A Process-Based Model Integrating Remote Sensing Data for Evaluating Ecosystem Services

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Abstract Terrestrial ecosystems provide multiple services interacting in complex ways. However, most ecosystem services (ESs) models (e.g., InVEST and ARIES) ignored the relationships among ESs. Process-based models can overcome this limitation, and the integration of ecological models with remote sensing data could greatly facilitate the investigation of the complex ecological processes. Therefore, based on the Carbon and Exchange between Vegetation, Soil, and Atmosphere (CEVSA) models, we developed a process-based ES model (CEVSA-ES) integrating remotely sensed leaf area index to evaluate four important ESs (i.e., productivity provision, carbon sequestration, water retention, and soil retention) at annual timescale in China. Compared to the traditional terrestrial biosphere models, the main innovation of CEVSA-ES model was the consideration of soil erosion processes and its impact on carbon cycling. The new version also improved the carbon-water cycle algorithms. Then, the Sobol and DEMC methods that integrated the CEVSA-ES model with nine flux sites comprising 39 site-years were used to identify and optimize parameters. Finally, the model using the optimized parameters was validated at 26 field sites comprising 135 site-years. Simulation results showed good fits with ecosystem processes, explaining 95%, 92%, 76%, and 65% interannual variabilities of gross primary productivity, ecosystem respiration, net ecosystem productivity, and evapotranspiration, respectively. The CEVSA-ES model performed well for productivity provision and carbon sequestration, which explained 96% and 81% of the spatial-temporal variations of the observed annual productivity provision and carbon sequestration, respectively. The model also captured the interannual trends of water retention and soil erosion for most sites or basins.

Plain Language Summary Terrestrial ecosystems simultaneously provide multiple ecosystem services (ESs). The common environmental drivers and internal mechanisms lead to nonlinear and dynamic relationships among ESs. Assessing the spatiotemporal changes of ESs have recently emerged as an element of ecosystem management and environmental policies. However, appropriate methods linking ESs to biogeochemical and biophysical processes are still lacking. In this study, we developed a process-based model Carbon and Exchange between Vegetation, Soil, and Atmosphere (CEVSA-ES) that integrates remote sensing data for evaluating ESs. We first described the model framework and detailed algorithms of the processes related to ESs. Then a model-fusion method was applied to optimize parameters to which the model was sensitive and to improve model performance based on multi-source observational data. The calibrated CEVSA-ES model showed good performance for carbon and water fluxes (i.e., gross primary productivity, ecosystem respiration, net ecosystem...
productivity, and evapotranspiration). The CEVSA-ES model performed well for productivity provision, and carbon sequestration. It also captured the interannual trends of water retention and soil erosion for most sites or basins in Chinese terrestrial ecosystems. The CEVSA-ES model not only has the potential to improve the accuracy of simulated ESs, but also can capture the relationships among ESs, which could support the trade-offs and synergies among ESs.

1. Introduction

Ecosystem services (ESs) are the ecological characteristics, functions, or processes that contribute to human wellbeing (Costanza et al., 2017; MEA, 2005). According to MEA (2005), ~60% of the global ESs are either degraded or used in an unsustainable way. These modifications highlighted the need and importance of monitoring ESs. The generation of ESs relies on the ecosystem structure and processes (Haines-Young, 2011; Lavorel & Hutchings, 2013). Accurately predicting the dynamic of ESs requires a considerable understanding of ecosystem structure and processes (Fu et al., 2013). The process-based ES models could support exploring the mechanisms underpinning synergies and trade-offs between ES and further guiding decision-making in ecosystem management, and environmental policies. However, appropriate methods linking ESs to processes in ecosystems are still lacking (Lavorel et al., 2017).

Vegetation dynamic and environmental change influence ESs by altering biogeochemical and ecological processes (Ouyang et al., 2016; Piao et al., 2020). Biophysical processes underline the production of a wide range of ESs (Bennett et al., 2009). For example, primary production (or productivity provision [PP]) represents an ecosystem’s capacity to produce food and raw materials and underline all other services (Costanza et al., 2017; Hao et al., 2017); carbon sequestration (CS) plays an important role in regulating regional and global climate (Chen et al., 2019); water retention (WR) refers to the amount of water retained in ecosystems within a certain time period (Ouyang et al., 2016), which regulates hydrological flows and further affects flood damages regulation (Bai et al., 2019); and soil retention (SR) is defined as the reduction of soil erosion by ecosystems through their structures and processes (Rao et al., 2014), which could affect soil organic carbon stocks and alters CO₂ fluxes (Yue et al., 2016). The above ESs are interrelated in complex dynamic ways, and accesses to the mechanisms behind the relationships among ESs are indispensable to minimize the trade-offs and to enhance the synergies among ESs (Bennett et al., 2009). However, many ES modeling and mapping approaches ignore the intrinsic link between ES and rely on secondary data or look-up tables to quantify ESs (Logsdon & Chaubey, 2013). For example, a statistical linkage of land cover with constant ecosystem values is the most widely used method (Egoh et al., 2012; Martínez-Harms & Balvanera, 2012). Approximately half of the ES studies are based on the relatively simple look-up table approach (Lautenbach et al., 2015). These models focus only on land use composition and ignore the land use configuration and intensity (Mitchell et al., 2015; Verhagen et al., 2016) and lack biophysical bases (Seppelt et al., 2011). Another widely used methodology is phenomenological models, which are based on qualitative or semiquantitative relationships between ES providers and ESs. This method usually considers the biological mechanisms underlying ESs (Lavorel et al., 2017).

Recently, integrated, dynamic, and spatially explicit models are increasingly being used to address the complex relationships that lead to ES supply (Costanza et al., 2017). For example, InVEST (Tallis & Polasky, 2009) and ARIES (Bagstad et al., 2011) are the two most notable methods to quantify ESs. The InVEST model can only simulate one ES at time, and it oversimplifies ecosystem processes, thus making the understanding of ES relationships difficult (Logsdon & Chaubey, 2013). On the other hand, the ARIES model uses statistical methods to calculate ESs, the complexity of its methods and code makes it difficult to understand the relationships among ESs (Vigerstol & Aukema, 2011). Therefore, to understand the complex relationships among ESs, there is a need to improve the quantifying method (Logsdon & Chaubey, 2013). Process-based models can incorporate explicit representations of the biogeochemical and biophysical processes and thus can overcome this limitation. It can quantify potential shifts in ESs under environmental change and policy scenarios and also reflect the relationships among ESs (Lavorel et al., 2017). Process-based models have been increasingly used to simulate ESs (Elkin et al., 2013; Gutsch et al., 2018; Stürck et al., 2014) and are required to manage ESs in the changing world (Cuddington et al., 2013). Traditional terrestrial biosphere process models (TBMs) focused on vegetation growth and the related biological and geochemical processes, by using which we can get PP, CS, and WR. Meanwhile, most TBMs usually ignored soil erosion processes,
while there are some exceptions (Chappell et al., 2016; Naipal et al., 2018). Soil erosion had removed considerable quantities of topsoil (Lal, 2001), and including soil erosion in process models could reduce uncertainty in carbon cycle simulation (Tian et al., 2015; Yue et al., 2016), which in turn could improve the interpretation of trends and variability in ecosystem (Chappell et al., 2016).

Leaf area index (LAI) is a key parameter of TBMs, which controls many biochemical processes at the canopy scale (Lian et al., 2018; Peréuelas and Filella, 2009; Piao et al., 2020) and further affects ESs. But there are biases in the growing season length and magnitude of the LAI simulated by TBMs compared to ground-based observation data (Kucharik et al., 2006; Richardson et al., 2012) or satellite-derived measurement LAI (Murray-Tortarolo et al., 2013; Randerson et al., 2009). This can result in systematic errors in model predictions of the carbon, water, and energy exchanges (MacBean et al., 2015; Richardson et al., 2012). Meanwhile, without an accurate assessment of LAI change, it is highly uncertain to simulate ESs. Fortunately, satellite-based vegetation indices have provided a useful data set for identifying and monitoring vegetation dynamic and key phenological transition since 1981 (Piao et al., 2020; H. Yan et al., 2014). The source of information is underutilized in simulating ESs, although scientists demonstrated the usefulness of satellite-based data in assessing several ESs (Braun et al., 2018). To make use of this information beyond assessing the vegetation greening/browning trend (Zhu et al., 2016), the integration of remote sensing observation with TBMs could greatly facilitate and improve the investigation of physical, biological, and ecological processes in vegetation (Sun et al., 2019). The complementarity of remote sensing and process-based models in studying terrestrial ecosystems has been demonstrated (Chen et al., 2019; Turner et al., 2004). However, there is a lack of remote sensing-based quantitative approaches that link multiple ESs to ecosystem processes across space and time (Lavorel et al., 2017).

Moreover, improving the accuracy of models is crucial for the assessment of ESs. By combining a set or sets of observations and a model, the model-data fusion method enables the optimization of model parameters and reduces the uncertainties of model output (Williams et al., 2009). The model-fusion method has been increasingly used to optimize the parameters of hydrological and biophysical models based on observed data sets; this has considerably improved the accuracy of model output (Ge et al., 2019; Lian et al., 2018; Niu et al., 2019). The model-fusion method may benefit the accuracy of ES simulations.

The first goal of this study was to present the new version of CEVSA-ES, focusing on the simulation of key ESs: Mainly the added modules for soil retention, and integrated satellite-based LAI data, but also improved the representation of photosynthesis and evapotranspiration. The second goal was to identify and optimize the sensitive parameters through applying the Sobol and DEMC methods that integrated CEVSA-ES model with nine flux sites comprising 39 site-years. The third goal was to describe the performance of CEVSA-ES model by replicating observations of 26 filed sites, including carbon and water fluxes data for nine sites comprising 17 site-years, and ESs data for 17 field sites comprising 118 site-years. We focus on the seasonal and annual variations of carbon and water fluxes (i.e., gross primary productivity, ecosystem respiration, net ecosystem productivity, and evapotranspiration), while only the annual variations of key ESs (i.e., PP, CS, WR, and SR) were validated due to the limitation of the observational data. The CEVSA-ES model has been calibrated and validated at certain sites and showed good performances in this study, meanwhile, the new model enables aggregation up to regional scale. Section 2 is devoted to the description of the model, focusing on the changes between versions, the introduction of the Sobol and DEMC methods, and the characterization of the observational data used for validation and calibration. Section 3 presents the evaluation of the simulated ecosystem processes and ESs. The discussion is presented in Section 4, followed by a brief conclusion in Section 5.

2. Materials and Methods
2.1. Model Description
2.1.1. Brief Review of the CEVSA Model

CEVSA model is a biogeochemical model that simulates carbon and water exchange between the atmosphere and the terrestrial ecosystem. The CEVSA model incorporates three submodels: The biophysical submodel, the vegetation submodel, and the biogeochemical submodel. The biophysical submodel was mainly used to estimate evapotranspiration and soil moisture. The vegetation submodel was used to calculate leaf
area, net primary productivity (NPP), and carbon allocation. The biogeochemical submodel simulates soil organic and nitrogen mineralization decay based on the CENTURY model. More details on this version can be found in Cao and Woodward (1998).

### 2.1.2. The New CEVSA-ES Model

Vegetation controls land surface processes, and remote-sensed vegetation indexes available to assess the actual vegetation dynamics (Chen et al., 2019; Piao et al., 2020). Based on the assumption that the satellite-based LAI is a well-defined physical attribute of vegetation, and diagnostic models could assimilate remotely sensed vegetative structural information to simulate the physical, biological, and ecological processes in vegetation (Chen et al., 2019; Piao et al., 2020), we have developed a new CEVSA-ES model, which directly driven by remote sensed LAI. The original CEVSA model estimated LAI by the DOLY model based on the assumption that the synthesis of living tissue is related to the rate of carbon assimilation (Woodward, 1995). The original CEVSA model could capture the effects of vegetation dynamics on ES supply. The new CEVSA-ES model is developed based on the assumption that the synthesis of living tissue is related to the rate of carbon assimilation (Woodward, 1995). The CEVSA-ES model could capture the effects of vegetation dynamics on ES supply.

### Table 1
Main Differences Between CEVSA and CEVSA-ES

| Processes          | CEVSA                                                                 | CEVSA-ES                                                                 |
|--------------------|-----------------------------------------------------------------------|-------------------------------------------------------------------------|
| Leaf area and assumption | LAI was estimated by the DOLY model based on the assumption that the synthesis of living tissue is related to the rate of carbon assimilation (Woodward, 1995) | Remote sensed LAI were directly used to drive the CEVSA-ES model. We assumed that satellite-based LAI is a well-defined physical attribute of vegetation, and diagnostic models could assimilate remotely sensed vegetative structural information to simulate the physical, biological, and ecological processes in vegetation (Chen et al., 2019; Piao et al., 2020). |
| Canopy photosynthesis | The maximum value when both hydrological and primary productivity constraints are satisfied (Woodward, 1995) | Satellite-based LAI data were directly used to calculate the canopy photosynthesis based on the concept of Farquhar equation (Farquhar et al., 1980) and the modified Ball-Berry model (Ball et al., 1987; Woodward, 1995) |
| Water Retention     | Separately simulates water input, evapotranspiration, and runoff, but does not calculate water retention | Estimated by using the water balance method, that is, water retention equals water input minus evapotranspiration and runoff |
| Evapotranspiration  | The lesser of a supply function and a demand function by empirical formulas (Federer, 1982) | Translating the estimated potential evapotranspiration into actual evapotranspiration based on plant physiological constraints and soil drought limitation (Fisher et al., 2008; Niu et al., 2019) |
| Soil retention      | No                                                                     | Calculated by the Universal Soil Loss Equation (McCool et al., 1989; Renard, 1997) |
| Soil carbon leaching| No                                                                     | Empirical equation (Yue et al., 2016) |
| Drivers             | Climate data set, nitrogen deposition, land cover, atmospheric CO₂ concentration, and soil texture | Remote-sensed LAI and the drivers of the CEVSA model |
| Temporal resolution | 10 days                                                                | 8 days                                                                  |

CEVSA, Carbon and Exchange between Vegetation, Soil, and Atmosphere; ESs, ecosystem services.

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Renard, 1997), and further quantifies the effect of soil erosion on soil carbon leaching based on an empirical equation (Yue et al., 2016).

The new CEVSA-ES model focused on biophysical indicators representing the production of ESs (Figure 1), NPP, net ecosystem productivity (NEP), changes in soil water content, and soil retention representing the productivity provision (PP), carbon sequestration (CS), water retention (WR), and soil retention (SR), respectively. Temporal input data intervals are 8 days for LAI and meteorological data; annual for atmospheric CO$_2$ concentration, nitrogen deposition, and land cover; and long-term for soil. The temporal resolution of model outputs was 8 days. The CEVSA-ES model can run from time scales of hours to centuries, but due to the absence of model forcing data and to reduce computational time and memory storage, the diurnal influences cycle was approximately simulated. The model evaluates variables daily at the interpolated values of temperature, relative humidity, and net radiation, and with rainfall distributed uniformly across the days of the 8-days interval. Midmorning radiation is assumed, and values are scaled by the number of daylight hours to approximate the diurnal cycle effect (Woodward, 1995). In the following section, we outline the major methodologies in the new CEVSA-ES model (Figure 1).

### 2.1.2.1. Productivity Provision and Carbon Sequestration

Productivity provision is the basis for several ecosystem functions and processes, and these underlie all other services (Costanza et al., 2017). The simulated productivity provision by the original CEVSA model was driven by environmental factors, which cannot well capture the effects of afforestation and reforestation, stand age, and forest density. The new model driven by remote-sensed LAI can provide simulations of actual primary productivity (Franklin et al., 1997). In the new CEVSA-ES model, leaf area is partitioned into layers each of which has a unity LAI. The number of layers equals the LAI of the canopy. The mean irradiance beneath a LAI is derived from Beer’s law. Then, the Farquhar model (Farquhar et al., 1980) was used to calculate the net rate of CO$_2$ assimilation driven by radiation and other climatic factors. Stomatal conductance controls the diffusion of CO$_2$ from the atmosphere into the intercellular air spaces and the supply of CO$_2$ also affects the CO$_2$ assimilation rate. Therefore, the modified Ball-Berry model was used to
calculate stomatal conductance based on soil water content and climate conditions (Ball et al., 1987; Woodward, 1995). Subsequently, a remote-sensed LAI was successively used to calculate the canopy transient photosynthesis, and the daily photosynthesis (gross primary productivity [GPP]) was calculated through combining transient photosynthesis and day length, based on the hypothesis that radiation was evenly distributed during the day to approximate the diurnal cycle effects. Finally, productivity provision is defined as the difference between GPP and autotrophic respiration (Ra). For more details, please see Texts S1 and S2.

Carbon sequestration is directly characterized by NEP, which is defined as the difference between productivity provision and soil heterotrophic respiration ($R_h$). Consistent with the CEVSA model, $R_h$ was calculated by the CENTURY model (Cao & Woodward, 1998; Parton et al., 1993). For more details, please see Text S3.

### 2.1.2.2. Soil Retention

Soil retention refers to the soil retained by the ecosystems within a certain period. Soil erosion is a major environmental problem and can alter soil carbon stocks (Yue et al., 2016). The CEVSA model does not consider this process, while the new CEVSA-ES model simulates soil retention by integrating the universal soil loss equation (USLE) (McCool et al., 1989; Renard, 1997), which can be expressed as:

$$\Delta S = S_p - S_a = R \times K \times LS \times (1 - C),$$

where $\Delta S$ represents soil retention ($t \cdot ha^{-1} \cdot yr^{-1}$), $S_p$ and $S_a$ represent the potential soil erosion without vegetation cover and actual soil erosion under current land cover, respectively. $R$, $K$, $LS$, and $C$ represent rainfall erosivity factor (MJ mm h$^{-1}$ h$^{-1}$ yr$^{-1}$), soil erodibility factor ($t \cdot ha^{-1} \cdot MJ^{-1} \cdot mm^{-1}$), topographic factor (unitless), and vegetation cover factor (unitless), respectively.

The $R$ factor reflects the potential ability for precipitation to cause soil loss. In the original USLE model, $R$ equals the product of kinetic energy of rainfall and rain intensity in 30 min. However, due to the limitation of 30 min precipitation intensity data, we used the following empirical formula to calculate the $R$ factor (Wischmeier & Smith, 1978):

$$R = \sum_{i=1}^{12} 1.735 \times 10^{1.5 \log(\frac{p_i}{p}) - 0.8188},$$

where $p_i$ is the monthly average of rainfall (mm) and $p$ is the annual average of rainfall (mm).

The $K$ factor is used to compute the average annual erosion (Renard, 1997), and the accuracy of the $K$ factor determined the efficiency of the soil erosion model (Ostovari et al., 2016). Based on the $K$ values from 325 sites published in 152 reports, we used Kriging interpolation to form a $K$ surface (Zhu et al., 2019).

The LS factors indicate the influence of topography on soil erosion. Based on slope gradient (Jiang et al., 2016), these factors are calculated as follows:

$$L = \left(\frac{\gamma}{22.13}\right)^m$$

where $\gamma$ is the slope length (m), $\theta$ is the percentage of slope (%), and $m$ is a constant, which depends on the percentage of slope.

$$S = \begin{cases} 10.8 \sin \theta + 0.03, & \theta < 9\%, \\ 16.8 \sin \theta - 0.50, & 9\% \leq \theta < 18\%, \\ 21.91 \sin \theta - 0.96, & \theta \geq 18\%, \end{cases}$$
The $C$ factor reflects the effect of vegetation cover on soil erosion. We first calculated the normalized difference vegetation index (NDVI) from LAI by an empirical formula (Zhao, 2014). Then, the $C$ factor was calculated as follows (Van der Knijff et al., 1999):

$$C = e^{-\alpha \text{NDVI}/(\beta - \text{NDVI})},$$  

where $\alpha$ and $\beta$ were the parameters with values of 2 and 1.

Actual soil erosion can affect soil organic carbon and further alter CO$_2$ flux between the ecosystem and atmosphere (i.e., carbon sequestration) (Yue et al., 2016). Actual soil erosion led to the loss of soil organic matter and can be calculated as follows:

$$E_c = C_{SOC} V_{ero} A_{ero},$$  

where $E_c$ is the amount of soil organic carbon loss due to soil erosion (g yr$^{-1}$), $C_{SOC}$ is carbon content in the soil (g m$^{-3}$), $V_{ero}$ is the water erosion rate (m yr$^{-1}$), which is the actual soil erosion in per unit area (that is $S_o$), and $A_{ero}$ is the erosional area (m$^2$). The enrichment ratio is assumed to be 1 (Yue et al., 2016). A part of the eroded soil carbon would eventually be deposited, and it could be estimated from the sediment delivery ratio (SDR):

$$D_c = E_c (1 - SDR).$$  

where $D_c$ is the amount of deposited organic carbon (g yr$^{-1}$) and SDR is obtained based on soil erosion severity. We developed SDR and $V_{ero}$ linear equations based on actual soil erosion based on Yue et al. (2016) (Table S1). The difference between $E_c$ and $D_c$ represents the amount of soil carbon change.

The soil organic carbon transported by sediment (the difference between soil erosion carbon and deposited soil carbon) is easily decomposed. According to Yue et al. (2016), we assume that the difference between decomposition in situ and during transport could be as much as 63%.

2.1.2.3. Water Retention

Water retention refers to the water retained in ecosystems (Ouyang et al., 2016). In this study, we estimate water retention using the water balance method, and it is expressed as:

$$WC = WATI - ET - RO,$$  

where WATI is water input (mm m$^{-2}$ d$^{-1}$), ET is the evapotranspiration (mm m$^{-2}$ d$^{-1}$), and RO is river runoff (mm m$^{-2}$ d$^{-1}$).

ET is the key variation to calculate water retention. In the CEVSA model, the total ET was calculated as the lesser of a supply function and a demand function (Federer, 1982), this method ignored the influence of heterogeneous surface. Based on recent advances in ecophysiological theory that allow the detection of multiple stresses on plant function using biophysical remote sensing metrics, we integrated the PT-JPL model (Fisher et al., 2008) to the new CEVSA-ES model. The PT-JPL model translated potential evapotranspiration into actual evapotranspiration based on plant constraints and soil limitation and performed best for most ecosystems and climate regions (Michel et al., 2015; Miralles et al., 2016). The total evapotranspiration consists of soil evaporation (ES), canopy interception evapotranspiration (ET), and biological transpiration (T). These are calculated as follows:

$$ET = ES + EI + T$$  

$$ ES = \left(f_{wet} + f_{am}(1 - f_{wet})\right)\Delta \frac{\Delta}{\Delta + \gamma} (R_{sc} - G)$$  

$$ EI = f_{wet}\Delta \frac{\Delta}{\Delta + \gamma} R_{sc}$$
\[ T = \left(1 - f_{\text{wet}}\right)f_Tf_M\frac{\Delta}{\Delta + \gamma}R_{\text{nc}} \]  

where \(\alpha\) is the PT coefficient of 1.26 for a water body (unitless); \(\Delta\) is the slope of the saturation-to-vapor pressure curve (kPa °C\(^{-1}\)); \(\gamma\) is the psychrometric constant (0.066 kPa °C\(^{-1}\)); \(G\) is ground heat flux (W m\(^{-2}\)); \(R_{\text{nc}}\) is the net radiation to the canopy (W m\(^{-2}\)) and is defined as \(R_{\text{nc}} = R_n - R_{\text{ns}}\), where \(R_n\) is the net radiation (W m\(^{-2}\)); and \(R_{\text{ns}}\) is the net radiation to the soil (W m\(^{-2}\)). \(R_n\) can be calculated as \(R_n = R_e e^{-k_{\text{rn}}LAI}\), where \(k_{\text{rn}}\) is the extinction coefficient (unitless) (Fisher et al., 2008; Niu et al., 2019). The other restricted parameters are described in Table S2 (Fisher et al., 2008; Niu et al., 2019). Transpiration is constrained using four vegetation-based physiological parameters. \(f_T\) and \(f_M\) represent the effects of temperature and plant moisture based on normalizing phenological parameters. \(f_g\) represents the effects of canopy greenness fraction based on \(f_{\text{APAR}}\) and \(f_{\text{IPAR}}\). The fourth constraint on transpiration is \(f_{\text{wet}}\), which based on atmospheric relative humidity. Meanwhile, soil evaporation constraints are determined by \(f_{\text{sm}}\) and \(f_{\text{wet}}\). Based on the assumption that soil moisture is reflected in the adjacent atmospheric moisture, the surface tends to be in equilibrium with the overlying atmosphere (Fisher et al., 2008). The \(f_{\text{sm}}\) and \(f_{\text{wet}}\) are good indicators of soil moisture over large enough spatial and temporal scales. Interception is estimated using the same \(f_{\text{wet}}\) value.

In this study, we also modified the calculation of WATI. According to the Biome-BGC model, precipitation is divided into snow and rain (Thornton, 2010). When temperature is greater than 0°C, the form of precipitation is rain and snow starts to melt, whereas when temperature is below 0°C, the form of precipitation is snow, and part of the snow is lost through sublimation.

\(RO\) can be calculated as the maximum of zero or the difference between soil moisture and saturated soil water content (\(W_{\text{sat}}\)). The soil moisture content (\(W_s\)) is calculated by adding the water input to the previous soil moisture content and subtracting evapotranspiration.

### 2.1.3. Parameters of the CEVSA-ES Model

Numerous parameters were used to numerically describe the processes of CEVSA-ES model in Table S3, which contained 61 parameters. Most of the parameters are leveraging on photosynthesis, respiration, and evapotranspiration processes due to our emphasis on adjusting the carbon cycle and hydrological cycle. The prior values of the model parameters were chosen to the same values used in Cao and Woodward (1998) and Niu et al. (2019). The defined intervals of variations were derived from relevant studies (Niu et al., 2019; Zhang, 2017; Zhang et al., 2012) and expert knowledge (Table S3).

As in most biogeochemical models, vegetation is classified into plant functional types (PFTs). The CEVSA-ES model covers nine different PFTs in China’s terrestrial ecosystems, namely, evergreen needleleaf forest (ENF), evergreen broadleaf forest (EBF), deciduous broadleaf forest (DBF), deciduous needleleaf forest (DNF), mixed forest (MF), shrubland (SHR), typical steppe (TS), alpine steppe (AS), and cropland (CRO). Different PFTs follow the same set of the governing equations, with different parameter values for each PFT.

### 2.2. Model-Data Fusion Framework

Model parameters are optimized using a model-data fusion framework. In this study, the Sobol method (Sobol, 1990, 2001) was used to identify the sensitive parameters of the CEVSA-ES model. Then, the Differential Evolution Markov Chain (DEMC) method (Ter Braak, 2006) that integrated the CEVSA-ES model with multiple observational data was used to optimize the sensitive parameters. The parameters were optimized at each site, which represents different PFTs. Meanwhile, the parameters were optimized at an 8-days timescale constrained by the observational carbon flux and water flux data.

### 2.2.1. Global Sensitivity Analysis

Sobol’ method (Sobol, 1990, 2001) is a popular global sensitivity analysis based on variance decomposition. It was integrated with multiple observational data to determine the sensitive parameters of the CEVSA-ES
model. Sobol’ method can quantify the sensitivity indexes of each parameters based on the partial variance and total variance:

\[
\text{First – order index } S_m = \frac{V_m}{V} \quad (13)
\]

\[
\text{Second – order index } S_{mn} = \frac{V_{mn}}{V} \quad (14)
\]

\[
\text{Total – order index } S_{Tm} = S_m + \sum_{n=m}^{\infty} S_{mn} = 1 - \frac{V_m}{V} \quad (15)
\]

where \( V_m \) is the partial variance with a first-order index of \( \theta_m \) on the model output, \( V_{mn} \) is the partial variance with a second-order index of the \( m \)th and \( n \)th parameter interactions, and \( V \) is the total model variance.

\( S_m \) is a measure ratio from the main effect of the individual parameter \( \theta_m \) to the total model variance \( V \), \( S_{mn} \) defines the sensitivity that results from the interactions between \( \theta_m \) and \( \theta_n \), and \( S_{Tm} \) represents the main effects of \( \theta_m \) and its interactions with the other parameters and can be calculated by the variance \( V_{\sim m} \), which is the variation of all parameters except \( \theta_m \) (Zhang et al., 2017).

The Latin hypercube sampling method (McKay, 1988) was used to sample the available parameter space. We categorized the sensitivity of the parameters as “highly sensitive,” “sensitive,” and “nonsensitive” when their contributions to the overall model output variance were >10%, >1%, and <1%, respectively (Tang et al., 2006).

2.2.2. Parameter Optimization

According to Bayes’ theorem, the posterior probability density function of parameter sets \( \theta \) can be written as:

\[
p(\theta | O) \propto p(O | \theta) p(\theta) \quad (16)
\]

where \( O \) is the observed data sets, \( p(\theta) \) is the prior probability distribution of parameter \( \theta \), \( p(\theta|O) \) is the posterior probability distribution after Bayesian inference conditioned on available observations \( O \), and \( p(O|\theta) \) is the likelihood function, which reflects the influence of the observational data sets on parameter identification (Zhang et al., 2017; Zhu et al., 2014). For each data set used in this study (GPP, NEP, and ET), the likelihood can be expressed as:

\[
p(O_i | \theta) = \prod_{t=1}^{T_i} \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\left(\frac{O_i(t) - f_i(t)}{2\sigma_i^2}\right)^2}, \quad (17)
\]

where \( T_i \) is the total length of observations of the \( i \)th data set, \( O_i(t) \) and \( f_i(t) \) are observed and model estimated values of \( i \)th data set at time \( t \), respectively. \( \sigma_i (i = 1, 2, 3, 4) \) is the standard deviation of the model error of the \( i \)th data set (Braswell et al., 2005), and \( \sigma_i \) can be expressed as:

\[
\sigma_i = \sqrt{\frac{1}{T_i} \sum_{t=1}^{T_i} (O_i(t) - f_i(t))^2}.
\]

The likelihood function for multivariate data sets \( p(O | \theta) \) used for parameter estimation is defined as the product of the individual \( p(O_i | \theta) \) (Richardson et al., 2010):

\[
p(O | \theta) = \prod_{i=1}^{I} p(O_i | \theta) = \prod_{i=1}^{I} \prod_{t=1}^{T_i} \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\left(\frac{O_i(t) - f_i(t)}{2\sigma_i^2}\right)^2}, \quad (18)
\]

where \( I \) is the number of data sets.
The posterior distribution was sampled by using the DEMC method, which was used for global optimization in the real parameter spaces (Ter Braak, 2006). Specifically, \( N \) chains are run in parallel and the proposals are generated on the basis of two randomly selected chains, the difference of which is multiplied by a scaling factor, and added to the current chain:

\[
\theta_p = \theta_i + \gamma(\theta_{R1} - \theta_{R2}) + e
\]

where \( \theta_p \) is the proposed parameter set; \( \theta_{R1} \) and \( \theta_{R2} \) are randomly selected without replacement from the population \( \theta_{-i} \) (the population without \( \theta_i \)); \( e \) is drawn from a symmetric distribution with a small variance compared to that of the target, but with unbounded support. \( \gamma \) is the scaling factor which can be set to \( 2.38/\sqrt{d} \) (Zhang et al., 2017). The Metropolis ratio is then used to decide whether to accept or reject the proposals (Moreno et al., 2016; Zhang et al., 2017).

2.3. Data

2.3.1. Forcing Data

Five climatic factors, namely, air temperature, soil temperature, precipitation, relative humidity, and net radiation, were used to drive the CEVSA-ES model. The observational climate data were acquired from ChinaFLUX (http://www.chinaflux.org/enn/index.aspx) and FLUXNET (https://fluxnet.org/). Three steps were used to prepare the data: (a) if data gap were less than 6 h in length, the linear interpolation method was directly used to calculate the missing data; (b) if the interpolated data were still not have a complete diurnal cycle, the data was not used in this analysis; (c) The daily values of climatic data were aggregated from the half-hourly values and the daily values were further averaged to 8-days intervals. Furthermore, we used the observational climate data from the nearest sites in China Meteorological Data Service Center (http://data.cma.cn/en) to validate some climatic data (Figure S1), and that showed good agreement performance.

LAI is another key driving variant in the CEVSA-ES model, and it was obtained from the MODIS LAI product (MOD15A2H, https://ladsweb.modaps.eosdis.nasa.gov/). The LAI data have a spatial resolution of 500 m, and temporal resolution of 8 days. The average value of the 3 × 3 pixel-images around the observation sites were used to drive the CEVSA-ES model.

Moreover, the annual atmosphere \( \text{CO}_2 \) concentration was downloaded from CO2·earth (https://www.co2.earth). Nitrogen deposition included wet and dry nitrogen depositions (Yu et al., 2019). Soil texture was acquired from the Food and Agriculture Organization Harmonized World Soil Database (http://www.fao.org/).

2.3.2. Data for Model Calibration

Four carbon and water flux data, that is GPP, ecosystem respiration (Re), NEP, and ET, were all used to calibrate the CEVSA-ES model. ET (i.e., latent heat) and NEP (i.e., the opposite values of net ecosystem exchange of \( \text{CO}_2 \), NEE) were directly measured by the eddy covariance approach. The observed half-hourly NEE values were processed by three-dimensional coordinate rotation, WPL correction, storage correction, and invalid data exclusion (Yu et al., 2006). A method presented by Reichstein et al. (2005) was used to estimate Re. Briefly, the valid nighttime NEE (i.e., nighttime Re) and soil temperature at 5 cm depth were used to fit model parameters of the Lloyd and Taylor model. Then the Lloyd and Taylor model with fitted parameters and soil temperature at 5 cm depth was executed to calculate the daytime Re and the missing nighttime Re (Reichstein et al., 2005). Subtracting NEE from Re gives GPP (Gao et al., 2014). The carbon and water fluxes values were further summed to 8-days intervals to be consistent with the time scale of the MODIS images. Meanwhile, the corrected errors between GPP and Re were ignored in this study.

The carbon and water flux data from nine flux sites (with seven sites from ChinaFLUX and two sites from FLUXNET) were used to calibrate the CEVSA-ES model. The sites cover nine ecosystems, namely, evergreen needleleaf forest (ENF), evergreen broadleaf forest (EBF), deciduous broadleaf forest (DBF), deciduous needleleaf forest (DNF), mixed forest (MF), shrubland (SHR), typical steppe (TS), alpine steppe (AS), and cropland (CRO) (Figure 2). The DBF and DNF were represented by the six FLUXNET sites because of the lack of relevant sites in ChinaFLUX. The flux data for each site were split into two parts, with the final 2
years (but just 1 year for DBF) of the time series are used for validation, and the other data of the time series are used for calibration (Table S4).

2.3.3. Data for Model Validation

Carbon and water fluxes and ESs were validated. The other group of the flux data introduced in Section 2.3.2 were used for carbon and water flux validation (Table S4). Additionally, multisource observational data were used to validate the model performance. Specifically, (a) Observational NPP from National Ecosystem Science Data Center (NESDC, http://ecodb-intl.cern.ac.cn/), with nine forest sites and eight grassland sites (Figure 2 and Table S5), were used to validate PP. The NPP was recalculated from above NPP by the ratio of aboveground and belowground biomasses in forests and grasslands, respectively (Fan et al., 2008; Sun et al., 2017). (b) NEP from seven sites of ChinaFLUX (Table S4) was used to validate CS. (c) Observational volumetric soil moisture from nine forest sites of NESDC (Table S5) were used to validate WR. Neutron Probe or TDR equipment was used to monitor soil moisture, with an interval of 10–20 cm. The average values of the monitored soil volumetric soil moisture from the topsoil layer to a depth of 90 cm were used in this study. (d) Observational soil retention data are difficult to obtain; therefore, based on the annual sediment loads at each hydrological monitoring station obtained from the River Sediment Bulletin during 2003–2015 in China (MWR, 2018), we calculated the modulus of sediment transport per unit area at the basin scale to validate the simulated actual soil erosion. The simulated soil erosion was validated at the basin scale (Text S4). As the simulated results of USLE characterize the relative values of soil erosion, the statistical data were standardized using the z-score method to validate the simulated soil erosion.

2.4. Model Simulation

The CEVSA-ES model was run at site scale in this study. First, for model spin-up, the CEVSA-ES model was driven by seasonally variable climate data averaged over the 1951–1981 period, seasonal variable LAI average over the 2000–2004 period, and fixed atmosphere CO₂ concentration in 1950 and run until the model reached equilibrium, i.e., the difference between annual NPP, litter production, and soil respiration and the interannual variations in soil moisture, carbon storage in vegetation, and soil are less than 0.1% (Gu et al., 2017; He et al., 2019). Then, a transient simulation was performed using historical climate data, dynamic LAI (the mean LAI between 2000 and 2004 was reused before 2000), atmospheric CO₂ concentration,
and nitrogen deposition from 1950 to 2015. Based on the initialization and transient simulation status, the Sobol method that integrated the CEVSA-ES model with multi-source observational data (i.e., GPP, ER, NEP, and ET) was applied to identify the sensitive parameters. Subsequently, the DEMC method was used to optimize the selected sensitive parameters based on the time-variant-driven data. Finally, based on the optimized parameters and time-variant-driven data, we ran the CEVSA-ES model for each ecosystem.

The CEVSA-ES model was coded in Fortran 99 using the text I/O format. The Sobol method and DEMC method were coded in Matlab. Meanwhile, Matlab was also used to analyze the model input data and model results.

3. Results

3.1. Parameter Sensitivity Analysis and Optimization

Seven parameters were the most sensitive among all ecosystems, whereas other parameters were less or nonsensitive to the model output (Figure S2). The sensitive parameters were divided into three groups: (a) photosynthetic parameters related to carbon assimilation: The slope of the response of stomatal conductance to increase in soil water content ($s_1$) has the highest first-order and total order sensitivity indices among different ecosystems (the first sensitivity index for different ecosystems were between 0.19 and 0.74), followed by multiplicative factor that adjust the maximum carboxylation rate ($PV_{cmax}$), and the optimum temperature for plant growth ($T_{opt}$); (b) respiration parameters: Fraction of growth respiration ($PR_g$) and the multiplicative factor that adjust the potential decay ($P_{decay}$). (c) Hydrological parameters related to evapotranspiration: The sensitivity of evapotranspiration for VPD ($\beta$) and parameter $k_1$, mean while $T_{opt}$ also affects water flux.

The posterior distributions of the sensitive parameters are shown in Figure 3. The optimized $s_1$ was above 1.0 for forests and shrubs, whereas it was relatively low for cropland and grassland, with values of only 0.73 and 0.62, respectively. While the optimized $PV_{cmax}$ values were relatively high for cropland and grassland, with the values of 1.07 and 1.42, respectively. The optimized $T_{opt}$ values showed obvious ecosystem differences, and they were highly correlated with the mean temperature of growth season across different ecosystems ($R^2 = 0.61$, Figure S3), suggesting that the obtained optimized values are reasonable. Large variability in the $PR_g$ and $P_{decay}$ was detected across different ecosystem types, with ranges of 0.15–0.36 and 0.50–1.02, respectively. The optimized median value of $k_1$ ranged from 0.31 to 0.77 with a mean value of 0.56 across different biomes. The optimized $\beta$ values for most ecosystems were above 1.0, whereas the optimized $\beta$ value was relatively low (0.89) for temperate grasslands. Based on the posterior distribution of the sensitive parameters, we tabulated the value of key parameters in the CEVSA-ES model for different Chinese terrestrial ecosystems (Table S6).

3.2. Model Validation

3.2.1. Validation of the Seasonal and Interannual Dynamics of Carbon and Water Fluxes

The simulated carbon and water fluxes (GPP, Re, NEP, and ET) were compared with those observed using the eddy covariance method for each ecosystem. Both the calibrated and validated data showed a good agreement with the ground-measured carbon and water fluxes on seasonal variability (Table 2). For GPP, the $R^2$ values of validation for different ecosystems were between 0.74 ($P < 0.05$) and 0.97 ($P < 0.05$), the RMSE values were between 0.46 and 2.23 g C m$^{-2}$ d$^{-1}$, and the percentage of RMSE to the mean values were

![Figure 3. Posterior distribution of the sensitive parameters of each ecosystem type. Boxes mark 75th and 25th percentiles and solid lines in the boxes refer median values. The dotted line represents the prior parameter values. $PV_{cmax}$, multiplicative factor that adjust maximum carboxylation rate (unitless); $s_1$, slope of the response of stomatal conductance to increase in soil water content (g g$^{-1}$); $T_{opt}$, Optimum temperature for plant growth (°C); $PR_g$, fraction of growth respiration (s$^{-1}$); $P_{decay}$, multiplicative factor that adjust the potential decay (unitless); $k_1$, Parameter of the fraction of PAR intercepted by canopy (unitless); $\beta$, sensitivity of the soil moisture constraint to VPD (unitless).](image-url)
lower than 36.02%. For NEP, the simulated results were significantly related to the observed data, with $R^2$ values ranging from 0.38 for the evergreen broadleaf forest to 0.89 for the shrub, while the percentage of RMSE to the mean values were between 14.35% and 53.83%. Collectively, for all ecosystems, the CEVSA-ES model could explain 88%, 63%, and 75% of the GPP, NEP, Re, and ET, respectively. The percentage of RMSE to the mean values were lower than 36.02%. For NEP, the simulated results were significantly related to the observed data, with $R^2$ values ranging from 0.38 for the evergreen broadleaf forest to 0.89 for the shrub, while the percentage of RMSE to the mean values range from 36.59% for evergreen needleleaf forest to 80.09% for alpine steppe. For Re, the $R^2$ values were between 0.61 and 0.94; the percentage of RMSE to the mean values were lower than 37.38%. For ET, the $R^2$ values were between 0.52 and 0.94; the percentage of RMSE to the mean values were between 14.35% and 53.83%. Collectively, for all ecosystems, the CEVSA-ES model could explain 88%, 63%, 88%, and 75% of the GPP, NEP, Re, and ET, respectively. The percentage of RMSE to the mean values were relatively low for GPP (25.2%), Re (27.11%), and ET (32.2%), while it was 74.28% for NEP. Moreover, the calibration results were similar to the validation results.

Figure 4 shows the model performance of interannual variabilities of carbon and water fluxes at multiple sites across different ecosystem types. The CEVSA-ES model explained 95%, 92%, 76%, and 65% of the interannual variabilities in GPP, Re, NEP, and ET by the validation data set, respectively. In comparison, the model explained 93%, 91%, 65%, and 60% of the calibration GPP, Re, NEP, and ET, respectively. The above results indicated that the CEVSA-ES model performed well for the seasonal cycle of carbon and water fluxes across different ecosystems.
3.2.2. Validation of ESs

The simulated ESs were compared with the observational data in Figure 5. Generally, the CEVSA-ES model performed well for productivity provision and carbon sequestration. Meanwhile, the model also captured the interannual trends of water retention and soil erosion for most sites or basins. Specifically, the model with optimized parameters explained 96% ($P < 0.01$) of the variations in annual productivity provision (Figure 5a) and 81% ($P < 0.01$) of carbon sequestration across different ecosystems (Figure 5b), with RMSE values of 64.16 g C m$^{-2}$ yr$^{-1}$ (14.59%) and 106.08 g C m$^{-2}$ yr$^{-1}$ (41.06%), respectively. For water retention, the CEVSA-ES model only explained 47% ($P < 0.01$) of the interannual variations across multiple sites (Figure 5c). However, the simulated water retention trends were consistent with those of the observed water retention in eight forest sites. Both the observed and simulated water retention showed increasing trends at all sites, except the BNF and ALF sites, which showed decreasing trends (Figure 6a). Additionally, the simulated soil erosion captured 52% ($P < 0.01$) of the observed soil erosion (Figure 5d). The trend direction of the simulated soil erosion was consistent with the observed soil erosion, although the trend slopes of the observed and simulated soil erosion were different (Figure 6b). Specifically, regarding soil erosion in the Southeast, Songhua, and Liao basins, both the observed and simulated data showed an increasing trend, whereas soil erosion in other basins all showed decreasing trends. Furthermore, Figure S4 shows the comparison of the relationship between the observed and simulated soil erosion, indicating that, except for the Yellow River and Southeast basins, the observed and simulated soil erosion were significantly correlated ($P < 0.05$).
4. Discussion

4.1. Integrated Modeling

The common driver and interaction mechanisms dominated the relationships among ESs (Bennett et al., 2009; Dade et al., 2018). Understanding these relationships among ESs are crucial for ecosystem management, especially in reducing the trade-offs or increasing the synergies among ESs (Cord et al., 2017; Zheng et al., 2019). This study presents a process-based ES model to depict major ESs and their relationships. Vegetation is the core that connected different ESs, and the satellite-based LAI data are available to assess vegetation changes (Piao et al., 2020). In the new CEVSA-ES model, remote-sensed LAI was directly used to drive the CEVSA-ES model; more specifically, LAI determined productivity provision through canopy photosynthesis; the transient canopy photosynthesis was calculated as the sum of the photosynthesis in various LAI layers. Meanwhile, LAI altered water retention through evapotranspiration. An increasing LAI, that is, greening, not only promoted evapotranspiration (Piao et al., 2020), but also changed the distribution of evapotranspiration between physical evaporation and vegetation transpiration by affecting the radiation penetration of the canopy (Niu et al., 2019). Additionally, LAI could affect soil erosion through the altered biological conservation measures such as vegetation cover (Guerra et al., 2016; Jiang et al., 2016). Although

Figure 5. Performance of the CEVSA-ES model in estimating productivity provision (g C m⁻² yr⁻¹), carbon sequestration (g C m⁻² yr⁻¹), water retention (%), and soil erosion (Pt yr⁻¹). CEVSA-ES, Carbon and Exchange between Vegetation, Soil, and Atmosphere-Ecosystem Service.

Figure 6. Temporal trends of water retention (%) in different NESDC sites from 2005 to 2015 and soil erosion (Pt yr⁻¹) in different basins from 2003 to 2015.
carbon sequestration was not directly linked to LAI, it is affected by soil moisture through altering the decay rate and affected by productivity via litter production (Cao & Woodward, 1998). Meanwhile, compared to the original CEVSA model, the CEVSA-ES model driven by satellite-based LAI could better simulate the seasonality inter-annual variability of GPP, NEP, and ET, especially in summer and autumn (Figure S6).

Moreover, the CEVSA-ES model considered the effects of soil erosion on carbon sequestration through altering soil carbon stocks; this was ignored in most land surface models (Chappell et al., 2016; Lal, 2004). Soil erosion accelerates the decomposition of soil carbon by disrupting the physical protection of carbon in soil aggregates (Yue et al., 2016). The decomposition of soil carbon in deeper horizons is also destabilized under favorable temperature and moisture conditions (Jacinthe & Lal, 2001; Lal, 2003). We reconstructed the relationships between erosion modulus, water erosion rate, and sediment delivery ratio based on Yue et al. (2016). We assumed that erosion and deposition occurred simultaneously, and the difference between in-situ deposition and during transport could be as much as 63% (Guenet et al., 2014; Yue et al., 2016). Soil erosion also affects ecosystem productivity through decreasing nutrient availability (Fontaine et al., 2007). In the CEVSA-ES model, the photosynthesis and maintenance of respiration were controlled by nitrogen uptake, which is determined by soil nutrient availability (Gu et al., 2010; Woodward, 1995). Due to the biological-physical relationships in the models, the integrated process-based model showed a prospective application for exploring the mechanisms underlying the trade-offs and synergies among ESs (Viglizzo et al., 2016).

### 4.2. Model Performance and Parameter Optimization

This study compared model performance using the optimized and original parameters against the directly observed carbon and water fluxes. Seasonally, the models had similar $R^2$ ranges, whereas the model using the optimized parameters performed better with significantly low RMSE values (Table S7). Moreover, the model with the optimized parameters could better capture the site-specific variation across different ecosystems well. When interannual variabilities are considered, the optimized model showed remarkably high $R^2$ and low RMSE values, which is more in line with observed measurements than the results for the original model (Figure S5). Moreover, the optimized results were comparable with the performance achieved using models across multiple sites in China's terrestrial ecosystems (Table S8). Meanwhile, for ESs, the explanatory rates of water retention and soil retention were relatively low. Water retention was validated by on-site measurements of soil water content, which was determined by multiple environmental factors (e.g., climate, vegetation, topography, and soil texture) (Vinnikov et al., 1996; Wang et al., 2017). The mismatch between pixel and footprint might lead to uncertainties. For example, 500 × 500 m² MODIS LAI pixels characterize the average conditions, whereas data from the on-site measurements tend to be more elaborate. Furthermore, soil erosion was validated at the basin scale. The annual sediment loads from each hydrological monitoring station cannot cover the entire watershed, whereas the statistical soil erosion tool contained the whole basin; however, sediment loads only indicate the soil transported by the rivers and ignore the sedimentary soil. Although there are uncertainties in the model validation, the interannual trends of the simulated water retention and soil erosion were consistent with the observed trend, which indicated that the CEVSA-ES model could be used for simulating the changes of ESs.

To obtain reliable results, a model-data fusion method was used to parameterize the CEVSA-ES model against multivariate data sets. The outputs of the model were most sensitive to parameters related to photosynthesis ($s_1$, $PV_{\text{max}}$, $T_{\text{opt}}$), growth respiration ($PR_g$), heterotrophic respiration ($P\text{decay}$), and evapotranspiration ($k_1$, $\beta$). The sensitive parameters affected ESs by altering the biophysical processes. $s_1$ was more sensitive than other parameters and it defines the slope of stomatal conductance response to the increase in soil water content. Stomatal conductance controls the diffusion of CO$_2$ from the atmosphere into the intercellular air spaces and, thereby, the supply of CO$_2$ that affects the rates of carboxylation (Woodward et al., 1995). Internal CO$_2$ adjusts to balance supply via diffusion and to demand via photosynthetic processes. Therefore, soil moisture content regulates stomatal conductance and determined the quantity of water that can be acquired by a plant, which further determines the rate of GPP (Sperry et al., 2016; Stocker et al., 2018). The optimized $s_1$ was relatively low for nonwoody vegetation, especially for temperate grassland, which indicated that species in dry climate usually have low water use efficiency (Manzoni et al., 2011). $PV_{\text{max}}$ adjusted the sensitivity of the maximum carboxylation rate to leaf nitrogen concentration. As shown in Figure 3, the
values of the optimized $PV_{\text{max}}$ in grassland and cropland were higher than those in forests, indicating that the maximal carboxylation rate was more sensitive to leaf nitrogen concentrations in grassland and cropland. These results were consistent with those of previous studies from 1990 to 2013 (S. Yan et al., 2014). $T_{\text{opt}}$ was another sensitive parameter of the CEVSA-ES model. It was set to a constant (25°C) in the CEVSA and CEVSA2 models. Although this value has been used in many modeling studies across different biomes (Yuan et al., 2010), the $T_{\text{opt}}$ should be reflective of specific regions (Cui, 2013). In our study, we obtained the optimized $T_{\text{opt}}$ values for each ecosystem, and found that the $T_{\text{opt}}$ was correlated well with the seasonal mean air temperature (Figure S3), which provided another way to run the model for different biomes. The above three parameters were closely related to canopy GPP, which provided the foundation for productivity provision.

PR$_{g}$ directly influenced growth respiration, which affected productivity provision by consuming photosynthetic products. The ratio of respiration to gross canopy photosynthesis varies within an expected limited range for both grassland and forests (Thorinley & Cannell, 2000). Several studies have reported lower growth respiration coefficients of forests (0.16–0.25) (Paembonan et al., 1992; Rambal et al., 2004; Waring et al., 1998) than those of grassland (0.25–0.40) (Lötscher et al., 2004), which is similar to our results.

The multiplicative factor, $P_{\text{decay}}$, directly affects heterotrophic respiration and carbon sequestration services by adjusting the potential decay rate of soil organic matter decomposition. Soil organic matter decomposition is a complex process, which is affected by not only biotic and abiotic factors (Chen et al., 2000; Progar et al., 2000), but also mechanical and chemical properties of the soil organic matter itself (Chambers et al., 2000; Taylor et al., 1991). The potential decay rate of soil organic matter across different ecosystems was consistent in the original model, although studies have reported that the decomposition rate varies among different tree species (Freschet et al., 2012; Herrmann et al., 2015). $k_1$ and $\beta$ were sensitive to evapotranspiration, which is consistent with the findings of previous studies (Niu et al., 2019). Both parameters could affect water retention by altering terrestrial water loss. $k_1$ could directly reflect the bio-constraints of the green canopy fraction and plant moisture and $\beta$ had the most significant effect on soil evaporation. $\beta$ was reduced in the grassland ecosystem, which indicated that the control of soil moisture stress should be strengthened in dry ecosystems; this is consistent with the findings of previous studies (Zhang et al., 2017; Zhu et al., 2019).

4.3. Uncertainties and Implications

Many terrestrial biosphere models represent the vegetation canopy using a column of green canopy for each plant functional type within grid cell (so-called “big-leaf” approach). Therefore, the stand age and within stand heterogeneity is often ignored. The CEVSA-ES model follows this method, except that the changes in remote-sensed LAI could reflect the heterogeneity of ecosystems (Piao et al., 2020), and the diagnostic models could assimilate remotely sensed vegetation structural information to simulate the physical, biological, and ecological processes (Chen et al., 2019) as well as ESs. Moreover, actual ecosystems were also disturbed by frequent wildfires, drought, heat stress, and insect-induced mortality (Anderegg et al., 2015; Liang et al., 2017). Further investigation is needed to see whether the LAI-derived diagnostic model can capture most stand dynamics processes/phenomena. Meanwhile, there were certain differences in the linear trends and interannual variability of different LAI products (Jiang et al., 2017; Xiao et al., 2017); obtaining high-quality LAI products could help reduce the uncertainties of the simulation results. For ecosystem processes, the CEVSA-ES model coupled soil erosion with biogeochemistry processes; however, we did not consider the transport of soil carbon, which may lead to uncertainties in the estimation of land carbon budgets.

The sensitive parameters were optimized in this study to improve the accuracy of the CEVSA-ES model. However, the issue of equifinality of the model-data fusion method is that different parameter values of a model could provide acceptable fits to observational data, and without the ability to distinguish which parameter values are better than others (Beven, 2006; Beven & Freer, 2001). Fortunately, multisource observational data simultaneously used to constraint the models could inhibit the problem of equifinality (Carvalhais et al., 2010; Luo et al., 2009); we, therefore, simultaneously used GPP, ER, NEP, and ET to constraint the CEVSA-ES model. Meanwhile, the traditional Markov chain Monte Carlo (MCMC) method often suffers from problems related to proper initialization and proposal density functions, which may prevent...
the algorithm from efficiently reaching convergence (Haario et al., 2006). The DEMC used in this study is a population MCMC algorithm, in which multiple chains are run in parallel (Ter Braak, 2006). The advantage of the DEMC over the conventional MCMC method is its simplicity, speediness of calculation and convergence (Ter Braak, 2006), making it more suitable to draw inference from high-dimensional models (Zhang et al., 2017). GPP, Re, and NEP are all used to calibrate the CEVSA-ES model in this study, given these three data sets are not independent of each other and they likely have correlated errors, which will lead to over-fitting of the data and possible inaccuracies in the optimized parameters and their uncertainty as a result.

Despite the uncertainties, the new CEVSA-ES model has been extensively validated in China, and the simulated results described the seasonal and interannual variabilities of most of the observed sites; therefore, we assumed that the CEVSA-ES model could capture the spatial variations in the present or in future surface climate conditions that force ES changes, which enables aggregation up to a regional scale. The CEVSA-ES model integrated remote sensing data and supported the regular monitoring of ESs at specific time intervals (i.e., monthly, seasonal, and yearly) and this method underpinned the trend analysis. Regular spatially explicit monitoring of ESs and their trade-offs can help evaluate whether policies, or conservation practices, have a positive or negative influence on ESs (Braun et al., 2018; Rose et al., 2015). Furthermore, if the process-based models have been applied to simulate the ESs, the strength of the method is that it allows scenario analysis (Gutsch et al., 2018; Lavorel et al., 2017).

5. Conclusions

To quantify ESs and their relationships more accurately, we developed a process-based ES model (CEVSA-ES) that was integrated with remote-sensed LAI. The model was designed to simulate four services: Productivity provision, carbon sequestration, water retention, and soil retention. In addition, a model-fusion method that integrated the CEVSA-ES model with multi-source observational data was used to improve model performance. The CEVSA-ES model showed good performance for ecosystem processes, explaining 95%, 92%, 76%, and 65% of the interannual variabilities of GPP, Re, NEP, and ET, respectively. The model also explained 96%, 64%, 47%, and 52% of the interannual variations in productivity provision, carbon sequestration, water retention, and soil erosion, respectively, in China’s terrestrial ecosystems. These results demonstrate the potential of the CEVSA-ES model for evaluating ESs. Moreover, the internal relations among ESs could support the trade-offs and synergies analysis. The CEVSA-ES model is now used to estimate only four ESs; more ESs could be added in the future based on their common drivers and interaction mechanisms.

Data Availability Statement

The ChinaFLUX data set are available at http://www.chinaflux.org/enn/index.aspx. The FLUXNET data set are available at https://fluxnet.org/. The remote-sensed LAI data set are available at https://modis.ornl.gov/globalsubset/. The atmosphere CO$_2$ concentration data set are available at https://www.co2.earth. The soil texture data set are available at http://www.fao.org/. The nitrogen deposition data set are available at http://www.dx.doi.org/10.11922/sciencedb.607. Observational net primary productivity and volumetric soil moisture data sets are available at http://ecodb-intl.cern.ac.cn/. Observational soil erosion data set is available at http://www.mwr.gov.cn/english/. The code of CEVSA-ES model is available upon request from Honglin He (hehl@igsnrr.ac.cn).

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