Global Pattern of Ecosystem Respiration Tendencies and Its Implications on Terrestrial Carbon Sink Potential

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Abstract As the largest component of carbon export from terrestrial ecosystems, ecosystem respiration (RECO), together with vegetation productivity, determines the carbon stock changes in terrestrial ecosystems, so it is crucial to reveal the response of RECO to climate change. However, the simulation of RECO is usually inaccurate due to the neglect of the lagged response of respiration to changes in water conditions. In this study, we integrated meteorological data, remote sensing data, and soil data, and introduced the indicators of the previous water conditions into the deep learning model to simulate RECO. The conclusions are as follows: (a) There is a 1–2 years' lagged response of RECO to changes in water conditions. (b) It is necessary to consider the influence of previous water conditions when simulating RECO. It not only improved the simulation accuracy of RECO, but also reflected its inter-annual fluctuations and change trends more accurately, avoiding the underestimation of RECO inter-annual fluctuations. (c) There is an inconsistency in carbon input and carbon output change trends which impacts the carbon sink pattern and potential of terrestrial ecosystems. The growth trend of Gross Primary Production (GPP) in global terrestrial ecosystems is greater than that of RECO, with a trend of increasing carbon sinks, especially in the northern extra-tropics; while the carbon sink capacity of tropical regions has gradually saturated, showing that the change trend of RECO is close to that of GPP, which poses a potential risk to the sustainable carbon sink capacity of global ecosystems in the future.

Plain Language Summary Ecosystem respiration (RECO) is the largest component of carbon export from terrestrial ecosystems and determines the carbon sink potential of terrestrial ecosystems. Consider from the perspective of carbon cycle mechanism, it is reasonable to believe that RECO has the lagged response to changes in water conditions. However, most studies usually consider the water conditions in growing season only, which caused the inaccurate RECO simulations and underestimation of RECO's interannual variation. In this study, we introduced the multi-time scale standardized precipitation evapotranspiration indexes—which can reflect the current and previous water conditions-into deep learning models to construct an optimal model for simulating global-scale RECO. We revealed the optimal time scales of the lagged effect that need to be considered in RECO simulations and analyzed the global pattern of RECO tendencies and its implications on terrestrial carbon sink potential. We believe this paper to be of particular interest to the readers of your journal as our method is novel that could well reveal the spatial pattern and the interannual variations of RECO at global scale and our results have important implications for the assessment of terrestrial ecosystem carbon sink. In addition, it revealed some new rules that are interesting for the academic community.

1. Introduction

Ecosystem respiration (RECO) is the process by which all organisms in an ecosystem convert organic carbon to CO2. It includes autotrophic respiration, which is generated by plant respiration, and heterotrophic respiration, which is generated by the decomposition of animals and microorganisms in the soil (Chapin et al., 2012). As the largest component of CO2 released to the atmosphere by terrestrial ecosystems, RECO together with vegetation productivity, controls the carbon balance of terrestrial ecosystems (Yvon-Durocher et al., 2012). Under the influence of climate change, the carbon balance of terrestrial ecosystems has been significantly perturbed. On the one hand, global warming and CO2 fertilization effects will prolong the vegetation growth period, increase vegetation productivity and enhance CO2 uptake (Bellassen & Luyssaert, 2014); on the other hand, global warming will accelerate permafrost melting, enhance RECO and release more CO2 into the atmosphere (Koven et al., 2011).
Studies have shown that carbon emissions from terrestrial ecosystems continue to increase in future scenarios (Cox et al., 2000; Trumbore, 2006). In the long run, it may exceed or offset the increase in vegetation productivity, reducing the carbon sink capacity of terrestrial ecosystems and posing a significant risk to global ecosystems (Dixon et al., 1994; Luyssaert et al., 2007).

Many factors affect RECO, such as temperature, water availability, vegetation productivity and external carbon input, specifically: (a) Temperature, on the one hand, directly affects the vegetation respiration rate and microbial decomposition rate. In the short term, the respiration rate and microbial enzyme activity increase exponentially with increasing temperature (Johnston et al., 2021; Lloyd & Taylor, 1994). On the other hand, temperature affects respiration indirectly by affecting the photosynthesis of vegetation and changing the magnitude of vegetation productivity (Garbulsky et al., 2010), which determines the quantity and quality of organic matter input to the soil (Janssens et al., 2001). (b) Water availability. The respiration rates are lower in water-deficient environments because water deficit can inhibit respiration through microbial drought stress and substrate limitation (Davidson et al., 2006). The respiration rates increase with increasing moisture until environments become saturation and anaerobic, which again inhibits respiration rates (Haynes, 1986; Hursh et al., 2017). (c) Vegetation productivity determines the quantity and quality of organic matter input to the soil and influences the rate of soil respiration (Janssens et al., 2001). (d) External carbon input includes vegetation litter and organic carbon stored in the soil. The vegetation litter mainly determined by the growth of vegetation in the current year, while soil organic carbon is the product of long-term accumulation in the ecosystem, and they both are the nutrients that supply soil microorganisms for decomposition (Chapin et al., 2012; Curiel Yuste et al., 2007).

One of the consequences of climate warming is the increase in precipitation and evapotranspiration, leading to an intensification of the water cycle. It greatly increases the degree of precipitation variability and affects the respiration rate of ecosystems, which can ultimately disrupt the carbon balance of terrestrial ecosystems (Dai et al., 2004; Stocker, 2014). Although many studies have concluded that respiration is less sensitive to changes in water than photosynthesis (Li et al., 2017; Schwalm et al., 2010; Shi et al., 2014), RECO determines the amount of carbon output from terrestrial ecosystems, therefore even small changes of RECO are critical and deserve more attention (Anderson-Teixeira et al., 2011; Jung et al., 2017; Xu et al., 2004). In addition, studies have shown that there is a significant lagged response of respiration to water condition changes (Van der Molen et al., 2011; Verburg et al., 2005) and the lag time of respiration may be longer than vegetation productivity. This may also be one of the reasons why the response of respiration to moisture changes is less pronounced than that of photosynthesis. After long-term field observations, Arnone III et al. (2008) found that there is a 1-year lag time in respiration response to drought, resulting in a longer time for the ecosystem carbon sink to recover to its original level. While considering that the raw materials for soil respiration mainly comes from the litter on the ground, Brando et al. (2008) found by isotope measurements that there is a 2-year interval between the fall of leaves and the release of carbon dioxide by soil decomposition. Therefore, we speculate that there is indeed a time lag in the effect of water changes on respiration. This probably because the organic matter decomposed by respiration, such as vegetation litter, is the product of early accumulation, and the quality of these accumulated organic matter is related to the previous vegetation growth and water conditions, which is shown as the lagged effect of previous water conditions on respiration.

Considering the potential relationship between RECO and previous water conditions, it is a challenge to choose a proper model to reveal the underlying mechanism between them. Currently, process models are the major methods to study the effect of water on RECO. They simulate RECO and assess the effect of water conditions by modeling the processes of carbon and water cycles. These models have the advantage of achieving a representation of the process mechanism (Raich et al., 1991; Running & Hunt, 1993). However, although process models attempt to reproduce the processes in the terrestrial carbon cycle through detailed parameters and complex structures, the structures of the models still rely on human experience. The processes that are not yet understood or discovered are not addressed in the models (Reichstein et al., 2019). For example, the lagged effect of water on RECO has not been considered. This will reduce the effectiveness of the model simulations.

In recent years, deep learning has been gradually applied to the field of ecology (Reichstein et al., 2019; Wagner et al., 2019). Compared with traditional process models, it has a powerful data fusion capability, which can combine massive remote sensing data to great advantage (Xiao et al., 2019), and has an autonomous learning capability, which means the model structure no longer depends on human design. It is only necessary to fully consider the environmental factors that may affect RECO in conjunction with ecological mechanisms before
the experiment and put them as variables into the model. It is also possible to assess the effects of environmental factors by controlling the input variables and evaluating accuracies. Taking these into account, deep learning will be the suitable method for our study.

At present, there is no definite conclusion about the optimal time scale of lagged effect of water on RECO, and few existing models consider this aspect. Therefore, with the help of data fusion ability and autonomous learning ability of deep learning, this study intends to incorporate various factors affecting RECO, such as temperature, precipitation, radiation, vegetation productivity, and soil organic carbon, into a deep learning model. At the same time, the previous water conditions at different time scales are introduced into the model to investigate the lagged effect of water on RECO and its optimal time scale. The Standardized Precipitation Evapotranspiration Index (SPEI) is widely used as an effective indicator of water balance (Vicente-Serrano et al., 2010). It combines the effects of temperature and precipitation and the flexibility of its time scale is advantageous in studying the effect of water conditions on different timescales (Barnes et al., 2016; Vicente-Serrano et al., 2013). The selection of SPEI at the optimal time scale can better characterize the lagged effects of water conditions (Huang et al., 2015; Luo et al., 2016, 2018).

In this study, first, based on deep learning models, we integrated flux observation data with meteorological data, remote sensing data and soil data, and selected SPEIs at different time scales as explanatory variables to represent the lagged effect of water conditions to simulate RECO. Second, by comparing the improvement degree of multi-time scale SPEIs (and its combination) on RECO simulation accuracies to evaluate the water lagged effect and its optimal time scale. Then the optimal model was established to simulate the spatial distribution and interannual variations of global RECO from 2000 to 2018. Finally, by comparing with gross primary production (GPP), we analyzed the regional differences in the inconsistency of RECO and GPP change trends and their effects on terrestrial carbon sink potential.

2. Data and Methods

In this study, we chose RECO observations from the FLUXNET 2015 data set (Pastorello et al., 2020) as standard, combined meteorological data, remote sensing data and soil data, used convolutional neural network (CNN) to simulate RECO.

2.1. Data

FLUXNET, founded in 1996, is a global flux network merged by multiple regional flux networks. FLUXNET 2015 data set contains more than 500 registered sites, of which more than 200 sites can share data (https://fluxnet.fluxdata.org/data/fluxnet2015-dataset/). These sites cover different ecosystems around the world and is a valuable data for studying terrestrial carbon cycle. In this study, we obtained RECO observations of 207 flux sites from FLUXNET 2015 data set, including observations from 2000 to 2014, for a total of 1,300 yearly data. We chose the yearly RECO value from yearly RECO_NT_VUT_REF, which is from nighttime partitioning method, reference selected from RECO versions using a model efficiency approach and summed from daily data. The spatial distribution and period of flux sites are shown as Figure 1.

The basic data for simulating RECO were selected according to the influencing factors of RECO, involving climate, vegetation and soil factors, specifically: (a) Climate indicators includes mean annual temperature (MAT), mean annual precipitation (MAP), mean annual photosynthetically active radiation (PAR), and December SPEI on different time scales (12, 24 and 36 months); (b) Vegetation indicators includes the mean annual normalized difference vegetation index (NDVI), mean annual leaf area index (LAI), mean annual fraction of absorbed photosynthetically active radiation (FAPAR) and annual cumulative NPP. (c) Soil indicators includes soil organic carbon (SOC) from 0 to 30 cm.

In detail, MAT and MAP are from CRU-TS 4.05 data set (http://www.cru.uea.ac.uk/data), which includes global monthly averaged daily mean temperature and monthly total precipitation data from 1901 to 2020, with a spatial resolution of 0.5°. We averaged the mean monthly temperature and monthly precipitation of each year from 2000 to 2018 to obtain the MAT and MAP. PAR is from global GLASS product GLASS04B01 V42 (Cheng & Liang, 2014) with a temporal resolution of 8-day and a spatial resolution of 0.05°, from which we calculated the average annual PAR from 2000 to 2018. SPEIs are from the SPEIbase V. 2.6 data set (http://sac.csic.es/spei),
which contains the global SPEI from 1901 to 2018 with a temporal resolution of months and a spatial resolution of 0.5°. The data set provides a timescale drought index from 1 to 48 months. We selected the December SPEIs with 12-month, 24-month, and 36-month time scales from 2000 to 2018, representing the water conditions of the current year, cumulative two years, and cumulative three years, respectively. NDVI is from the MODIS product MOD13A3 V006 (Didan, 2015) with a temporal resolution of months and a spatial resolution of 0.5°. We averaged the monthly NDVI of each year from 2000 to 2018 to obtain the annual mean NDVI. NPP is from the MODIS product MOD17A3HGF (Running & Zhao, 2019), which is annual cumulative NPP with a spatial resolution of 500 m. We obtained the annual cumulative NPP from 2000 to 2018. LAI is from the GLASS product GLASS01B01 V50 (Xiao et al., 2014, 2016) and FAPAR is from GLASS09E01 V50 (Xiao et al., 2015). They are both 8-day composite data with a spatial resolution of 0.05° and we calculated the annual mean LAI and FAPAR from 2000 to 2018. SOC is from the SoilGrids250 m data set (Hengl et al., 2017). This data set contains multiple soil attributes with global spatial distributions generated by machine learning algorithms based on 150,000 soil profiles and remote sensing data. Its spatial resolution is 250 m. We selected soil organic carbon at depths of 0, 5, 15 and 30 cm to represent the soil factor.

Considering the spatial matching problem between flux sites and spatial data, and the efficiency of simulating global spatial data, all the raster data mentioned above were resampled to 0.05° pixel size according to the nearest neighbor image method.

2.2. Method

2.2.1. Selection of Model Parameters

There are many factors that affect RECO, including climate, vegetation and soil factors. To accurately simulate RECO, these factors need to be parameterized in the model. In this study, MAT, MAP and PAR were chosen to reflect the basic climatic conditions; NDVI, LAI and FAPAR were used to reflect the photosynthesis and growth state of vegetation. In addition, NPP was selected to reflect the carbon sequestration ability of vegetation, and it also can characterize the carbon input of vegetation. In order to explore the validity of these indicators,
this study conducted a correlation analysis between RECO observations and various parameters (Supporting Information S1).

2.2.2. Details of the Model

The CNN used in this study is one of the most representative models in deep learning, which is based on artificial neural networks and makes a deeper network structure through weight sharing and sparse connections. The CNN not only has the strong data fusion ability and autonomous learning ability, but it also reads information of a neighborhood size and is able to retain certain geospatial structural features.

The CNN constructed in this study contains three convolutional layers, three maximum pooling layers and one fully connected layer. The first convolution layer contains 8 convolution kernels of 3 × 3 size, the second convolution layer contains 32 convolution kernels of 3 × 3 size, and the third convolution layer contains 64 convolution kernels of 2 × 2 size. Each convolutional layer was followed by a max pooling layer. In max pooling, the insufficient edges were filled with zero to ensure the constant size of the input and output. The parameter settings are shown in Table 1.

All the raster data were centered on the latitude and longitude of each flux site and were extracted with the neighborhood size of 3 × 3. Therefore, the data we constructed for CNN is formed as 3 × 3 × n, where n is the number of the input parameters. When the training started, each network parameter was given a random value, then the training data were input and transformed through layers. After convolution and max pooling, the predicted value was output by the ReLU activation function (Glorot et al., 2011). During the training process, the Adam algorithm (Kingma & Ba, 2014) was used for parameter optimization. The network parameters were continuously adjusted by minimizing the difference between the predicted and observed values. Until the difference was less than a certain threshold and no longer changed significantly, the training was complete (Figure 2). Then we imported the new data as the same 3 × 3 × n format into trained CNN to get the predicted values, so as to simulate global RECO. The construction and training of CNN in this study is implemented in python TensorFlow (Abadi et al., 2016).

In this study, we collected 1,300 sample data for CNN training. During the training process, for each iteration, the sample data was randomly allocated to the training set and the testing set at a ratio of 10:3. The training set was used to train the model, while the testing set was used to verify the model accuracy and monitor the model training process to prevent overfitting. At the end of training, we took the average of the accuracy of the last 10 iterations as the final training accuracy and testing accuracy. The accuracy of the model simulation was evaluated by the coefficient of determination ($R^2$), Lin's concordance correlation coefficient (CC) (Lawrence & Lin, 1989), the root mean square error (RMSE), and the standard deviation of error (SDE).

In order to find the optimal time scale for the lagged response of RECO to water conditions, we designed six CNN models. CNN1 is the model without SPEI except for the basic parameters (MAT, MAP, PAR, FAPAR, LAI, NDVI, NPP, SOC), that is, the original model CNN-ORIGIN. And in order to investigate whether there is a lag effect of RECO at certain time scales, SPEI12, SPEI24, and SPEI36 were introduced separately in CNN2, CNN3, and CNN4, respectively. The effects of previous water conditions on RECO at different time scales

| Table 1
| CNN Parameters |
| --- |
| Layer | Kernel size | Input | Output |
| Convolutional layer 1 | [3, 3, n, 8] + 8 | [3, 3, n] | [3, 3, 8] |
| Max pooling layer 1 | [1, 2, 2, 1] | [3, 3, 8] | [3, 3, 8] |
| Convolutional layer 2 | [3, 3, 8, 32] + 32 | [3, 3, 8] | [3, 3, 32] |
| Max pooling layer 2 | [1, 2, 2, 1] | [3, 3, 32] | [3, 3, 32] |
| Convolutional layer 3 | [2, 2, 32, 64] + 64 | [3, 3, 32] | [2, 2, 64] |
| Max pooling layer 3 | [1, 2, 2, 1] | [2, 2, 64] | [2, 2, 64] |
| Fully connected layer | [2 × 2 × 64, 128] + 128 | [1, 2 × 2 × 64] | [1, 128] |
| Output | [128, 1] + 1 | [1, 128] | [1] |

Note. n is number of the input parameters.
were evaluated by observing the improvement degree of these three models. SPEI12 and SPEI24 were added jointly in CNN5, and SPEI12, SPEI24, and SPEI36 were added jointly in CNN6. In this way, we can explore the optimal time scale and optimal combination of SPEIs to obtain the model with the best performance. Based on the accuracy evaluation results of the models, the optimal model CNN-SPEIopt was selected to simulate the spatial pattern and interannual variation of global RECO from 2000 to 2018 and calculate the change rates of each grid point in the global spatial distribution from 2000 to 2018. For the comparison between RECO and GPP, the values of RECO and GPP were z-score standardized according to Equation 1:

$$\text{Value}_z = \frac{\text{Value}_{\text{origin}} - \text{Value}_{\text{mean}}}{\text{Value}_{\text{std}}}$$

(1)

3. Results

3.1. Simulation Results of RECO

During the experiment, each CNN model reached a stable state after 100,000 iterations with high accuracies in both the training and testing phases, indicating that the model did not overfit during the training process (Table 2).

The experimental results showed that the training accuracy $R^2$ of CNN1 was 0.979, CC was 0.988, RMSE was 0.098, and SDE was 0.093. When introducing SPEI at different time scales, respectively, it was found that the introduction of SPEI12 did not improve the performance of the model, that is, the simulation accuracy of CNN2 was not improved compared to that of CNN1. However, SPEI24 and SPEI36 improved the model significantly. The training accuracy of CNN3 was 0.986 for $R^2$, 0.991 for CC, 0.085 for RMSE, and 0.074 for SDE; the training accuracy of CNN4 was 0.987 for $R^2$, 0.992 for CC, 0.078 for RMSE, and 0.072 for SDE, all of which were improved compared to that of CNN1. This shows that the effect of water conditions in the previous one to 2 years is more obvious than the effect of current water condition, indicating that there may be a significant lagged effect on the response of RECO to water condition changes, with a time scale of one to 2 years. The effect of the model was optimized when SPEI12 and SPEI24 were added jointly, that is, CNN5, which had the highest accuracy and included the water conditions of the current year and the previous year, and could reflect the lagged effect of RECO on water condition changes. Therefore, CNN5 was taken as the optimal model CNN-SPEIopt in this study, and the results of this model were subject to the subsequent analysis.

The RECO simulation results of CNN-SPEIopt are shown in Figure 3. The mean value of global multi-year average RECO from 2000 to 2018 is about 0.87 kg·C·m$^{-2}$·y$^{-1}$, and the maximum value is about 3.75 kg·C·m$^{-2}$·y$^{-1}$. The high value areas are mainly distributed in tropical rainforest areas, followed by mid-latitude and mid-high latitude forest-covered areas. While the lowest RECO values are found in areas covered with grass and shrub and high latitude areas in the northern hemisphere. Figure 3b shows the global spatial distribution of the standard deviation (STDEV) of RECO from 2000 to 2018, which reflects the magnitude of interannual fluctuations of RECO. The mean value of global RECO STDEV is about 0.22 kg·C·m$^{-2}$·y$^{-1}$, and the maximum value is 1.87 kg·C·m$^{-2}$·y$^{-1}$.

To validate the simulation results of CNN-SPEIopt, we compared it with six commonly used process models (Figure 3). The mean value of RECO simulated by CNN-SPEIopt is close to most models, but its standard deviation is much higher than others. It can be speculated that although the traditional process models can simulate RECO, the interannual fluctuations of RECO may be significantly underestimation (about 71%–88% underestimation).
To reveal whether these models can accurately reflect the interannual fluctuations of RECO, this study collected 173 observations from 30 sites of AmeriFlux (https://ameriflux.lbl.gov) and ChinaFlux (http://www.cnern.org.cn) to validate each model. A few of these data may have repeated in individual years of individual sites with FLUXNET data set, but most of them are from different observation years and did not participate in CNN training. First, by comparing the 173 observations with the simulated values of the models, we found that CNN-SPEIopt had the highest accuracy and the smallest simulation error, with $R^2$ of 0.535 and RMSE of 0.444. While the $R^2$ of the other models ranged from 0.002 to 0.468 and RMSE from 0.475 to 0.856 (Figure 4). Second, we calculated the standard deviation of the multi-year observations for each site and the standard deviation of the models' simulations, and conducted correlation analysis between the standard deviation of the observations and the standard deviation of the simulations (Figure 5). The results show that the Pearson correlation coefficient between CNN-SPEIopt and site observations is 0.475, which is significantly correlated at the level of $p < 0.01$. While the Pearson correlation coefficients between other process models and site observations are very low and some models even show negative correlation. This indicates that among these models, only CNN-SPEIopt can capture the interannual fluctuations of RECO because it is more consistent with the observed interannual fluctuations of RECO. While the standard deviations of the other models' simulations are generally low and inconsistent with the site observations, indicating that these models would seriously underestimate the interannual fluctuations of RECO. We also used the same observation data to validate the CNN-ORIGIN model (i.e., CNN1 without SPEIs), and it can be seen that the introduction of SPEIs improved the accuracies of CNN model and strengthened the interannual fluctuations of RECO (Figure S2 in Supporting Information S1). Specifically, when the SPEIs were included into model, the RMSE of 0.545 (CNN-ORIGIN) will decrease to 0.444 (CNN-SPEIopt) and the correlation coefficient of the standard deviation between observed and modeled RECO will increase from 0.217 (CNN-ORIGIN) to 0.475 (CNN-SPEIopt).

### 3.2. Spatial Patterns and Changing Trends of RECO and GPP

This study chose MODIS GPP as the carbon input of terrestrial ecosystem. MODIS GPP provides global scale, long time series and high spatio-temporal resolution GPP data, which is widely used in global vegetation biomass estimation and terrestrial ecosystem carbon cycle simulation. The MODIS GPP product used in this study is MOD17A2HGF V006 (Running & Zhao, 2019), which is an annual cumulative GPP calculated based on 8-day GPP with a spatial resolution of 500 m. Based on this product, we obtained global GPP from 2000 to 2018 and compared it with RECO to explore the differences in changes of terrestrial carbon input and carbon output. And in order to make them comparable, we resampled MODIS GPP to 0.05° using the nearest neighbor pixel method.

| CNN model | CNN1 | CNN2 | CNN3 | CNN4 | CNN5 | CNN6 | n |
|-----------|------|------|------|------|------|------|---|
| Input    | Basic Data | Basic Data, SPEI12 | Basic Data, SPEI24 | Basic Data, SPEI36 | Basic Data, SPEI12, SPEI24, SPEI36 | Basic Data, SPEI12, SPEI24, SPEI36 |
| Training | $R^2$ | 0.979 | 0.972 | 0.986 | 0.987 | 0.990 | 0.983 | 1,000 |
|          | CC   | 0.988 | 0.984 | 0.991 | 0.992 | 0.994 | 0.987 |
|          | RMSE | 0.098 | 0.113 | 0.085 | 0.078 | 0.068 | 0.103 |
|          | SDE  | 0.093 | 0.105 | 0.074 | 0.072 | 0.064 | 0.083 |
| Testing  | $R^2$ | 0.979 | 0.974 | 0.986 | 0.988 | 0.989 | 0.982 | 300 |
|          | CC   | 0.988 | 0.985 | 0.991 | 0.993 | 0.994 | 0.986 |
|          | RMSE | 0.096 | 0.114 | 0.084 | 0.079 | 0.070 | 0.103 |
|          | SDE  | 0.091 | 0.106 | 0.074 | 0.072 | 0.066 | 0.085 |

Note. Basic Data contains MAT, MAP, PAR, FAPAR, LAL, NDVI, NPP, SOC00, SOC05, SOC15 and SOC30; $n$ is the number of samples. The bold values are the best results of six CNN models.

Table 2

CNN Experimental Results
The global temperature and precipitation are increasing, especially the temperature, which is showing a significant increasing trend due to the climate change. The CNN-SPEIopt shows that the global average RECO has a significant increasing trend \((p < 0.01)\) with climate change (Figure 6a). Spatially, 55.01% of the global RECO...
show an increasing trend, 13.03% show a significant increase trend ($p < 0.1$), while 44.99% show a decreasing trend, and 8.33% show a significant decrease trend (Figure 7a, Table 3). This indicates that the global RECO is dominated by growth.

The global average GPP also shows a significant increasing trend ($p < 0.01$), and the growth rate of GPP (slope of 0.166) is higher than that of RECO (slope of 0.142; Figure 6a). In terms of spatial distribution, GPP shows a significant increasing trend in most of the global regions, except for the Amazon region. Globally, 76.28% of the GPP show an increasing trend and 34.90% show a significant increase; 23.72% show a decreasing trend and 5.21% show a significant decrease (Figure 7b, Table 3). This indicates that although the growth trends of global average RECO and GPP are similar, the proportional of increasing GPP is higher than that of increasing RECO, and the carbon sink potential of global terrestrial ecosystem is generally on an increasing trend.

The land area of the northern extra-tropics (30°N ~ 90°N) accounts for about 60% of the world, with extensive forest cover and high carbon sink potential. On the one hand, influenced by the warming and humidification of climate and the effect of CO$_2$ fertilization, the growth period of boreal vegetation is prolonged and vegetation productivity is increasing (Bellassen & Luyssaert, 2014), which enhances terrestrial carbon sink capacity. On the other hand, the boreal permafrost contains a large amount of soil carbon, and warming will accelerate the permafrost melt and release CO$_2$, which also has the risk of enhancing terrestrial carbon emissions (Koven et al., 2011). The result of CNN-SPEIopt shows that the average RECO in the northern extra-tropics has a significant increase ($p < 0.01$; Figure 6b). The spatial distribution of RECO is dominated by growth, with 55.95% of RECO showing an increasing trend and 13.23% showing a significant increasing trend; 44.05% showing a decreasing trend and 7.74% showing a significant decrease (Table 3).
Meanwhile, MODIS GPP also shows a significant increasing trend ($p < 0.01$) in the northern extra-tropics, but the growth rate of GPP (slope of 0.159) is much higher than that of RECO (slope of 0.107; Figure 6b). In terms of spatial distribution, 82.67% of GPP show an increasing trend, 36.56% show a significant increase trend, while 17.33% of GPP show a decreasing trend and only 2.44% show a significant decrease trend (Table 3). The increasing proportion of GPP is much larger than that of RECO. In other words, the GPP in the northern extra-tropics shows a substantial increase, while RECO does not increase so significantly. The carbon sink potential of this region has a gradual increase trend dominated by the growth of GPP.

The tropics (30°N ∼ 30°S), which covers about 36% of the global land area, has the largest tropical rainforests and the highest vegetation productivity in the world, as well as the largest carbon sink. CNN-SPEIopt shows that RECO in this region has a significant increasing trend ($p < 0.01$; Figure 6c). In terms of spatial distribution, 53.48% of RECO show an increasing trend, 12.71% show a significant increase trend, while 46.52% show a decreasing trend and 8.99% show a significant decrease trend (Table 3). GPP in the tropics also shows a significant increasing trend ($p < 0.01$) and the growth rate of GPP is higher than that of RECO (slope of GPP is 0.141 and that of RECO is 0.114; Figure 6c). Spatially, 66.91% of GPP show an increasing trend and 33.72% show a significant increase trend, while 8.99% show a decreasing trend and 9.53% show a significant decrease trend. The percentage of increasing RECO in the tropics is close to that in the northern extra-tropics, but the percentage of increasing GPP is much lower than that in the northern extra-tropics. Although the increasing area of GPP in the tropics is larger than that of RECO, the excess area is less than 14%. The advantage of carbon sink growth in the tropics is weaker than that in the northern extra-tropics where the area of increasing GPP is about 26% more than that of RECO (Table 3).
The southern extra-tropics (30°S–90°S) has a small land area covered by vegetation, accounting for only about 4% of the globe except for the Antarctic continent. The RECO in this region still shows an increasing trend, but with a lower significance ($p < 0.1$) than other regions (Figure 6d). Spatially, 56.13% of RECO show an increasing trend and 13.35% show a significant increase trend. While 43.87% of RECO show a decreasing trend and 9.37% show a significant decrease trend (Table 3).

The GPP in the southern extra-tropics shows an increasing trend, with a slight lower significance ($p < 0.05$) than other regions (Figure 6d). Spatially, 72.76% of GPP show an increasing trend and 22.77% show a significant increase trend. While 27.24% show a decreasing trend and 4.27% show a significant decrease trend. The percentage of increasing GPP in the southern extra-tropics is larger than that of RECO, about 16% more (Table 3). However, because of the small land area of this region, it has less impact on the global carbon sink.

In addition, we calculated the proportions of spatial grids where RECO and GPP changed in the same and opposite directions globally and regionally (Figure 8, Table 4). The areas with increasing GPP indicate that vegetation in these areas is in good condition. The areas with increasing GPP and decreasing RECO are obvious carbon sinks with the greatest carbon sink capacity. The areas with decreasing GPP imply vegetation death or reduced productivity. And decrease in GPP and increase in RECO means that these areas are at risk of becoming carbon sources.

The result shows at present, the global carbon sink potential of terrestrial ecosystems can be seen to be increasing, as near half areas where GPP and RECO are increasing simultaneously (42.68%) and the proportion of areas with increasing GPP and decreasing RECO is also higher (33.68%). The proportions of other two scenarios are lower, 12.35% are GPP decreasing and RECO increasing, and 11.29% are both GPP and RECO decreasing.

The northern extra-tropics has 46.37% of areas where both GPP and RECO are increasing and 36.60% of areas where GPP are increasing and RECO are decreasing. Both are lower in the tropics, with 37.33% of the area where both GPP and RECO are increasing and 29.69% of the areas with increasing GPP and decreasing RECO. The

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**Figure 6.** Global and regional interannual variations of ecosystem respiration (RECO) and gross primary production (GPP).
proportion of area with increasing carbon sink potential is much higher in the northern extra-tropics than in the tropics.

On the contrary, in the northern extra-tropics, 9.62% of areas have decreasing GPP and increasing RECO, and 7.41% have decreasing both. These regions are mainly concentrated in the west coast of the United States, eastern

Figure 7. Spatial distribution of global ecosystem respiration (RECO) and gross primary production (GPP) growth rates. The figures in the lower left boxes show the growth rates of RECO/GPP significantly at $p < 0.1$ level.
North America, central Europe, and central and southwestern Russia. In the tropics, there are 16.14% of areas with decreasing GPP and increasing RECO, and 16.84% of areas with decreasing both. These two are the highest in the tropics. This means that the regions with the highest carbon source risk are most concentrated in the tropics, mainly in the southern tip of North America, Amazonia, eastern Brazil, central Africa, eastern India, southeastern China and Southeast Asia.

In summary, the growth trends of global RECO and GPP show imbalances. First, the growth rate of RECO and GPP is unbalanced, the growth rate of GPP is larger than that of RECO, and the proportion of GPP increasing area is also higher than that of RECO, which contribute to maintain the carbon sink of global terrestrial ecosystem in an increasing trend. Second, the carbon sink potential of different regions is unbalanced. In the northern extra-tropics, the growth rate of GPP is significantly larger than that of RECO, and the proportion of GPP increasing area is also the highest. While in the tropics the growth rates of RECO and GPP are very close, and the proportion of GPP increasing area is much lower than that in the northern extra-tropics.

### 3.3. Global and Regional Carbon Sink Capacities and Potential Risk Assessment

In this study, the difference between the growth rate of GPP and the growth rate of RECO at each spatial grids was calculated (Figure 9) to quantitatively assess the global and regional capacities and potential risk of carbon sink. The areas dominated by GPP growth are carbon sink potential areas (the area where GPP grows faster is

| Table 3 | Increase or Decrease Percentages of Global and Regional RECO and GPP |
|---------|------------------------------------------------------------------|
|         | Global          | Northern extra-tropics | Tropics          | Southern extra-tropics |
|         | Increase | Decrease     | Increase | Decrease | Increase | Decrease | Increase | Decrease |
| RECO    | 55.01%   | 44.99%       | 55.95%   | 44.05%   | 53.48%   | 46.52%   | 56.13%   | 43.87%   |
| $\rho < 0.1$ | 13.03% | 8.33%       | 13.23%   | 7.74%    | 12.71%   | 8.99%    | 13.35%   | 9.37%    |
| GPP     | 76.28%   | 23.72%       | 82.67%   | 17.33%   | 66.91%   | 33.09%   | 72.76%   | 27.24%   |
| $\rho < 0.1$ | 34.90% | 5.21%       | 36.56%   | 2.44%    | 33.72%   | 9.53%    | 22.77%   | 4.27%    |

Figure 8. Spatial distribution of global ecosystem respiration (RECO) and gross primary production (GPP) change directions.
larger than the area where RECO grows faster), and the areas dominated by RECO growth are carbon source risk areas (the area where GPP grows faster is smaller than the area where RECO grows faster).

We calculated the carbon sink potential of major ecosystem types (Figure 10a), from which we can see that the vegetation distributed in the northern extra-tropics is extensive and rich in types, such as deciduous broadleaf forest (DBF), evergreen coniferous forest (ENF), grassland (GRA), and savanna (SAV), all of which have high carbon sink capacities, implying that the northern extra-tropics has great carbon sink capacity. While in tropics, the carbon sink capacity has been severely disturbed in recent years, mainly due to the destruction of tropical rainforests and the fact that their carbon sink capacity has become saturated. Figure 10a shows that the evergreen broadleaf forest (EBF), which is widely distributed in the tropics, has a smaller carbon sink capacity and the strongest capacity to release carbon by respiration among the many vegetation types. Several high-risk carbon source regions such as Amazonia, central African and Southeast Asia, all of which are widely distributed in tropical forests, now have significantly reduced carbon sink capacity. This could cause a break in the global terrestrial ecosystem carbon cycle and threaten the entire planetary ecosystem.

In addition, this study assessed the capacities of several major economies about their contributions to the global terrestrial ecosystem carbon sink, including the United States, China, the European region (except Russia), Brazil, and India (Figure 10b). Among these countries and regions, China has the largest carbon sink capacity, followed by India, the U.S. and the European region. Brazil has the smallest carbon sinks. The United States and the European region have high forest cover and rich vegetation carbon stocks, and the forests in these two countries are generally older and most ecosystems are very mature. The old-growth forests play an important role in the protection of terrestrial ecosystem carbon pool (Pregitzer & Euskirchen, 2004), but their growth potential of carbon sink is not prominent and in a more stable state. Brazil, as a country with a large area of tropical rainforest, is no longer outstanding for its carbon sink, which is caused by the decrease of tropical rainforest area and the saturation of carbon sink capacity. Most notably, China and India are both countries with large-scale greening areas subject to anthropogenic regulation, and together dominate the global trend of vegetation greening, but China's carbon sink

| Table 4 Proportions of Global and Regional RECO and GPP in the Same and Opposite Change Directions |
|---------------------------------------------|
|                | Northern extra-tropics | Tropics | Southern extra-tropics |
|----------------|------------------------|---------|------------------------|
| GPP + RECO+    | 42.68%                 | 46.37%  | 37.33%                 | 41.76% |
| GPP + RECO-    | 33.68%                 | 36.60%  | 29.69%                 | 30.90% |
| GPP-RECO+      | 12.35%                 | 9.62%   | 16.14%                 | 14.41% |
| GPP-RECO-      | 11.29%                 | 7.41%   | 16.84%                 | 12.92% |

Figure 9. Difference between the growth rate of gross primary production (GPP) and the growth rate of ecosystem respiration (RECO).
capacity is higher than India. The expansion of greening in China is attributed to the national policy of returning farmland to forest and grassland, of which forests contribute 42% (Chen et al., 2019), thus enhancing the carbon sink capacity. In contrast, 82% of greening in India come from farmland, with forest greening accounting for only 4.4% (Chen et al., 2019). The respiration rate of farmland is relatively high which is likely to be underestimated by flux observations, therefore, there may be large uncertainty in the assessment of India’ carbon sink capacity. However, it can be found from the assessment results that positive policy regulation will make a significant contribution to the increase of carbon sink potential of terrestrial ecosystems.

4. Discussion

In this study, the training and optimization of the CNN models revealed that the introduction of the SPEI of the current year did not optimize the model, indicating that RECO is not sensitive to the water condition of the current year. While the effect of the model was improved when the SPEI of cumulative 2 years and cumulative 3 years were introduced, indicating that RECO has sensitivity to the water conditions of the previous one to 2 years. It can be inferred that the effect of water condition on RECO has a one to 2 year lagged effect. Our experimental results suggest that RECO is insensitive to water changes in the current year. We speculated that it probably due to two causes. One is that the RECO is mainly related with SPEI of relatively long time-scale (e.g., SPEI24) and is insensitive to current water condition, because it takes some time for changes in water conditions to be reflected in changes in RECO. The other one is that the impact of SPEI12 on RECO has spatial heterogeneity at global scale, which would improve accuracy for some sites but reduce accuracy for other sites, as the SPEI has dual roles (positive or negative correlation) on ecosystems (Luo et al., 2021). Whereas studies have shown that vegetation productivity is most sensitive to water changes in the current year (Liu et al., 2021), there is also a lagged effect on vegetation productivity (Barnes et al., 2016; Vicente-Serrano et al., 2013), but the lag time of RECO may be longer in comparison. This is because the changes of water conditions first act on vegetation growth, then the organic matter is imported into the soil and used for respiration decomposition. A process like that takes some time (Brando et al., 2008), so the response of respiration to water changes will take longer time. In addition, the organic matter decomposed by respiration is not all produced in the current year, but also includes organic matter stored by vegetation during previous years (Martínez-Vilalta et al., 2016), so the vegetation growth conditions affected by previous water conditions will also respond to the current respiration. It follows that the lagged effect of water conditions has a more profound and complex impact on ecosystems, and that the ecosystem carbon cycle balance takes longer to recover once it is perturbed by changes in water conditions (Arnone III et al., 2008). Therefore, it is essential to consider the previous water conditions when simulating RECO. In this study we only considered the interannual lag effect based on the annual data, instead of imploting intra-annual effect based on data with higher temporal resolution, such as monthly data. Because for the global scale, there are huge differences between different ecosystems in different regions, including intra-annual climate change, vegetation phenology, etc. As a result, monthly data for different regions can vary even more, making it difficult to draw a unified conclusion. However, for the regional studies, it may be necessary to consider data with higher temporal and spatial resolutions.

Based on the results of models training, we obtained the optimization model (CNN-SPEIopt) with the highest accuracy for simulating RECO. The validation of CNN-SPEIopt and commonly used process models with site observations shows that CNN-SPEIopt not only has the highest accuracy, but also can accurately simulate the
interannual fluctuations of RECO, compared with other process models that severely underestimate the interannual fluctuations. The deficiency of process models in simulating interannual fluctuations of RECO is an important factor leading to uncertainty in the simulation results of the carbon sink potential of global terrestrial ecosystems, which needs to be strengthened in future studies.

The comparison between the changes of ecosystem carbon output (RECO) and the changes of carbon input (GPP) shows that during 2000–2018, under the combined influence of global climate change and human activities, both global RECO and GPP show an increasing trend, but their increasing trends are in an unbalanced state. One is the imbalance between GPP growth rate and RECO growth rate, and the other is the imbalance of carbon sink potential among different regions.

The northern extra-tropics shows the greatest carbon sink potential, with the growth of GPP increasing more rapidly and at a much higher rate than that of RECO. This is mainly due to the prolonged vegetation growing season in the mid and high latitudes of the northern hemisphere due to the influence of climate warming. Meanwhile, the higher atmospheric CO2 concentrations and the CO2 fertilization effect result in enhanced photosynthesis of vegetation, which ultimately leads to higher vegetation productivity (Bellassen & Luyssaert, 2014). While higher temperatures lead to higher rates of microbial activity and therefore to a faster rate of oxygen (Moyano et al., 2013) and substrate consumption (Eliasson et al., 2005), which may inhibit respiration. In addition, Reich et al. found that vegetation respiration in boreal regions is adaptive to climate warming (Reich et al., 2016). In that case, although RECO tends to increase during warming period, the increase is not as pronounced as expected. Thus, the northern extra-tropics are in a trend of increasing carbon sink potential dominated by GPP growth.

GPP and RECO are also increasing in the tropics, but the extent of GPP growth in the tropics is less pronounced than in the northern extra-tropics. On the one hand, it has been shown that the carbon sink capacity of tropical forests has reached saturation in the last decade or so (Hubau et al., 2020). Especially the regions with tropical rainforest distribution, such as the Amazon, central Africa, and Southeast Asia, have higher growth rate of RECO and potential risk of carbon sources (Figure 9). On the other hand, tree mortality has increased due to the high frequency of extreme drought events (Feldpausch et al., 2016; Lewis et al., 2011), further leading to a decrease in forest carbon sink capacity. In addition, it has been shown that the CO2 fertilization effect, previously thought to be most significant in the tropics, is not as much significant as expected. The growth of vegetation in the tropics is dominated by other factors, such as water utilization (Rahman et al., 2019; Van der Sleen et al., 2015). Therefore, the decreasing carbon sink potential in the tropics implies that the tropics has gradually lost their dominant position in the carbon sink of global terrestrial ecosystems and becomes a potential risk to global terrestrial ecosystems (Brienen et al., 2015). Therefore, protecting tropical rainforests from further destruction is the most urgent task nowadays.

In addition, national policy regulation can also have an impact on global carbon sinks, for example, Brazil, a country with large tropical rainforests, has no advantage in carbon sink growth, mainly due to the deforestation (Turubanova et al., 2018). While U.S. and European regions have high quality of forest protection and more stable carbon sinks. The large-scale greening of farmland in India has greatly increased the growth rate of GPP, and also has a certain contribution to its carbon sink. China has been implementing the policy of returning farmland to forests and grassland since 1999. The greening area has been expanding and the forest growth is right at a stage of high carbon sink capacity, which contribute more to carbon sinks.

5. Conclusion

In this study, with the help of a deep learning model, the lagged effect of water conditions on RECO at different time scales was considered, by introducing multi-time scale SPEIs to represent the effect of previous water conditions. It was found that considering the previous water conditions could not only improve the simulation accuracy of RECO, but also reflect its interannual fluctuation more accurately. The experimental results of CNN models show that RECO is more sensitive to the water conditions in the previous one to 2 years, which indicates that the time lag of water influence on RECO is larger than that on vegetation productivity, and the latter tended to be most significantly affected by the current year’s water condition. The comparison between the spatial and temporal patterns of RECO and GPP shows that the interannual change trend of global RECO due to climate change differs significantly from that of GPP. It is shown that the inconsistency between the trends of carbon input and carbon output, which affects the carbon sink pattern and potential of terrestrial ecosystems. From the global
pattern and regional differences, the growth trend of GPP in global terrestrial ecosystems is larger than that of RECO, which results in the tendency to increase carbon sinks, especially in the northern extra-tropics. While the trend of RECO in tropics is close to that of GPP which means tropics has limited carbon sink capacity. This will have potential impacts on the sustainable carbon sink capacity of global ecosystems in the future.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The data that support the findings of this study were derived from the following resources available in the public domain: FLUXNET2015 data set is available from https://fluxnet.org/data/fluxnet2015-dataset/. AmeriFlux data set can be downloaded from https://ameriflux.lbl.gov/data/download-data/. You need to register/login first, then select the data set to download. ChinaFlux data set can be downloaded from http://www.cnern.org.cn/data/initDRresearch. CRU-TS 4.05 data set can be downloaded from https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.05/. SPEIbase v2.6 data set can be downloaded from https://spei.csic.es/spei_database. MOD17A3HGF is accessed from https://doi.org/10.5067/MODIS/MOD17A2HGF.006. MOD13A3 V006 is accessed from https://doi.org/10.5067/MODIS/MOD17A3HGF.006. MOD17A2HGF V006 is accessed from https://doi.org/10.5067/MODIS/MOD13A3.006. GLASS products can be downloaded from http://www.glass.umd.edu/Download.html. SoilGrids250 m data set can be downloaded from https://soilgrids.org/. The data set CNN-SPEIopt RECO produced by this study is available from the public repository, you can cite it by using the https://doi.org/10.5281/zenodo.6541254.

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