil} variability ($R^2 = 0.25$; Figure 4). This is likely to be because the range of T_{air} (20 to 30 °C) in tropical regions was much narrower than in other climate regions, and the small amount of temperature variation led to the lower T_{soil} to T_{air} correlation. SWC and precipitation were significantly correlated in only one out of four climate regions (Figure 4, right panels).

4 | DISCUSSION

We found T_{air} was able to explain as much variability in R_S as the factor it was substituted for, T_{soil} at the site scale. T_{air} data have been well recorded for decades or centuries across the globe (Willmott et al., 2001), supporting robust ecological and biogeochemical reanalysis in the global Rs (Bond-Lamberty & Thomson, 2010; Raich & Potter, 1995). Furthermore, earth system models can now reasonably predict T_{air} over a long period in the future under different greenhouse gas emission scenarios (Stocker et al., 2013). Because temperature is such a strong determinant of R_S across so many ecosystems and biomes (Bond-Lamberty & Thomson, 2010), this study, by quantifying the robustness of local-scale T_{air} in the service of large-scale modelling, provides important support for analyses of how soil carbon will respond to global warming in the future.

Unlike temperature, P_m was not a good surrogate for SWC (Figure 4) at the site scale. In general, SWC is influenced by not only precipitation but also other factors, including soil properties such as texture, snow cover, pore size distribution, and their interactions (Gaur & Mohanty, 2013; Holsten et al., 2009; Wohl et al., 2012). Soils with different textures, but the same volumetric SWC, could have very different amounts of available soil water (Wu, Huang, & Gallichand, 2011). Fine-textured soil has more micropores than coarse-textured soil, for example, and thus holds water more tightly. We conclude that soil texture should be considered when analysing the

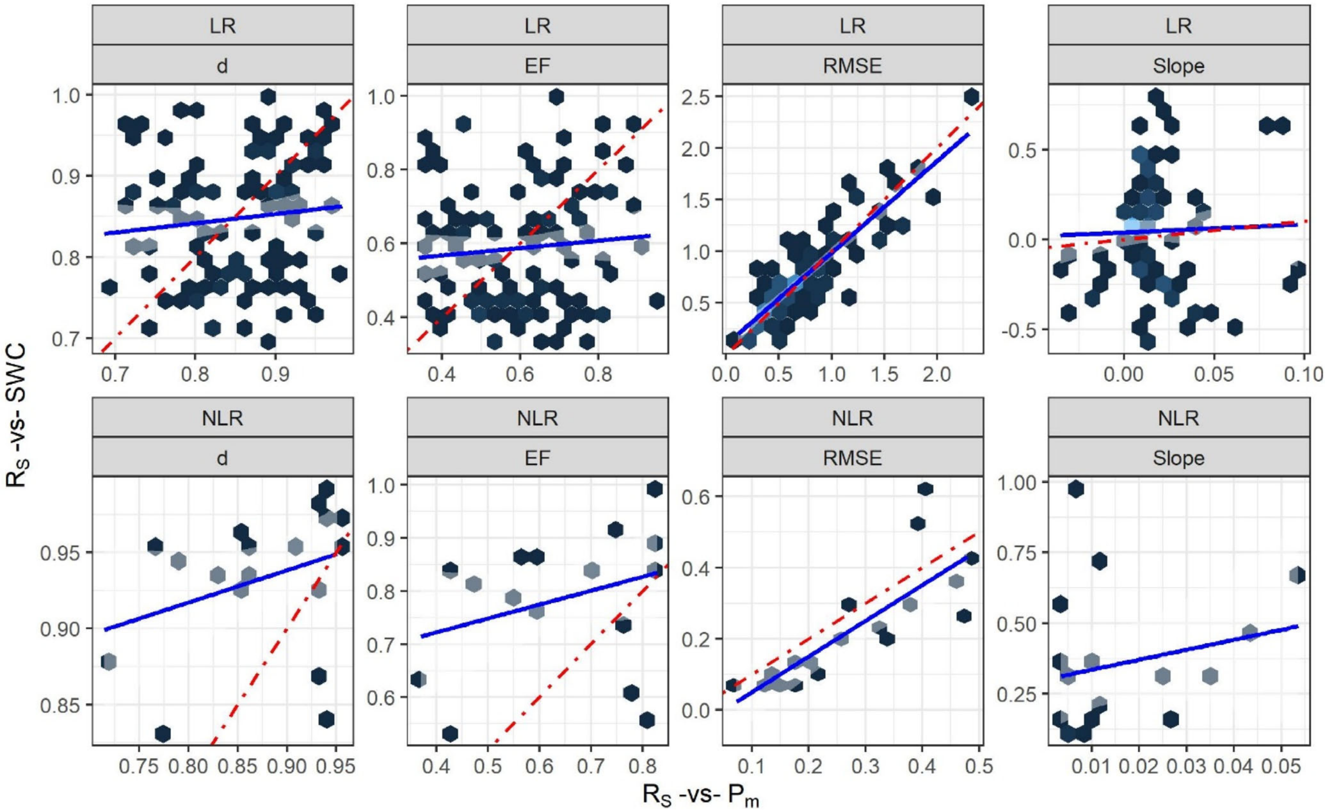

FIGURE 3 Relationship between model evaluation metrics (i.e., index of agreement [d], model efficiency [EF], root mean square error [RMSE] and slope) of regression between soil respiration and monthly precipitation (LR/NLR(RS-vs.-P_m)), and linear regression between soil respiration and soil water content (LR/NLR(RS-vs.-SWC)), with outliers (whenever Cooks distance <0.1 or standardized residual >2) excluded. The relationships showed precipitation is not a good surrogate for soil water content in predicting soil respiration when using simple linear regression (LR, above panels), but it is better if using non-linear regression (NLR, bottom panels). Each dot represents a model result from a site. The red dashed lines are the 1:1 line the and solid blue lines are the regression trend

relationship between R_S and SWC, and thus in future large-scale R_S modelling efforts precipitation should not be used by itself as an R_S predictor. This would be consistent with laboratory-based R_S studies, which have consistently found that factors such as gravimetric moisture, volumetric moisture, fraction of water saturation and water potential are affected by soil organic carbon, soil clay content and soil bulk density (Moyano et al., 2012; Yan et al., 2018).

The patterns and thus presumably mechanisms underlying the observed effects of SWC on R_S were quite site and soil specific. In this study, the sites could be split into four groups, according to the relationship of R_S to SWC (or P_m), with different mechanisms explaining the response of R_S to SWC/P_m in each (Figure 5). Theoretically, group A was characterized by water-limited systems in which R_S is controlled by both SWC and P_m. Sites in group B are soil moisture-limited systems, but not limited by precipitation; these sites may have plants with a large canopy evaporation ratio and/or large Bowen ratio (the ratio of sensible to latent heat), and thus large amounts of water from precipitation would be lost due to canopy evaporation or soil surface evaporation (Figure 5). Group C is an interesting case because the R_S at these sites exhibits strong relationships with P_m, but not with SWC. This may perhaps occur due to large SWC spatial variability, SWC measurement error, heterogeneity between different SWC measurement methods (Vaz, Jones, Meding, & Tuller, 2013), or roots in those sites getting water primarily from bedrock cracks rather than SWC, and then respiring (Barbeta & Peñuelas, 2017). Sites in the group D system are not water limited, as neither SWC nor P_m showed a significant relationship with R_S (Figure 5). This classification of sites underscores the complexity of the relationship between R_S and soil moisture (Hawkes, Waring, Rocca, & Kivlin, 2017), and that a common mechanism to explain the relationship between R_S and SWC may not exist (Jung et al., 2017; Moyano, Manzoni, & Chenu, 2013). Therefore, more SWC measurements covering a variety of conditions, and the

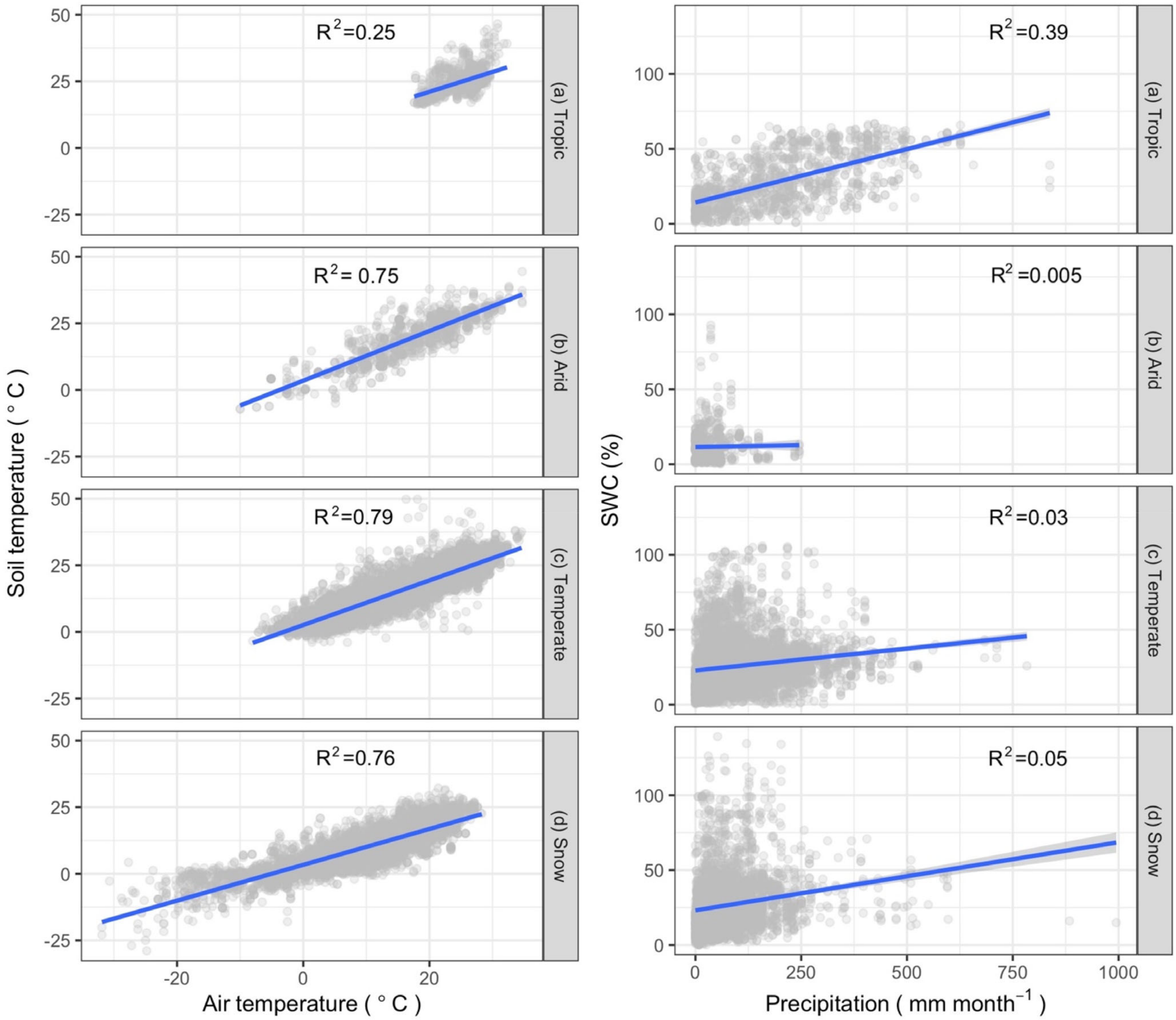

FIGURE 4 The relationship between soil temperature and air temperature for different climate types (left panels), and the relationship between soil water content and monthly precipitation for different climate types (right panels). Air temperature is generally highly correlated with soil temperature, but soil water content is usually poorly correlated with precipitation. SWC, soil water content

development of high-quality and spatial resolution global soil moisture data, are important for future soil carbon studies under global climate change.

The close correlation between R_S and SWC or precipitation drastically decreased when data from different sites were integrated at larger scales (e.g., four climate regions; Figure S6), further supporting the conclusion that mechanisms underlying the relationship between R_S and SWC are site and soil specific. When data were integrated into four climate types, only in the 'snow' region did precipitation explain more than 10% ($R^2 = 0.12$; Figure S6) of R_S variability. In other regions, SWC and precipitation explained very limited (<5%) R_S variability. One possibility is that the response of microbes and plant roots to SWC does not follow a universal pattern, but may diverge under different conditions.

Such a divergence of relationships between respiration and SWC has been demonstrated by many studies. For instance, an incubation of soil samples from a gradient of ~460 mm to ~860 mm mean annual precipitation (MAP) across the Edwards Plateau in central Texas by Hawkes et al. (2017) found that climate legacies (MAP gradient and SWC variation) control R_S response to current SWC. Similarly, Averill, Waring, and Hawkes (2016) found that historically drier sites' microbial respiration was more sensitive to moisture change. In Para State,

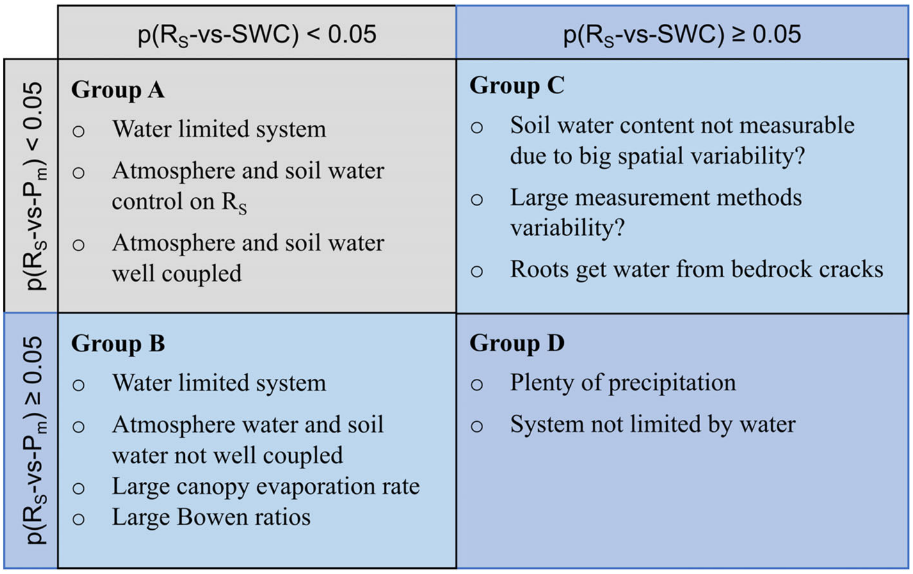

FIGURE 5 Diagram shows the control of soil water content or precipitation (P_m) over soil respiration (R_S), with different scenarios and the possible mechanisms to explain the relationship. Group A: R_S significantly correlated with soil water content (SWC) and P_m; Group B: R_S was significantly correlated with SWC but showed no correlation with P_m; Group C: R_S was significantly correlated with P_m but showed no relationship with SWC; Group D: R_S showed no relationship with SWC or P_m

Brazil, Davidson, Verchot, Cattanio, Ackerman, and Carvalho (2000) found R_S negatively correlated with SWC in both forest sites and pasture sites. However, soils from a tropical forest in Thailand showed a linear relationship between R_S and SWC (Adachi, Ishida, Bunyavejchewin, Okuda, & Koizumi, 2009). It is thus possible that because soils of this study did not cover wide ranges of soil textures, SWC could explain site-scale R_S variation, but not R_S variation at the global scale; similar scale dependencies have been observed in other analyses of water effects on the global C cycle (Jung et al., 2017).

More SWC measurements from sites covering a variety of environmental conditions are thus important for improving the simulation of the moisture–respiration relationship. Ecosystem models generally use a uniform function to describe the average response of respiration to soil moisture (Parton & Rasmussen, 1994; Sierra, Trumbore, Davidson, Vicca, & Janssens, 2015). Comparing functions currently used in different biogeochemical models, Moyano et al. (2012) found that including data from sites with different soils can reconcile differences and correct biases within and among those models.

Continental- to global-scale high spatial resolution SWC products are critical for future research and synthesis in the simulation of R_S responses to SWC. Given our results, significant regression relationships might only be possible at relatively small spatial scales, where soil properties are more consistent; this is the approach taken by most modern studies estimating global R_S (e.g., the 1 km^2 product of Warner, Bond-Lamberty, Jian, Stell, & Vargas, 2019). Designing a common data framework and compiling publicly available SWC into a global database is important in building continental- to global-scale SWC products. Efforts have been made to achieve continental- to global-scale SWC products. For instance, global soil respiration databases (i.e., SRDB and DGRsD) provide a common framework for sharing and using field R_S measurements under different SWC conditions (Bond-Lamberty et al., 2020; Bond-Lamberty & Thomson, 2018; Jian et al., 2021; Jian, Steele, Day, & Thomas, 2018). Currently, carbon flux (CO_2 or CH_4) responses to abiotic drivers (e.g., T_{soil}, SWC, pH) in laboratory incubations have been compiled into a new, publicly available database (Soil Incubation Database, SIDb, version 1.0) (Schädel et al., 2019). The SIDb provides a common framework for carbon flux incubation data. Based on the historical satellite data, a global soil moisture dataset with 15-km resolution has been developed (Guevara et al., 2019). Those datasets will finally connect the site-level SWC measurements with global satellite-based data (e.g., https://smap.jpl.nasa.gov/data/), supporting future research such as continental- to global-scale carbon decomposition and carbon turnover.

Even though precipitation was not a good surrogate for SWC in R_S modelling, precipitation explained a similar (slightly higher, results not shown) amount of R_S variability to SWC. The possible reason for P_m explaining slightly higher R_S variability is that SWC data used in this study were from hundreds of different publications and collected by different scientists, and different methods and equipment were used for measuring SWC, which adds heterogeneity to SWC variance. For instance, data in this study showed that more and more SWC data after 1990 were measured using TDR, but earlier SWC data were from the oven-dry method (Figure S7). To minimize the effects of SWC heterogeneity caused by the measuring method, we built the regression models in each site and the comparison was conducted at the site level. As precipitation data have been well recorded for decades or centuries across the globe (Willmott et al., 2001) and P_m explained a certain amount of R_S variability, this study provides support for analyses of how change in precipitation under global warming may affect soil carbon decomposition in the future.

5 | CONCLUSIONS

This study compiled T_{soil}, T_{air} and corresponding R_S data from almost 900 sites across the globe and showed that T_{air} is a good surrogate for T_{soil}. Given the numerous robust temperature records available for the past decades, our results are encouraging for future research on R_S modelling, soil carbon dynamics and soil carbon response to temperature change in the future. We emphasize, however, that a good surrogate variable is not the same thing as an interchangeable one; T_{soil} will always, inherently, contain more information about conditions at the physical site of R_S generation, and thus be of greater use for mechanistic modelling. Meanwhile, SWC, precipitation and corresponding R_S data from 507 sites across the globe showed that precipitation was not a good surrogate for SWC, but explained similar R_S variability. This highlights the urgent need for SWC measurements and data products at continental to global scales and across different environmental conditions, for the modelling and evaluation of future soil carbon dynamics under global climate change.

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AUTHOR CONTRIBUTIONS

Jinshi Jian: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; supervision; validation; visualization; writing - original draft; writing-review & editing. **Meredith Steele:** Conceptualization; methodology; project administration; writing - original draft; writing-review & editing. **Lin Zhang:** Formal analysis; writing-review & editing. **Vanessa Bailey:** Formal analysis; funding acquisition; methodology; project administration. **Jianqiu Zheng:** Investigation; methodology; writing-review & editing. **Kaizad Patel:** Methodology; writing-review & editing. **Benjamin Bond-Lamberty:** Formal analysis; funding acquisition; investigation; methodology; writing-review & editing.

DATA AVAILABILITY STATEMENT

All code and data to reproduce all results in this study are available at: Jinshi Jian. (2020, June 12). jinshijian/Surrogates: Surrogates version 2.0 (Version v2.0.0). Zenodo. http://doi.org/10.5281/zenodo.4745953.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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