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Responses of soil respiration and its sensitivities to temperature and precipitation: A meta-analysis

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ABSTRACT

Global warming has caused changes in temperature and precipitation patterns, and the subsequent effects on the dynamics of soil respiration (Rs) have had a significant impact on the global carbon balance. Despite numerous studies, the interacting responses of Rs to multiple causes of global change are unknown. We combined studies of 178 temperature treatments and 134 precipitation treatments in a global meta-analysis to examine the response of Rs to temperature and precipitation treatments in terrestrial ecosystems. The results showed that the average warming and precipitation increased Rs by 13.1% and 33.1%, respectively. The effect sizes of Rs were positive for other global variables (mean annual temperature (MAT), mean annual precipitation (MAP), elevation and duration of experiment (DUR)). Moreover, the effect size of Rs decreased exponentially with increasing DUR warming and decreased parabolically with increasing precipitation change, indicating a strong dependence of Rs on global climate conditions. Moreover, the two-way and multi-dimensional interactions of global changing factors have created the positive effects of the individual effects. Rainfall is a key factor in the interaction experiments between precipitation and warming in farmland and urban grassland ecosystems, and other environmental factors interacted significantly with precipitation and temperature, indirectly altering Rs. As multiple global climate change factors often occur simultaneously, it is important to conduct long-term multifactorial experiments to assess the response of Rs to global changes.

1. Introduction

Given the increasing importance of global climate change, some studies predict that climate change will increase the global mean temperature by 1.5–2 °C (Oreskes, 2005) and affect global or regional precipitation patterns (Chimner et al., 2010; Ofipcc, 2013). It is widely accepted that increasing emissions of greenhouse gases (CO_2, etc.) are the main cause of global warming (Levermann et al., 2013). Soil is one of the most important carbon (C) pools in terrestrial ecosystem (Endsley et al., 2022), and soil respiration (*Rs*) can release carbon from terrestrial ecosystems into the atmosphere, primarily in the form of CO_2. Soil respiration releases about 78 Pg C y^{-1} to 100 Pg C y^{-1} of CO_2 per year, accounting for 65% to 85% of total terrestrial ecosystem respiration. Therefore, identifying *Rs* responses to global change could significantly improve our understanding of C cycling and climate change response mechanisms. (Peng et al., 2009; Raich, 2003).

Soil temperature and moisture are the two major environmental factors affecting *Rs* (Wu et al., 2011). It is widely accepted that warming will accelerate *Rs* (Makita et al., 2021; Zhang et al., 2021; Zhu and Cheng, 2011). Changes in precipitation were positively correlated with *Rs* in climatic conditions (e.g. grassy climate and continental climate) with limited precipitation (Yu et al., 2017; Zhao et al., 2016). Many previous studies have focused on the effect of individual global environmental change factors (e.g. ecosystem, climate, altitude, etc.) on soil respiration (Liu et al., 2010; Mao et al., 2017; Soinne et al., 2021; Wu et al., 2011; Xiao et al., 2020; Zhou et al., 2016a). With the rapid increases in the number of *Rs* experiments around the world, the understanding of how *Rs* responds to biotic and abiotic factors has improved significantly. As terrestrial ecosystems experience higher concentrations of atmospheric CO_2, changes in precipitation or global warming may occur simultaneously (Sheik et al., 2011; Ware et al., 2019). To obtain average trends from different results at different scales, multiple meta-

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analyses were performed to probe the effects of individual drivers on global change. For example, Yan et al. (2022) found that *Rs* in global grasslands has continuously increased an average of 9.5% over the years due to climate warming. Morris et al. (2022) compiled a variety of data and showed that decreased precipitation would reduce *Rs*, compared with increased precipitation having a weak and irregular positive effect on *Rs*.

Over the past decades, an increasing number of multifactor experiments have demonstrated that global environmental factors may also influence interactively with *Rs* in temperature and precipitation treatment experiments (Selsted et al., 2012; Zhou et al., 2016b. With the development of analytical methods and detection techniques, these experiments were designed to combine effects of two or more global changing factors on *Rs*. A modeling analysis has showed that the positive effects of warming can be negated by altered precipitation (Lu et al., 2013). Adaptation of *Rs* has occurred in several key ecosystems in both warming and precipitation treatments (Carey et al., 2016; Jiang et al., 2013; Zhang and Zhang, 2016). Our comprehension of the potential effects of future global changes on terrestrial C cycles could be greatly enhanced by determining whether various environmental factors have additive or antagonistic effects on *Rs*.

To study the response of *Rs* to precipitation and temperature, various publications on precipitation and temperature above *Rs* have been collected around the world, covering different climates, altitudes, ecosystem types, etc. Q_{10} function is commonly used to estimate *Rs* under different environmental conditions, but Q_{10} can be affected by substrate availability, soil moisture, and initial temperature sensitivity of *Rs* (Davidson et al., 2006; Liu et al., 2016). Furthermore, the high spatial and temporal heterogeneity of precipitation and warming leads to considerable uncertainty in predicting global *Rs* patterns in future extreme climate scenarios (Wu et al., 2011). Therefore, Q_{10} was not evaluated in this study.

Meta-analysis is a statistical method to quantify the effects of each influencing factor by aggregating the results of two and more related independent studies in order to increase the sample size and ensure the accuracy and authenticity of the results (Abbasi et al., 2020; Ni et al., 2019). Therefore, our objective was to address the following important questions: (1) What are *Rs* responses to global change factor interactions under temperature and precipitation treatments? (2) Are there any patterns in the response of *Rs* to different warming and precipitation amplitudes and durations? (3) What are the potential factors driving these individual and interacting effects of global change factors on *Rs*? We synthesized and compared publications on temperature and precipitation manipulation experiments, and used meta-analysis to assess the main factors and clarify process mechanisms driving *Rs* under precipitation and temperature changes at a global scale, with the aim of providing insight into the future climate change context of terrestrial ecosystems.

2. Materials and methods

2.1. Sources of data

Articles from peer-reviewed journals were searched using the ISI Web of Science (WOS) database and the China National Knowledge Infrastructure (CNKI) database (2001−2021) with the following keyword combinations: (rainfall addition OR rainfall exclusion OR rainfall/precipitation manipulation OR increasing precipitation OR decreasing precipitation), (warming OR soil warming OR soil temperature OR climatic change) and (soil respiration OR CO_2 release OR carbon cycle OR soil CO_2 efflux). Data collection criteria can directly influence the study results (Song et al., 2019), and to avoid bias in publication selection, articles were selected according to the following inclusion/exclusion criteria: (i) The selected studies were field experiments and have at least one pair of treatment and control groups, and in the same study, the control and treatment groups must have the same site conditions, vegetation types, animals, and climatic conditions; (ii) For experimental observations spanning multiple time periods, observations were collected as needed; (iii) Experimental implementation regime was clearly described, including the duration of the experiment (DUR), and temperature and precipitation variability; (iv) Only studies performed in terrestrial ecosystems were selected; (v) *Rs* was determined primarily though infrared spectroscopy, excluding alkali absorbance studies; (vi) The mean, standard deviation (SD)/standard error (SE), and sample size (n) for treatment and control group variables could be extracted directly from articles, tables, and figures.

If multiple articles provided results from the same site, the most recent or most comprehensive research data on research methodology were accepted. For multi-factor control experiments, the rainfall/warming treatment group and the blank treatment group were applied as base data. For treatment groups with common controls such as nitrogen use and pH change, the experimental group controlled for univariate variables was used as the treatment group for meta-analysis to expand the sample size and draw broader patterns. In addition, studies where experiments were conducted on soils at multiple depths, the results from the uppermost soil layer were selected as the base data.

2.2. Data acquisition

For each study, data for environmental variables such as latitude and longitude, mean annual temperature (MAT), mean annual precipitation (MAP), ecosystem type, climate type, elevation, and year of experiment were collected from the experimental sample sites. For individual studies that did not report the climate types, climate information for sample sites was extracted by importing the latitude and longitude coordinates of the site from the WorldClim database (http://www.worldclim.org/). All of the above study site was classified as an ecosystem type based on the modified terrestrial ecoregion as defined by the World Wildlife Fund (WWF).

For studies where the error type was not indicated, the error type was assumed to be SE and it was converted by the equation: $SD = SE \times \sqrt{n}$. When means and errors for treatment and control groups were presented graphically in the article, the data were digitally extracted using Engauge Digitizer 11.1 (http://digitizer.sourceforge.net). An important assumption of meta-analysis is that studies are independent of each other (Wang and Wang, 2021). If a publication focused on multiple experiments that could be considered reasonably independent (e.g., elevation, ecosystem, precipitation, temperature, etc.), each experiment was identified as a different study.

After strict data screening based on the data requirements in section 2.1, a total of 81 studies on the response of *Rs* to temperature were selected with 178 independent observations (Data S1). Another 69 studies on the response of *Rs* to precipitation were selected with 134 independent observations (Data S2). Overall, the above two datasets covered six ecosystems types: desert, farmland, forest, wetland, urban, and grassland. A total of 13 climate types were covered in Data S1 with MAT (−6.9 to 32 °C), MAP (25 to 3601 mm), elevation (4 to 7556 m), DUR (1 to 8760 h), and latitude (43°S to 62°N). A total of 14 climate types were covered in Data S2 with MAT (−4.6 to 27.6 °C), MAP (13 to 3743 mm), elevation (8.8 to 2900 m), DUR (0.083 to 8760 h), and latitude (34°S to 49°N) (Fig. 1).

2.3. Meta-analysis

Meta-analysis and meta-regression were performed on two datasets (Data S1 and Data S2) to evaluate the responses of *Rs* and other environmental indicators to warming and precipitation. The natural logarithm of the response ratio (*RR*) was used to quantify the effect of temperature or precipitation treatment on *Rs* (Feng et al., 2017). Due to the relatively small number of replicates (n) in the ecological experiments, the natural log allows the linearization of the indicators compared to Hedges' d-effect-values, thereby reducing the sensitivity of

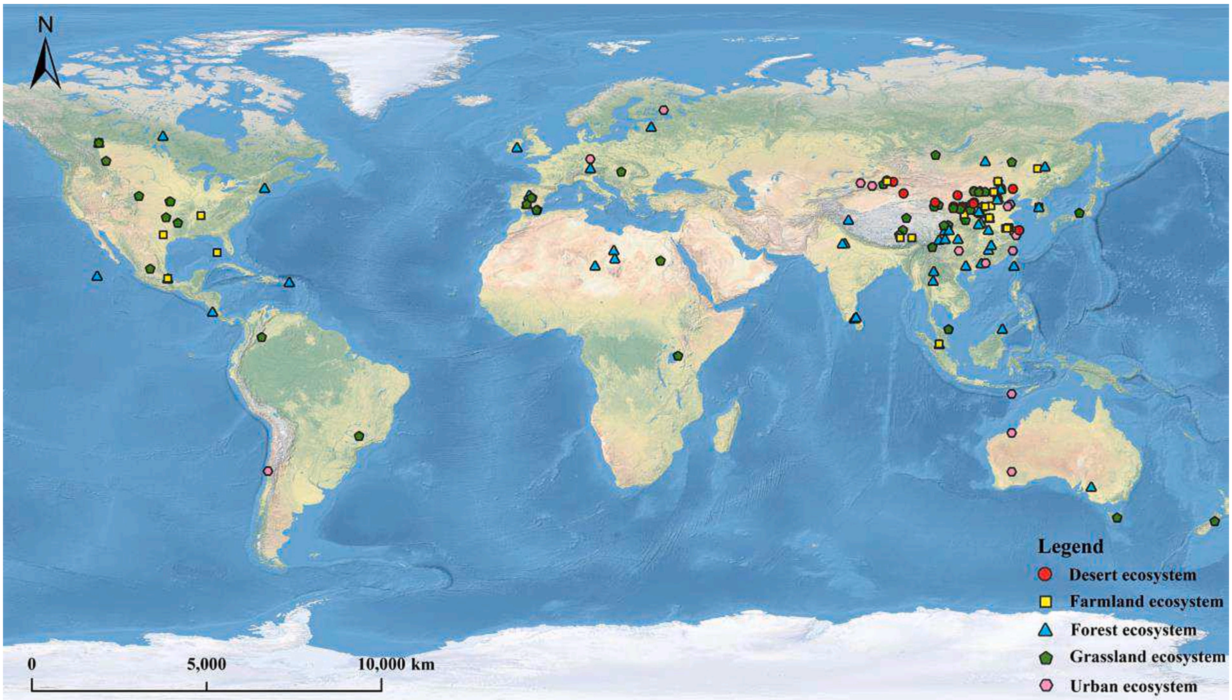

Fig. 1. Global distribution of simulated precipitation and temperature change experiments selected in this meta-analysis.

the treatment groups with a small sample size and increase the interpretability of the results (Dieleman et al., 2010). The *RR* was calculated as:

$$RR = ln\left(\frac{\overline{X_T}}{\overline{X_C}}\right) = ln(\overline{X_T}) - ln(\overline{X_C}) \quad (1)$$

where $(\overline{X_T})$ and $(\overline{X_C})$ are the arithmetic means of soil respiration rates in the treatment (temperature/precipitation treatment) and control groups, respectively. The variance (v) was calculated by:

$$v = \frac{SD_T^2}{n_T\overline{X_T^2}} + \frac{SD_C^2}{n_C\overline{X_C^2}} \quad (2)$$

where n_T and n_C are the number of replications in the treatment and control groups, respectively, and SD_T and SD_C are the standard deviation (SD) of the treatment and control groups, respectively. The inverse of the variance is considered as the weight (w) of each *RR* (Chen et al., 2017). The weighted response ratio (RR_{++}) was calculated from the *RR* corresponding to the individual studies between the treatment and control groups:

$$RR_{++} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{k} w_{ij}RR_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{k} w_{ij}} \quad (3)$$

where m is the number of comparison groups (e.g., ecosystem type), k is the number of comparisons in the corresponding ith group, and RR_{++} amplifies the weighting coefficients for studies with higher precision (i.e., higher w), thereby improving the precision of statistical analyses between groups (Liao et al., 2008). The standard error (SE) of the weighted response ratio was estimated as follows:

$$SE(RR_{++}) = \sqrt{\frac{1}{\sum_{i=1}^{m}\sum_{j=1}^{k} w_{ij}}} \quad (4)$$

Since *Rs* varies with ecosystem, the globalized response ratio was introduced by combining the area weights and the average rate of *Rs* for each ecosystem (Zhou et al., 2014). The global terrestrial response ratio (RR_{++}^{GT}) was estimated as follows:

$$RR_{++}^{GT} = ln\left(\frac{\sum_{j=1}^{m} W_{aj}Rs_jE_j}{\sum_{j=1}^{m} W_{aj}Rs_j}\right) \quad (5)$$

where W_{aj} is the share of each terrestrial ecosystem in the total land area (Whittaker and Likens, 1973); Rs_j is the average *Rs* rate of the control group in each ecosystem. For each ecosystem, R_{++} was transformed to average amount of change in the treatment group compared with the control group using the equation $E_j = \exp.(RR_{++})$.

For Data S2, *Rs* shows a similar trend as precipitation decreased/increased (Abbasi et al., 2020). To expand the sample size to obtain generalization patterns, the precipitation reduction treatment was set as the control group and the blank treatment was set as the treatment group. The effect of precipitation was uniformly considered to be the effect of increased precipitation. To compare the changes of *Rs* at uniform precipitation levels, all *Rs* were normalized to the percentage change in precipitation for the year (Liu et al., 2016), and MAP for this sample site was used as a proxy if annual precipitation was not reported. The median value (50%) of all studied precipitation changes in Data S2 was used as the criterion to standardize all precipitation treatments to ~50% of the current year's precipitation using the following equation:

$$\overline{X_{NT}} = \overline{X_C} + \frac{(\overline{X_T} - \overline{X_C})}{P} \times (\sim 50\%) \quad (6)$$

where $\overline{X_{NT}}$ denotes the mean of soil respiration normalized to 50% of the current year's precipitation for the precipitation treatment, P denotes the current year's precipitation, and the standardized response ratio was calculated according to the equation: $RR_{norm} = ln(\overline{X_{NT}}/\overline{X_C})$. The percentage change in *Rs* due to temperature/precipitation treatments was estimated:

$$[exp(RR_{++}) - 1] \times 100\% \quad (7)$$

The *RR* of each study was combined using a random effects model, which assumes that the differences in studies within each subgroup are due to sampling error and random variation, and thus the assumptions of the random effects model are easier to meet than those of the fixed effects model (Valkama et al., 2007). In addition, the total heterogeneity

(Q_T) of each subgroup consists of between-group heterogeneity (Q_B) and within-group heterogeneity (Q_M), and these Q statistics obey a chi-square distribution. A significant Q_B indicates the presence of between-group heterogeneity and sampling error, which does not satisfy the null hypothesis of unstructured data and can be interpreted in groups (Chen et al., 2013). The frequency distribution of the individual *RRs* for each *Rs* was verified using the Gaussian function (i.e., normal distribution):

$$y = \alpha exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right] \tag{8}$$

where y is the frequency (i.e., number of *RR* values); x is the *RR* of each *Rs*; α is the coefficient representing the number of expected *RR* values at x = μ; and μ and σ are mean and variance of the frequency distributions of *RR*, respectively.

Due to the ease of selecting positive results through literature publications and data screening, a number of complementary methods were used to check for publication bias in the selected data (Table S3 and S4). Kendall's tau rank correlation test and Spearman's rank correlation test were applied to test the relationship between the number of replicates and the standardized effect size for each study (Deng et al., 2021). If the statistical result of the test is significant ($P < 0.05$), it indicates that results with larger effect sizes are more likely to be published and that publication bias exists (Chen et al., 2020a). Calculating the number of fail-safes (Rosenthal's method) was used to determine the number of studies required for a significant result to change from significant to non-significant (Chen et al., 2017). Finally, publication bias was determined by visual inspection of the scatter distribution of treatment effects in the funnel plot with respect to their standard errors, while the potential asymmetry of the funnel plot was assessed by Egger regression (Holden and Treseder, 2013).

All meta-analysis methods were performed on MetaWin 2.1 (Rosenberg et al., 1997), where a 95% confidence interval (CI) was also calculated for each subgroup using the bootstrap method (64,999 iterations), and the treatment effect estimates was considered significant if the CI did not overlap with zero (Zhou et al., 2014). The two-, three-, four- and five-way interaction effects of global changing factors for *Rs* were explored using multiple regression analysis, and *p*-values were determined by permutational multivariate analysis of variance (PERMANOVA), with the "Adonis" function in R 4.1.3 software (https://cran.r-project.org/bin/windows/base/old/4.1.3/). Furthermore, the impact of a two-way interaction between warming and rainfall on *Rs* was also tested.

The "PCA" function in R software was used to perform the principal component analysis (PCA) to determine the relationship among the global changing factors for *Rs*. Similarly, the relative importance of factors affecting response variables was assessed by random forest analyses using the "rfPermute" package. Thereafter, the linear/nonlinear regression relationship between *Rs* and other environmental/experimental factors as well as DUR were examined, and the goodness-of-fit of these models was assessed using R^2 and significance (*p*-value). Regression analysis was performed with MATLAB software version R2017a (Mathwork, USA). The "vegan" package in R was used to conduct redundancy analysis (RDA) and variance partitioning analysis (VPA). The relative importance of warming and rainfall in influencing the *Rs* was quantified by performing VPA. The impact of global change factors on *Rs* due to the interaction of warming and rainfall was analyzed using structural equation modeling (SEM), and the "sem" function in R software was used for model development.

3. Results

3.1. Response of Rs to temperature

Subgroup analysis were performed for indicators (including: ecosystem, climate, elevation, warming/rainfall amplitude, and DUR) in Data S1 and Data S2. Among them, subgroups were considered groupable when the number of observations in the subgroup was >10. For subgroups with observations <10, only results from at least 3 independent articles were discussed. If the 95% CI of *RR* did not overlap with other subgroups, the grouping approach was considered to be significantly different between groups for *Rs*. If there was overlap in the 95% CI of the *RR*, the *t*-test was used to further test whether there was a significant difference between or among them.

The integration analysis showed that the RR_{++} of *Rs* for all the temperature treatments with 178 comparison pairs was 0.177 ± 0.002 ($P < 0.05$, Fig. 2a, b and Table S1) in the comparison of all ecosystems. When the area and averaged rate of *Rs* in each ecosystem was taken into account in terms of weight (eq.22), RR_{++}^{GT} decreased to 0.131 ($P < 0.05$, Table S1), which is slightly lower than the RR_{++}. *Rs* in agricultural fields. Forests and grasslands had a significant positive stimulatory effect under warming conditions, where *Rs* increased by 24.28%, 19.69% and 15.05% ($P < 0.05$), respectively. Comparing all climates, Alpine climate, Temperate continental climate, Temperate grassy climate, and Subtropical humid monsoon climate had a significant stimulatory effect under warming conditions, where *Rs* increased by 17.71%, 15.1%, 27.04% and 49.4% ($P < 0.05$, Fig. S1a), respectively, and RR_{++} of 0.182 for *Rs* ($P < 0.05$, Table S1). Some climates with too few (<3) observations of *Rs* (e.g., Tropical desert climate, Tropical rainforest climate, etc., Table S1) were excluded from the group.

The elevation was divided into six subgroups with a 500 m gradient. It showed that warming significantly stimulated *Rs* from 16.05% to 30.24% ($P < 0.05$, Fig. S1b and Table S1) as the elevation increased. The temperatures were divided into seven subgroups with a 1 °C gradient. The stimulation of temperature to *Rs* showed an enhancement with increasing temperature (12.82% to 148.22%, $P < 0.05$, Fig. S1c and Table S1), except for the insignificant effect of 4 °C < x ≤ 5 °C, where x is the observed temperature increase.

Correspondingly, the DUR was divided into four subgroups by quarter (q) and year (y). On average, a significantly stimulated 35.46% of *Rs* under short-term warming (<1q), and the effects under long-term warming on *RRs* of *Rs* were insignificant ($P > 0.05$, Fig. S1d and Table S1).

3.2. Response of Rs to precipitation

Results of the subgroup analysis revealed that the RR_{++} of *Rs* across 134 comparision pairs was 0.284 ($P < 0.01$, Fig. 3a, b and Table S2) when the magnitude of precipitation variation was normalized to 50% of the current year. When the area and mean rate of *Rs* for each ecosystem were considered by weight, the RR_{++}^{GT} decreased to 0.331 ($P < 0.05$, Table S2), which is slightly higher than the RR_{++}. The effect of precipitation on *Rs* was significant in all ecosystems ($P < 0.05$, Fig. S2 and Table S2), with the largest increase of *Rs* in deserts (83.25%) and the smallest increase in wetlands (32.92%).

The effects of precipitation on *Rs* in different climates, elevations, variation of precipitation and DUR factors were significant and stimulating ($P < 0.05$, Fig. S2 and Table S2). The precipitation variation was divided into four subgroups with nodes of 20%, 50%, and 100%. It is worth mentioning that the positive effects of *Rs* was 90.33% for precipitation changes ≤20% and 17.29% for precipitation changes >100%, with a decreasing trend. As a result, the effect of precipitation on *Rs* decreased as DUR increased from 61.07% to 16.88%.

3.3. The correlations of Rs with global change factors under temperature and precipitation treatment

In this study, four factors were studied for global change: MAT, MAP, elevation and DUR. According to the meta-regression under temperature treatment, there was a parabolic relationship between *RRs* of *Rs* and MAP ($R^2 = 0.082$, $P < 0.05$). When MAP<2500 mm, *Rs* was significantly

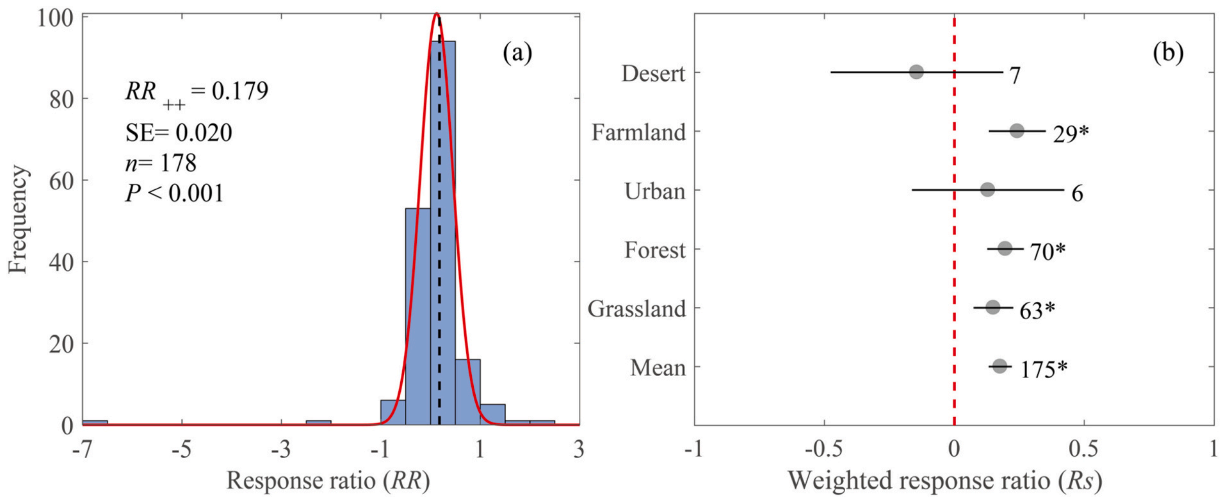

Fig. 2. Frequency distribution of soil respiration response ratios (*Rs*, panel a). Weighted response ratios (RR_{++}) of *Rs* (panel b) to temperature treatments in individual ecosystems (farmland, grassland, forest, etc.) and in all ecosystems (mean). Error bars indicate 95% confidence intervals (CI), sample size for each variable is shown next to the configuration term, the * in panel b indicates statistical significance ($P < 0.05$), and SE represents standard error.

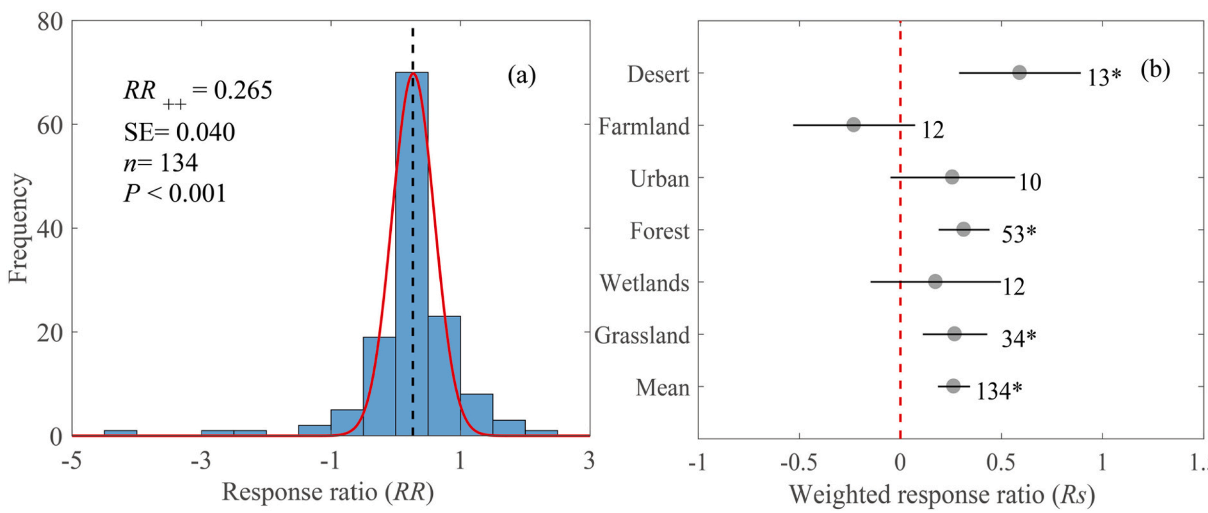

Fig. 3. (a) Frequency distribution of soil respiration response ratios (*RR*), SE represents standard error. (b) Weighted response ratios (RR_{++}) of *Rs* (panel b) to precipitation treatments in individual ecosystems (farmland, grassland, forest, etc.) and in all ecosystems (mean). Error bars indicate 95% confidence intervals (CI), the sample size for each variable is shown next to the configuration term, the * symbol in panel b indicates statistical significance ($P < 0.05$).

enhanced by warming and peaked at MAP = 1100 mm; when MAP>2500 mm, the warming suppressed the *Rs* (Fig. 4a). The *RRs* of *Rs* was positively correlated with elevation ($R^2 = 0.016$, $P < 0.05$, Fig. 4b) and temperature ($R^2 = 0.047$, $P < 0.05$, Fig. 4c). However, *RRs* of *Rs* declined exponentially with DUR ($R^2 = 0.052$, $P < 0.001$, Fig. 4d). The correlation between the *RRs* of *Rs* and MAT was not significant (Fig. S3).

According to the results of meta-regression on precipitation treatment, the *RRs* of *Rs* was positively correlated with MAT ($R^2 = 0.002$, $P < 0.05$, Fig. 5a) and elevation ($R^2 = 0.01$, $P < 0.05$, Fig. 5c), and negatively correlated with MAP ($R^2 = 0.027$, $P < 0.05$, Fig. 5b) and DUR ($R^2 = 0.019$, $P < 0.05$, Fig. 5d). Specifically, the *RRs* of *Rs* were parabolically correlated with the variation of precipitation ($R^2 = 0.018$, $P < 0.05$, Fig. S4); the *RRs* of *Rs* decreased with the decrease of precipitation. *RRs* increased with precipitation when precipitation increase was <50% and vice versa.

3.4. Effects of multiple global change factors on Rs

Principal component analysis revealed that the main factors affecting *Rs* were global variable factors (MAT, MAP, Elevation, warming/Rainfall and DUR), and were represented in the first three PCs (Fig. S5).

For the temperature treatments, MAT explained 59.5% of the total variance, while DUR explained 0.9%. It was discovered that there existed a correlation between different factors (Table S5). Among them, MAT, MAP and warming were positively correlated with each other while a negative correlation between warming and DUR was noticed. Elevation was negatively correlated with other factors except warming (Fig. 6a).

For the precipitation treatments, MAT explained 83.9% of the total variance, while DUR explained 27.9% (Table S5). The rainfall, MAT and MAP were positively correlated, while elevation was negatively correlated with all other factors (Fig. 6b). Furthermore, random forest analyses revealed that global variation factors (especially elevation, MAT and rainfall) had strong impacts on *Rs* (Fig. 6c and d).

The interacting effects of warming and rainfall on *Rs* were examined in more detail. Among Data S1 and Data S2, 14 studies were extracted on the interactive effects of warming and rainfall on *Rs*, from which 29 independent observations were selected for further investigation. Even though all ecosystems were analyzed, sample limitations caused farmlands and urban grasslands to dominate the dataset.

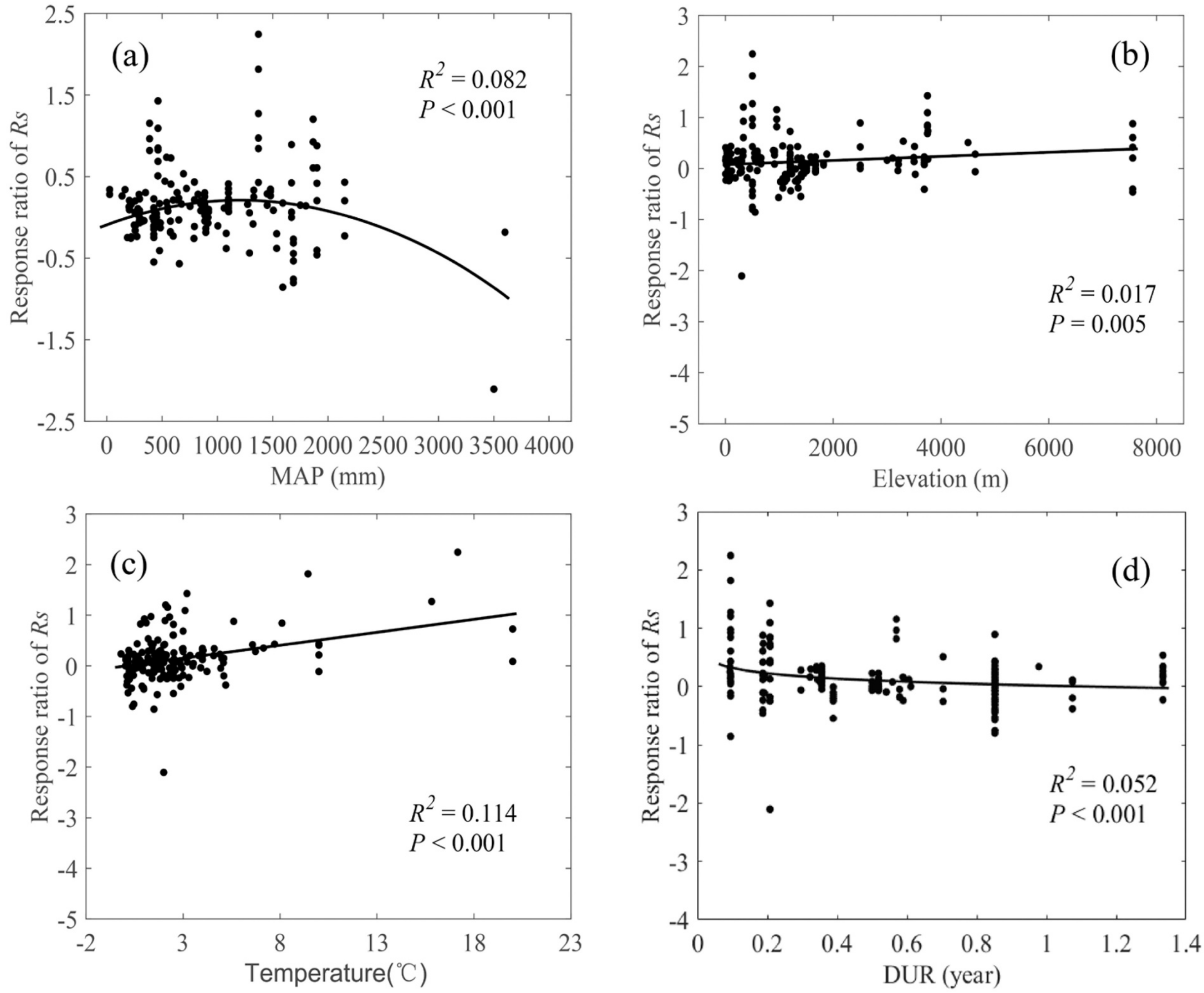

Fig. 4. Relationship of the response ratio of *Rs* to MAP (panel a), elevation (panel b), temperature (panel c), and DUR (panel d) with temperature treatments.

Together, the VPA and SEM results showed that warming and rainfall influenced the response of *Rs* in farmland and urban grassland ecosystems, respectively (Figs. 7 and 8). The warming and rainfall observations were performed independently to obtain the RDA analysis for the overall variance-corrected explanatory degree of each factor for *Rs*. The VPA revealed that both rainfall and warming played important roles in regulating CO_2 accumulation of soil across the study area. Warming and rainfall totally explained 93.31% of the spatial variance in *Rs* (Fig. 7), with rainfall explaining a much higher proportion (86.78%) compared to warming (45.72%).

The SEM model performed well with a goodness-of-fit index (GFI) >0.95, and low Akaike information criterion (AIC), a significant chi-square (χ^2) value, and mean square error of approximation (RMSEA, <0.05) (Fig. 8). It illustrated that *Rs* was dominantly and directly affected by rainfall (Fig. 8a) with a standardized direct effect of 0.371 (Fig. 8b). In addition, MAT, MAP, Elevation and DUR had indirect effects on *Rs* (Fig. 8a).

4. Discussions

Rs plays vital roles in regulating atmospheric CO_2 concentrations and the climatic dynamics of ecosystems. Empirical evidence and meta-analyses indicate that *Rs* responds differently to temperature and precipitation treatments (Feng et al., 2017; Romero-Olivares et al., 2017; Xiao et al., 2020; Zhang et al., 2020). However, most of the past studies have focused on the effect of a single factor on *Rs* and some studies have evaluated the interacting effects of multiple factors. With the aid of meta-analysis, this study showed that global change has a positive effect on *Rs*, which was enforced with the interaction of multiple-factors. Those effects were predominantly linked to warming, rainfall and DUR, supporting results of other studies at local and global scales (Peng et al., 2009; Raich, 2003; Wang et al., 2014; Xia et al., 2009).

4.1. *Response of Rs to temperature treatment in different environment factors*

The results of this study indicate that increasing soil temperature promotes *Rs*. Specifically, an increase in soil temperature of 0.2 to 17 °C would result in a 13–21% increase in soil respiration rate (Fig. S1c). Overall, the rate of nutrient mineralization, plant biomass, and microbial and enzyme activities in the soil will increase with soil temperature, resulting in an increased rate of *Rs* (Campos, 2014; Escolar et al., 2015; Rey et al., 2011). In arid and semi-arid regions, low soil water content and low porosity, particularly in summer, will lead to reduced microbial activity, which inhibits *Rs* (Dacal et al., 2020; Zhong et al., 2013). In humid areas with MAP >1800 mm, warming only slightly increased *Rs*. However, excessive precipitation in wetter areas increases soil water content, replacing a large amount of air in soil pores with water, thus reducing soil porosity and permeability, limitng the diffusion of oxygen in the soil and possibly inhibiting root and microbial activity. The inhibition of *Rs* will become more pronounced as soil water content increases thereafter (Estiarte et al., 2016). The results of the subgroup analysis support this observation in different climates (Fig. S1a and Table S1).

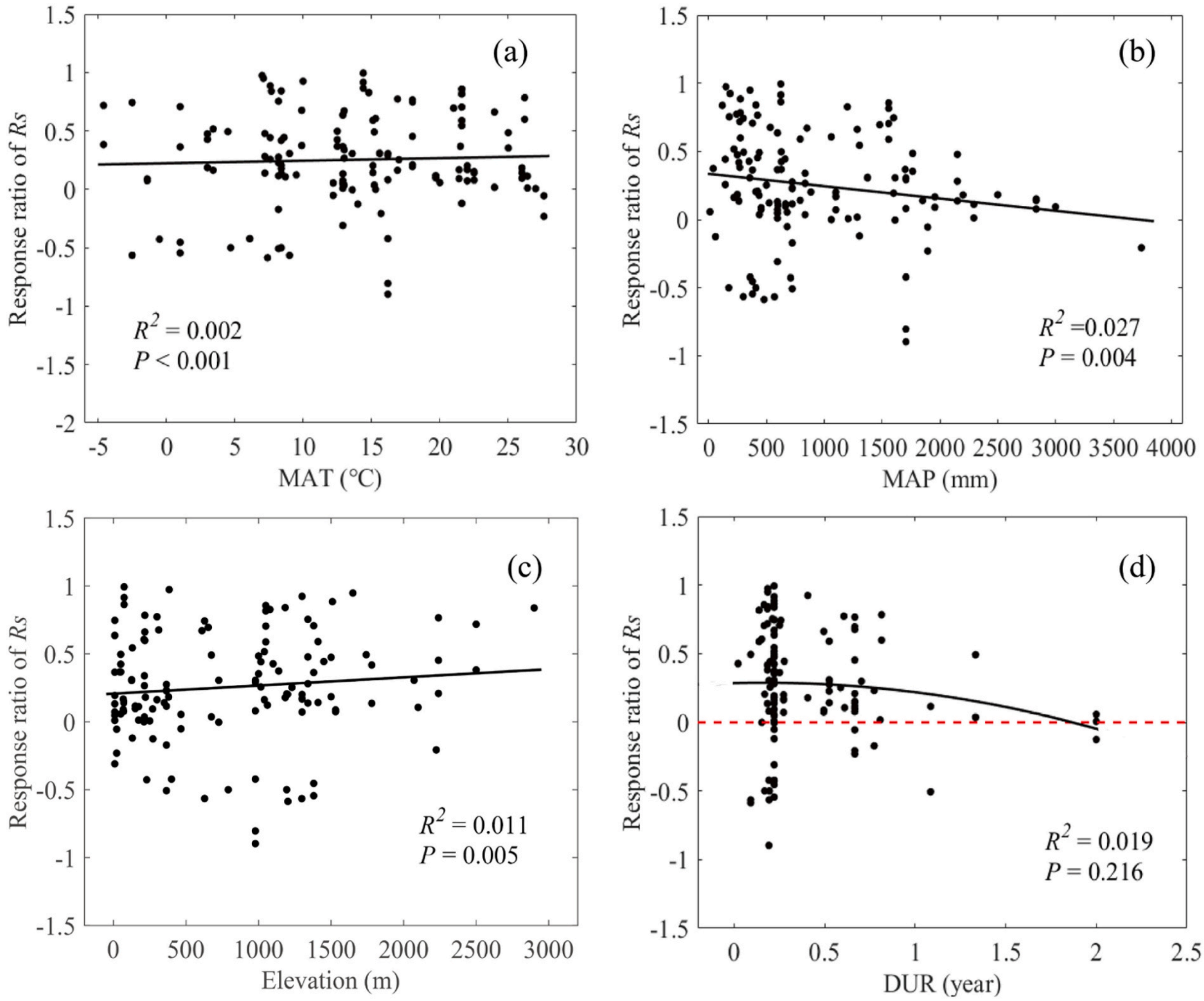

Fig. 5. Relationships of the response ratio of *Rs* to MAT (panel a), MAP (panel b), elevation (panel c) and DUR (panel d) with precipitation treatments.

The results also showed that the intensity of *Rs* increased with a gradient increase in temperature (Fig. S1c), which is consistent with the results of Wang et al. (2014) and Pries et al. (2017). Both short-term and long-term warming promoted *Rs*. But in comparison, short-term warming increased *Rs* more significantly, while the pattern of increase under long-term warming could not be determined because of the differences in natural factors (Fig. S1d), similar to that found by Sun and Han (2016) and Melillo et al. (2017). It is worth mentioning that the sensitivity of *Rs* to temperature increase may decrease or "domesticate" or "adapt" with the increase of DUR (Fig. 4), indicating that soil microorganisms, enzymes and roots have a certain range of adaptation to temperature sensitivity (Luo et al., 2001), which Carey et al. (2016) have similarly concluded.

4.2. Response of Rs to precipitation in different environment factors

Soil moisture affects *Rs* by participating directly or indirectly in the various processes of *Rs*. As a result, *Rs* and soil temperature are both significantly influenced by soil moisture (Abbasi et al., 2020). However, there is a lot of complexity and confusion surrounding how soil moisture affects *Rs*. This study found that the general pattern of soil respiration response to precipitation at the global level is that increasing precipitation promotes soil respiration (Fig. 3b).

In agreement with findings of Shang et al. (2019) and Xu et al. (2004), this study demonstrated that soil CO_2 fluxes are significantly enhanced for a short period during rainfall, whereas long-term rainfall increases in some areas (e.g., rainy season) directly caused the *RRs* of *Rs* to become negative (Fig. 5d). When the soil moisture content is relatively high or there is extreme rainfall, the limiting effect of moisture decreases, the soil rapidly reaches saturation or waterlogging, and soil moisture response to *Rs* decreases (Abbasi et al., 2020; Chen et al., 2011). Rainfall-induced alternating wet and dry soil processes make the soil more porous and becomes anaerobic (Liu et al., 2014; McIntyre et al., 2009; Wang et al., 2012). This process dramatically reduces soil CO_2 emission (Bond-Lamberty and Thomson, 2010). Additionally, during a soil moisture deficit period, the alternating wet and dry soil processes brought about by rainfall induced a significant increase in soil respiration rate, first through increasing soil moisture and then decreasing soil moisture (Almagro et al., 2009; Rey et al., 2017). Meanwhile, the rate of soil respiration increased significantly as rainfall decreased (Cleveland et al., 2010; Zhang et al., 2015).

Due to the small number of studies with added rainfall addition ranging from 50% to 100% (Table S4), the overall response of *Rs* over this time period differs from the general trend, and it can not be concluded that they react differently to precipitation. Clearly, additional long-term experiments are needed to better understand the response patterns of *Rs* to different precipitation intensities.

4.3. Factors driving Rs under global changes and the interaction of warming and rainfall

The frequency and intensity of extreme weather events are expected

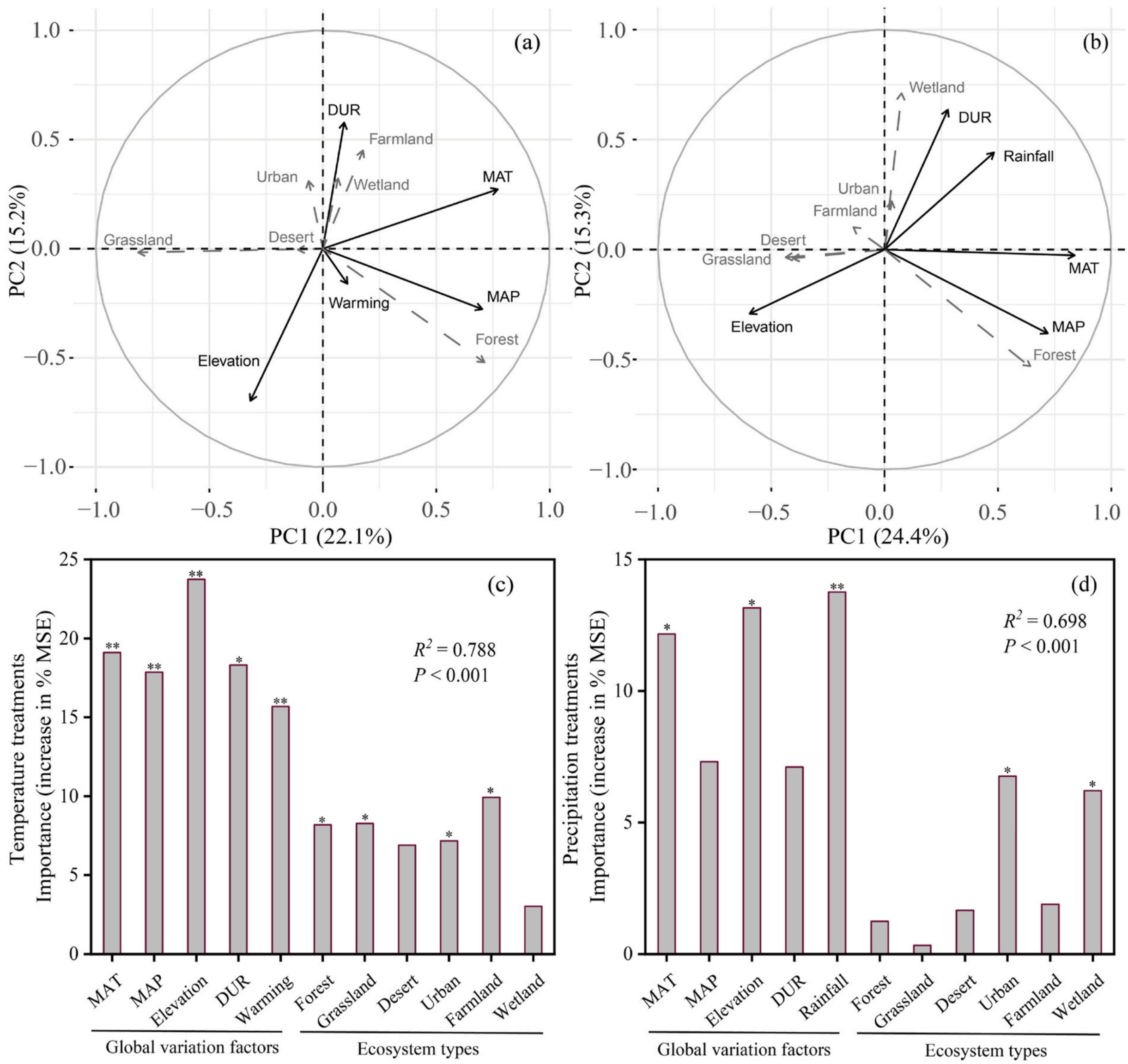

Fig. 6. PCA ordination of the distribution of *Rs* across ecosystem types. (a) Temperature treatments. (b) Precipitation treatments. The details of Intra-set correlations are presented in Table S5 and Fig.S5. Random forest analysis was used to identify the best individual predictors for soil respiration. (c) Temperature treatments. (d) Precipitation treatments. The predictors included MAT, MAP, elevation, DUR and warming/rainfall treatment. Significance levels are as follows: **P* < 0.05 and ***P* < 0.01. MSE, mean square error.

to increase every year as a result of global warming (Ofipcc, 2013). Many current studies have shown that multiple global change factors have an interactive effect on *Rs* (Chen et al., 2020b; Post and Knapp, 2020; Wu et al., 2011). The responses of *Rs* to multiple global change factors are very complex because these factors are temporally and spatially complex and often occur simultaneously (Wu et al., 2011). Interactions among two or more global change factors may result in additive or antagonistic effects (Bai et al., 2020; Zhou et al., 2016b). For example, warming and DUR often occur synchronously and lead to drought at the regional scale (Kukumagi et al., 2014). Therefore, the combined DUR and warming can lead to inhibitory effects on *Rs*. The combined elevation and warming can lead to an antagonistic interaction on *Rs* (Huang, 2022).

By integrating global precipitation data, combined rainfall and MAT/MAP may lead to an antagonistic interactions of *Rs* (Table S6 and S7). In warmer climatic zones, rainfall will partially offset soil water loss from high temperature evapotranspiration (Cusack et al., 2019; Tomar and Baishya, 2020), whereas reduced precipitation will exacerbate soil water loss (Hawkes et al., 2020; Ondier et al., 2020) and thus significantly suppress *Rs* (Table S2 and S7). In contrast, in climatic zones with high MAP, decreased rainfall may help to advance *Rs*. Rainfall and DUR combined may result in antagonistic effects of *Rs*. With prolonged precipitation (> four months (1 quarter)) soil permeability could be reduced (Table S7 and Fig. 5d). The research results of the effects of rainfall reduction on arid climate are inconsistent. The results of this study and other studies (Liu et al., 2017; Wang et al., 2021) suggest that reduced precipitation in arid environments inhibits *Rs*. However, some studies (Flanagan et al., 2002; Knapp and Smith, 2001) indicate that plants and microorganisms in arid climates are resistant to reduced precipitation. Research results on the effects of reduced precipitation on arid climate soils have been inconsistent. Even though this study included several controlled experiments of precipitation reduction treatments, the relationship between precipitation and *Rs* in arid soils could not be confirmed.

In this meta-analysis, the synergistic interaction on *Rs* mainly occurred in combination of warming and rainfall, especially in grassland, urban and desert ecosystems (Fig. 6), because more precipitation can mitigate water loss brought on by increasing temperatures and boost

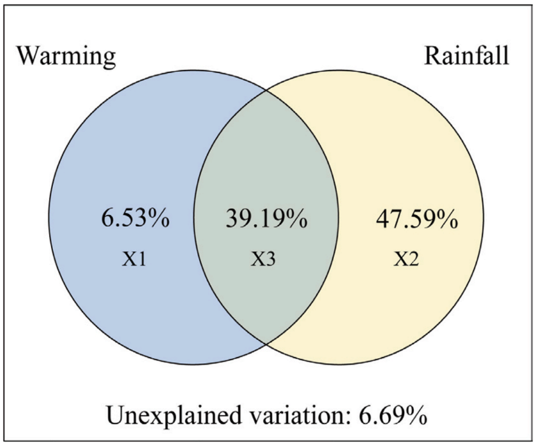

Fig. 7. Results of VPA illustrating the relative contributions of warming and rainfall treatments to soil respiration. X1 and X2 represent the pure effect of each treatment type, and X3 shows the overall effect of the two types of treatment.

soil moisture availability (Gu et al., 2015; Wang et al., 2022; Wu et al., 2016). However, most *Rs* data are primarily based on short-term experiments since long-term study data are insufficient. We therefore caution readers that the findings of this meta-analysis need further evaluation regarding long-term references. Long-term experiments with multiple global change factors are essential to assess their long-term interactive effects on *Rs*.

In the analysis of temperature and precipitation interaction in urban grassland and farmland ecosystems, our SEM models showed that MAT, MAP, elevation and DUR indirectly affected *Rs* through changing rainfall, warming interactions. Rainfall and warming interaction were positively correlated with *Rs*. This emphasizes that rainfall is a key global predictor of *Rs* and is consistent with earlier findings (Guo et al., 2018; Sharkhuu et al., 2013; Wang and Yu, 2018; Zhang et al., 2013). MAP, DUR and elevation were all negatively correlated with *Rs*. These findings indicate that MAP, elevation and DUR indirectly impacted on *Rs* by strongly influencing temperature and precipitation.

It should be noted that the absence of temperature or precipitation as a stress factor is a necessary and sufficient condition for aforementioned discussion. When the stress factor is temperature, the stimulatory effect of rainfall on *Rs* is counterbalanced by the negative impact of cold temperatures (Dong et al., 2021; Gao et al., 2020); when the stress factor is precipitation, the stimulatory effect of warming on soil respiration is counterbalanced by the negative impact of drought (Bao et al., 2010; Bontti et al., 2009; Liu et al., 2012).

5. Conclusions

The responses of *Rs* to a variety global changing factors is potentially important but rarely studied. This meta-analytic review provides a broader perspective on how precipitation and temperature changes affect soil respiration, individually or interactively. We conclude that rainfall and warming have positive effects, while environmental factors (e.g.: climates, altitudes, and ecosystems) can also interfere indirectly with *Rs*. Importantly, *Rs* showed a parabolic tendency with increasing rainfall and DUR, and an exponential decreasing trend with increased warming DUR; *Rs* was also significantly dependent on the climate. In particular, the combined effect of multiple global change factors other than warming and rainfall on *Rs* was greater than the individual effect; DUR or elevation combined with other environmental factors had an antagonistic effect on *Rs*; and rainfall is a key factor affecting *Rs* in farmland and urban grassland ecosystems. Rainfall and DUR are directly impacted by MAT, MAP, and elevation, which also indirectly affects *Rs*.

Overall, this study has improved our understanding of factors driving changes in *Rs* as part of global change. Concurrently, ecosystems in different climates and biological communities also lead to different responses of *Rs* to temperature and precipitation treatments. These differences have been documented and used to design globally standardized carbon sinks and prediction models, and to reveal the response patterns of *Rs* with global temperature and precipitation change.

CRediT authorship contribution statement

Zheyu Zhang: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization. **Yaoxiang Li:** Supervision, Project administration, Funding acquisition, Writing – review & editing. **Roger A. Williams:** Writing – review & editing. **Ya Chen:** Data curation, Investigation, Methodology. **Rundong Peng:** Data curation, Investigation, Conceptualization. **Xiaoli Liu:** Data curation, Software. **Yuanda Qi:** Data curation, Software. **Zhiping Wang:** Investigation, Software.

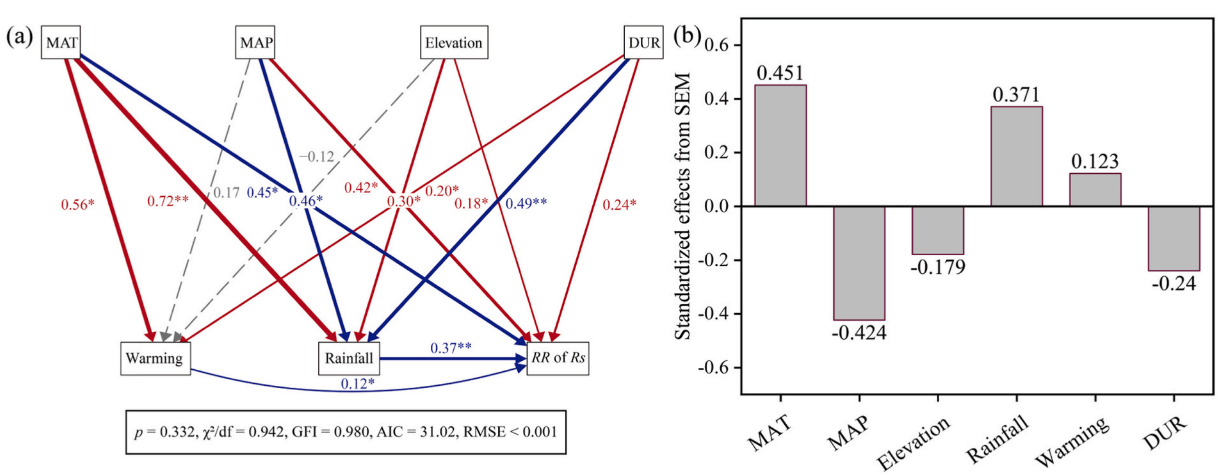

Fig. 8. SEM describing the effects of global change factors on soil respiration (a). Total and direct and indirect standardized effects from the SEM on soil respiration (b). Red and blue arrows represent significant negative and positive pathways, respectively, while the gray dashed arrows represent no significant pathways. Numbers adjacent to the arrows are standardized path coefficients, analogous to relative regression weights and indicative of the effect size of the relation. The thickness of the arrows is proportional to the magnitude of the standardized path coefficient s. The arrow width is proportional to the strength of the relationship. *$P < 0.05$, **$P < 0.01$, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2023.102057.

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