

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology



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Climate-shaped vegetation dominated the spatial pattern of the Bowen ratio over terrestrial ecosystems in China

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Received 16 September 2023; Received in revised form 9 November 2023; Accepted 13 November 2023 Available online 20 November 2023

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https://doi.org/10.1016/j.agrformet.2023.109816

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ARTICLE INFO

Keywords: Bowen ratio Heat flux Sensible heat Eddy covariance Spatial patterns Energy partitioning

ABSTRACT

The Bowen ratio (β), which is the ratio of sensible heat (H) to latent heat (LE), reflects the energy balance and partitioning processes among soil, vegetation, and the atmosphere. Although the spatial patterns of β have been clearly delineated, the importance of vegetation in the spatial variation of β is frequently underestimated. Revealing the spatial patterns of β would improve the understanding of the variation in energy partitioning in terrestrial ecosystems and its reciprocal relationship with environmental change. Here, we calculated β by integrating H and LE flux values from 80 flux observation sites based on the eddy-covariance method in ChinaFLUX to analyze the spatial pattern and mechanism of β in China. Terrestrial ecosystems in China had an average β of 0.64 \pm 0.47. β varied significantly among ecosystem types. Deserts had the highest β (2.08 \pm 0.17), while wetlands had the lowest β (0.37 \pm 0.11). The β values of terrestrial ecosystems exhibited a significant latitudinal pattern of β was dominated by climate-shaped vegetation factors, including leaf area index (LAI) and fractional vegetation cover (FVC). Nevertheless, as water and thermal conditions decline, the contribution of vegetation factors gradually wanes. These findings demonstrated the spatial variations and driving mechanisms of terrestrial ecosystem β and provided insights into the mitigation of future climate change by vegetation.

1. Introduction

Since the onset of the Industrial Revolution, the escalating emissions of greenhouse gases have significantly contributed to the intensification of the greenhouse effect and, consequently, the persistent increase in land surface temperatures. Terrestrial ecosystems feed back to climate change through biophysical and biochemical ways, leading to varied regional effects, including both warming and cooling (Bonan, 2008; Chapin et al., 2011; Peñuelas et al., 2009; Wu et al., 2015; Popkin, 2019). However, it is noteworthy that biophysical feedback mechanisms have received limited attention in previous studies (Alkama and Cescatti, 2016). Even in internationally significant climate agreements such as the Kyoto Protocol and the Paris Agreement, there is no mention of the extent to which vegetation influences climate through biophysical processes. This introduces significant uncertainty into the development of future strategies aimed at mitigating climate change. The Bowen ratio (β) , which is the ratio of sensible heat flux (H) to latent heat flux (LE), has been acknowledged as a crucial parameter in elucidating the biophysical processes through which ecosystems feed back to climate change (Bowen, 1926; Bonan, 2008; Lee et al., 2011).

The Bowen ratio serves as a reliable indicator of the equilibrium between H and LE. H and LE play pivotal roles as they link the land surface and the atmosphere through the transfer of water and heat (Wilson et al., 2002b; Zeng and Zhang, 2020). The equilibrium between these two components directly influences the partitioning of energy within ecosystems (Arora, 2002; Takle, 2015; Ning et al., 2019; Lian et al., 2022), which have direct and indirect effect on local climates and, in some cases, can even interact with large-scale circulation systems, culminating in temperature effects on regional and global scales (Beringer et al., 2011; Burakowski et al., 2018; Moon et al., 2020; Lian et al., 2022; Shen et al., 2022; Du et al., 2022). Therefore, the study of β contributes to a more comprehensive understanding of the biophysical processes within ecosystems and provides a valuable perspective for assessing biophysical effects on climate change.

As one of the vital parameters influencing regional climate change, β has been widely used for the estimation of evapotranspiration (Perez et al., 1999; Pauwels and Samson, 2006; Zhang et al., 2008). Nevertheless, our understanding of its spatial patterns at national, regional, and even global scales remains limited, primarily due to the inherent

challenges in obtaining accurate sensible heat flux values. Leveraging the eddy covariance method, ChinaFLUX has amassed over two decades of sensible and latent heat flux observations, yielding a wealth of long-term, site observational data. Simultaneously, China's extensive latitudinal range, spanning from north and south, encompasses a multitude of climate types and a diverse array of ecosystems (Yu et al., 2006, 2016). This provides both a data foundation and a platform for analyzing the spatial pattern of β .

In recent years, numerous studies have focused on the factors influencing β on temporal scales or at small spatial scales. The results have shown that β is influenced by climate factors such as near-surface air temperature (Cho et al., 2012), ground temperature difference and vapor pressure deficit (Ren et al., 2022), precipitation (Tang et al., 2014; Gong et al., 2015), and soil factors such as soil water content (Jongen et al., 2011; Shang et al., 2015; Jiang et al., 2022; Alves et al., 2022). Many studies have also reported the relationship between β and LAI (Launiainen et al., 2016; Forzieri et al., 2020; Zhao et al., 2021; Chen et al., 2022). However, most studies regarding the influence of vegetation factors on β has been concentrated on temporal variations (Launiainen et al., 2016; Forzieri et al., 2020; Chen et al., 2022; Ping et al., 2018: Zhao et al., 2021), which limits our understanding of the dominant factors contributing to the β spatial variation. Previous studies, such as that by Huang et al. (2021), constructed a valuable dataset for β in China by collecting β from literature. They pointed out that the spatial variation of β in China is primarily influenced by mean annual precipitation (MAP), with no direct impact from leaf area index (LAI). However, vegetation, serving as a crucial link between the land surface and the atmosphere, controls the exchange of carbon, water, momentum and energy between them (Bonan et al., 1992; Bonan, 2008). Therefore, vegetation should have a strong direct control over β , but this is not confirmed by their study. Indicating that solely using LAI may not be sufficient to represent the vegetation characteristics of ecosystems. Additionally, as the key factors affecting vegetation variation, climate factors may indirectly affect β by affecting vegetation.

Therefore, to investigate the role of vegetation factors in the spatial variation of β and provide a scientific understanding of ecosystem feedback to regional climate, this study incorporated more vegetation factors to reflect vegetation characteristics, and analyzed the dominant factors and formation mechanism of the spatial patterns of β in

terrestrial ecosystems in China based on the cascade effects among vegetation, soil, and climate factors by integrating sensible heat flux and latent heat flux data from 80 ChinaFLUX sites.

2. Materials and methods

2.1. Observation sites

In this study, the sensible and latent heat data observed by the eddy covariance method from ChinaFLUX 2020 datasets were used to calculate β , and the dataset contained 80 sites and 390 site-years, covering five ecosystem types: forest, grassland, wetland, cropland and desert (Fig. 1a, Table A1). The open-path eddy covariance (OPEC) system was used to measure sensible and latent heat fluxes at ChinaFLUX sites. The OPEC system consisted of a 3D ultrasonic anemometer (Model CAST3, Campbell Scientific Inc., USA) to measure three-dimensional wind speed and temperature fluctuations and an infrared gas analyzer (Model Li-7500, Li Cor Inc., USA) to measure CO2 and water vapor densities. All signals were sampled at a frequency of 10 Hz, and the H and LE fluxes were calculated and recorded at 30-min intervals by a CR5000 datalogger (Model CR5000, Campbell Scientific Inc., USA). The meteorological variables, including solar radiation, air temperature, precipitation, soil temperature, and soil water content, were measured simultaneously at each site, and they were sampled at a frequency of 0.5 Hz and recorded at 30-min intervals (Yu et al., 2006).

2.2. Data collection and processing

2.2.1. The calculation of β

The fluxes and climate data were processed by the standard process of ChinaFLUX. Two-dimensional coordinate rotation was used to remove the influence of terrain. Then, WPL correction and stored item calculation of the storage terms were performed. For the nighttime flux data, the critical u* value was determined to eliminate the flux data under low turbulent flux. The minimum u* threshold is usually 0.1 m/s in forests and 0.01 m/s in low vegetation (Papale et al., 2006), and the u* threshold is usually between 0.1 m/s and 0.4 m/s (Reichstein et al., 2005). The missing data were interpolated by the nonlinear fitting method. See Yu et al. (2006) for the detailed data processing procedure.

In this study, β was calculated by the average annual H and LE obtained after treatment by a standard process:

$$\beta = H/LE \tag{1}$$

See appendices for calculations of sensible and latent heat fluxes.

2.2.2. Climatic, soil, and vegetation data

The observation of meteorological elements was synchronized with the observation of energy flux, and their original sampling frequency was 10 Hz, which was collected by the data harvesters (CR10X and CR23X, Campbell Scientific Inc., Logan, Utah, USA) and calculated and output 30-min statistics. The annual total downward shortwave radiation (DSR), total net radiation (Rn), total photosynthetically active radiation (PAR), and mean annual precipitation (MAP) of each ecosystem were obtained by the accumulation of 30 min of data during the observation period, and the annual values were obtained as multiyear averages. For sites that lacked meteorological data, we used the daily global weather dataset from the National Climatic Data Center (National Climate Data Center) (ftp://ftp.ncdc.noaa.gov/pub/data/noaa/isd-lite/ , accessed using FileZilla) to obtain the surface of the Earth observation data.

To provide a more comprehensive representation of vegetation characteristics in ecosystems, we chose both Leaf area index (LAI) to represent vegetation greenness and Fraction of vegetation cover (FVC) to represent the extent of vegetation cover. The LAI and FVC used in this study were based on the annual latitude and longitude information of 390 site-years and were corresponding extracted by the Global Land Surface Satellite (GLASS) with a temporal resolution of 8 days and a spatial resolution of 500 m from 2002 to 2020. The average annual LAI and FVC values of each ecosystem were calculated.

For comparing the differences in β between terrestrial ecosystems in China and those in other regions of the world, we calculated sensible heat and latent heat fluxes using the FLUXNET 2015 dataset to calculate β . After screening, we selected 104 sites in Europe, North America, and Oceania with observation times longer than 3 years and annual effective observation data greater than 75 %, which included 56 forest sites, 28 grassland sites, 8 wetland sites, and 12 cropland sites.

2.2.3. Energy closure analysis

The energy balance ratio (EBR) is an important index used to evaluate data quality, which can be affected by many factors, such as rainfall, water vapor pressure deficit, and terrain (Wilson et al., 2002a; Cui and Chui, 2019), and directly affects the accuracy of data. In this study, the EBRs of the selected sites were evaluated using net radiation (Rn), sensible heat flux (H), latent heat flux (LE), and soil heat flux (G) data with a time scale of 30 min after screening. See Li et al. (2005) for the detailed screening procedure. The EBR was calculated by the following formula:

$$EBR = \left[\sum (LE+H)\right] / \left[\sum (Rn-G)\right]$$
⁽²⁾



Fig. 1. Distribution (a) and climate distribution (b) of observation sites used in this study. TRO: Tropical monsoon rainforest; SUT: Subtropical evergreen broadleaved forest; QTB- Qinghai-Tibet Plateau alpine meadow; WTM- Warm temperate deciduous broadleaved forest; TMD- Temperate desert; TMG-Temperate grassland; TEM-Temperate deciduous broad-leaved forest; CTM- Cold temperate deciduous coniferous forest.

The results showed that the EBR ranged from 0.54 to 1.07, with an average value of 0.81 \pm 0.13 (Fig. A1). This result was consistent with the evaluation results of Li et al. (2005) on the energy closure of different sites in ChinaFLUX, indicating that the observation data had high quality.

2.3. Statistical analysis

In this study, linear regression was used to analyze the correlation between the Bowen ratio and geographical factors (latitude, longitude, and altitude), climate factors (net radiation, total downward shortwave radiation, mean annual temperature, mean annual precipitation, and water vapor pressure deficit), soil factors (soil temperature, soil water content) and vegetation factors (gross primary productivity and leaf area index). One-way analysis of variance (ANOVA) was used to test the significance of the β difference between different ecosystems in China. Two-way analysis of variance (ANOVA) was used to test the significance of the β difference among ecosystems and regions. The significance level was α < 0.05. Fisher's LSD post hoc test was used for post hoc multiple comparisons. The canonical analysis method based on hierarchical segmentation theory applied in the R package rdaccp.hp was used in attribution analysis (Lai et al., 2022). This method established a mathematical connection between hierarchical segmentation and variational decomposition to evaluate the relative importance of explanatory variables in canonical analysis. To minimize the influence of multicollinearity among factors on the attribution analysis results, the mean annual soil temperature (MAT_s) was not considered in the attribution analysis due to the extremely high correlation coefficient between MAT and MAT_s (Table A2).

Based on the attribution results, structural equation models were performed in IBM SPSS Amos 23 to evaluate the direct and indirect effects of climate, soil, and vegetation on β . Prior to constructing the structural equation model (SEM), we employed Principal component analysis (PCA) to reduce dimensionality for factors of the same type, such as climate and vegetation factors, and the first component after dimension reduction was used to represent each factor category and included as a variable in the structural equation model (Wang et al., 2018). The chi-square value, P value, and GFI (goodness-of-fit index) value were selected to assess the goodness of fit of the model.

3. Results

3.1. Statistical characteristics of the Bowen ratio of terrestrial ecosystems in China

The Bowen ratio (β) of terrestrial ecosystems in China ranged from 0.06 to 2.37, with an average of 0.64 \pm 0.47 (Fig. 2), and more energy was partitioned into latent heat than sensible heat. The β showed significant variation among the five types of ecosystems (desert>grassland>forest>cropland>wetland). The β of the desert ecosystem was the highest (2.08 \pm 0.17), which was significantly higher than that of the other ecosystems (P < 0.05, F_{4,76}=44.16), and the energy partitioned into sensible heat was twice as much as that into latent heat. The β for grassland ecosystems was 0.86 \pm 0.37, which was significantly higher than that for forest, cropland, and wetland ecosystems. The β values for desert and grassland ecosystems were higher than those of terrestrial ecosystems in China. There was no significant difference in the β values among forest (0.44 \pm 0.21), cropland (0.40 \pm 0.25), and wetland (0.37 \pm 0.11) (P > 0.05, F_{2,49}=17.22), which all had lower values than the mean β of terrestrial ecosystems in China.

The β significantly varied among continents due to the variation in global climate conditions and vegetation types. The variation of region and type has significant interaction effect on β ($P=0.047, F_{9,165}{=}1.95$) (Fig. 3). In general, the β values of all ecosystems in China (0.64 \pm 0.47) were significantly lower than that of typical ecosystems in Europe (0.80 \pm 0.45), North America (0.81 \pm 0.50) and Oceania (1.63 \pm 0.76) (P <



Fig. 2. Statistical characteristics of the Bowen ratio (β) in terrestrial ecosystems of China. The box represents the interquartile range (IQR), which spans from the 25th percentile to the 75th percentile of the data distribution. The line inside the box represents the median (50th percentile) of the data. The letters a, b, and c represent significant differences, with different letters indicating statistically significant differences (P < 0.05). SD stands for standard deviation.

0.05, $F_{3,165}{=}6.78$). The β values of forest (0.44 \pm 0.22), wetland (0.37 \pm 0.12) and cropland (0.40 \pm 0.26) in China were significantly lower than those in Europe, while the values in grassland were not significantly different from that in Europe ($P>0.05, F_{1,32}{=}0.003$), which reduced the total β . Similarly, the β in China was significantly lower than that in North America ($P<0.05, F_{1,105}{=}2.85$) because of the lower β of forest and cropland in China than that in North America, while there was no significant difference in grassland ($P>0.05, F_{1,35}{=}1.53$) and wetland ($P>0.05, F_{1,5}{=}2.21$) between the two regions. The β of Oceania forest (1.58 \pm 0.93) ($P<0.05, F_{1,22}{=}41.95$) and grassland (1.66 \pm 0.71) ($P<0.05, F_{1,29}{=}11.88$) was significantly higher than that of China, making the β of all ecosystems significantly higher than that of China.

3.2. Spatial pattern of β of terrestrial ecosystems in China

The β of terrestrial ecosystems in China exhibited significant latitudinal patterns (Fig. 4a), β increased significantly with increasing latitude ($P < 0.001, F_{1,78} = 11.13, R^2 = 0.12$), and that latitudinal pattern was observed in all types of ecosystems and was particularly pronounced in forests ($P < 0.01, F_{1,20} = 10.52, R^2 = 0.34$) and croplands ($P = 0.04, F_{1,22} = 4.72, R^2 = 0.18$). A 1° increment in latitude led to a 0.022 increase in β . The β of terrestrial ecosystems in China decreased with increasing longitude, but the β of forest and grassland showed the opposite pattern (Fig. 4b). The β increased with elevation, but the β values of grassland and desert showed the opposite altitudinal pattern; only cropland increased significantly with elevation ($P = 0.04, F_{1,22} = 4.66, R^2 = 0.17$) (Fig. 4c).

3.3. β across biomes and vegetation types over China

Fig. 5 shows the distribution of the sites used in this study in 8 typical biomes (Fig. 5e), the β statistics of each region (Fig. 5f), and the β statistics of forest, grassland, wetland, and cropland ecosystems in different biomes (Fig. 5a, b, c, d). The β values of terrestrial ecosystems in China varied significantly among biomes due to the variation in vegetation types and climatic conditions. The highest β exhibited in TMG (1.05 \pm 0.59) was significantly higher than that in other biomes except QTB (0.75 \pm 0.21) and CTM (0.92) (P < 0.05, $F_{7,72}$ =4.941) (Fig. 5f). The lowest β was exhibited in TRO (0.28 \pm 0.08).

The β of each ecosystem type also varied significantly among biomes (Fig. 5a). The forest ecosystem sites were widely distributed in tropical to cold temperate zones, and β also showed significant variation among



Fig. 3. Statistical characteristics of the Bowen ratio (β) in typical ecosystems in different countries and regions. The error bar represents the standard deviation.



Fig. 4. Spatial pattern of β of terrestrial ecosystems in China. NS is the abbreviation of no significance, meaning that P > 0.05.

zones. The β of the forest ecosystem was the highest in CTM (0.92) and significantly higher than that in TEM (0.47 \pm 0.049), SUT (0.36 \pm 0.19), and TRO (0.28 \pm 0.11) (P<0.05, $F_{5,16}{=}4.325$), but there was no significant difference between TMD, TEM, WTM, and SUT (P>0.05, $F_{3,46}{=}2.94$).

Grassland ecosystem sites were mainly distributed in the QTB and TMG (Fig. 5e), and β decreased from the TMG to the SUT, but there was no significant difference between zones (P > 0.05, $F_{4,20}=0.77$) (Fig. 5b). Wetland ecosystem sites were distributed in the TMD, QTB and SUT (Fig. 5e), and β was the highest in the QTB (0.46 ± 0.11), followed by the TMD (0.34 ± 0.11) and SUT (0.25). There was no significant variation in β among bimoes (P > 0.05, $F_{2,2} = 1.44$) (Fig. 5c).

Cropland ecosystem sites were distributed in the TMD, TMG, QTB, WTM, and SUT and were more concentrated in the WTM, and β was the highest in the QTB (0.74) (Fig. 5d), which was significantly higher than that in the SUT (0.17 \pm 0.093) (P < 0.05, F_{4,19}=1.836). There was no significant difference in the β between TMG (0.50 \pm 0.40), TMD (0.44 \pm

0.056) and WTM (0.42 \pm 0.25) (P > 0.05, $F_{2,15}$ =0.13).

3.4. The correlation between β and climate, soil and vegetation factors

Fig. 6 shows the correlation between β and the major climatic factors, soil factors and vegetation factors. Although there was no statistical significance between β and Rn, a highly statistically significant positive correlation was found between β and the downward shortwave radiation (DSR) (P < 0.001, $F_{1,78}=21.39$, $R^2 = 0.22$), that trend was significant in croplands (P = 0.017, $F_{1,22}=6.64$, $R^2 = 0.2$).

The β of terrestrial ecosystems presented a highly statistically significant negative correlation with mean annual temperature (MAT) ($P < 0.001, F_{1,78} = 11.86, R^2 = 0.12$) and mean annual precipitation (MAP) ($P < 0.001, F_{1,78} = 14.72, R^2 = 0.14$) (Fig. 6c, d). β decreased with increases in MAT and MAP. β showed a statistically significant correlation with MAT in forest ($P < 0.001, F_{1,20} = 16.79, R^2 = 0.42$)and cropland ($P < 0.001, F_{1,22} = 16.41, R^2 = 0.4$) ecosystems and with MAP in grassland (P



Fig. 5. Statistical characteristics of the Bowen ratio (β) of forest (a), grassland (b), wetland (c) and cropland (d) in China in different biomes, the Chinese vegetation map (*Vegetation Map of the People's Republic of China* (1:1,000,000)) and site distribution used in this study (e), statistical characteristics of β of different biomes (f). The colors of the columns in the bar chart correspond to the colors of the partitions in panel e. TRO: Tropical monsoon rainforest; SUT: Subtropical evergreen broad-leaved forest; QTB- Qinghai-Tibet Plateau alpine meadow; WTM- Warm temperate deciduous broad-leaved forest; TMG-Temperate grassland; TEM-Temperate deciduous broad-leaved forest; CTM- Cold temperate deciduous coniferous forest.

< 0.001, $F_{1,23}{=}6.56,$ R^2 = 0.15) and desert ecosystems (P = 0.027, $F_{1,2}$ = 34.91, R^2 = 0.92). There was a statistically significant positive correlation between the β of the terrestrial ecosystem and the vapor pressure deficit (VPD) (P< 0.001, $F_{1,78}{=}12.46,$ R^2 = 0.13) (Fig. 6f).

The β of terrestrial ecosystems showed a statistically significant negative correlation with soil water content (SWC) (P < 0.001, $F_{1,78}{=}24.28$, $R^2 = 0.23$) and mean annual soil temperature (MAT_s) (P < 0.01, $F_{1,78}{=}11.08$, $R^2 = 0.13$) (Fig. 6f, g). With a 0.1 increase in SWC and a 1 °C increase in MAT_s, β decreased by 0.214 and 0.026, respectively. There was a positive correlation between β and SWC in forest and wetland ecosystems under long-term humid conditions. The β values of cropland ecosystems was significant negatively correlated with SWC (P = 0.016, $F_{1,22}{=}6.69$, $R^2 = 0.23$), the slope of the cropland ecosystem was the highest. Similar to the relationship between β and MAT, the correlation between β and MAT, swas statistically significantly negative

in forest (P < 0.001, $F_{1,20}$ =15.39, $R^2 = 0.44$) and cropland (P < 0.001, $F_{1,22}$ =20.55, $R^2 = 0.48$) ecosystems.

As the leaf area index (LAI) (P < 0.001, $F_{1,78}=18.92$, $R^2 = 0.18$) and the fractional vegetation cover (FVC) (P < 0.001, $F_{1,78}=25.71$, $R^2 = 0.36$) increased, the β had a statistically significant linear decreasing trend. β of forest ecosystems had a statistically significant linear decreasing trend with LAI (P = 0.015, $F_{1,20}=7.06$, $R^2 = 0.26$) and FVC (P = 0.012, $F_{1,20}=7.56$, $R^2 = 0.27$). β had a statistically significantly negative correlation with LAI (P = 0.04, $F_{1,22}=4.54$, $R^2 = 0.17$) and FVC (P = 0.035, $F_{1,22}=5.04$, $R^2 = 0.19$) in cropland ecosystems. According to the correlation between the β and LAI or FVC in different types of ecosystems, we found that the β of the desert ecosystem with the lowest LAI and FVC was the most sensitive to LAI and FVC changes because it had the absolute value of the highest slope.



Fig. 6. Linear relationship between the β values of terrestrial ecosystems and climatic, soil and vegetation factors in China.

3.5. Impact of climate, soil and vegetation factors on the spatial patterns of β

Attribution analysis showed that the contribution of SWC to the spatial variation in β was the highest (26.95 %), followed by FVC (22.61 %), and the contribution of MAT was the lowest (4.99 %). Adding up the contributions of different types of factors separately, we found that climate factors had the highest total relative contribution (37.34 %), followed by vegetation factors (35.72 %), and soil factors had the lowest relative contribution (26.95 %). Climate, soil, and vegetation factors jointly explained 53 % of the spatial variation in β (Fig. 7a).

The dominant factors of the spatial variation in β varied among ecosystem types. MAT dominated the spatial variation in β in forest and cropland ecosystems, contributing 39.74 % and 32.58 %, respectively. In grassland ecosystems, the spatial variation in β was dominated by MAP, which contributed 40.85 % (Fig. 7b). Vegetation factors played a dominant role in temperate grassland and subtropical evergreen broad-

leaved forest zones. However, in regions characterized by limited moisture or temperature conditions, such as temperate desert areas and the Tibetan Plateau, soil moisture content plays a predominant role in the spatial variation in β , surpassing the influence of vegetation factors (Fig. 7c).

Fig. 7d shows the structural equation model of influencing factors of the spatial variation in β constructed with the results of importance ranking as a reference, and the explanatory skill of the model reached 0.46. We found that climate factors composed of MAT, MAP, and VPD increased significantly with decreasing DSR. The increase in climate factors led to a significant increase in SWC due to the complementary effect of MAP on SWC. Under the combined influence of climate factors and SWC, the FVC and LAI of terrestrial ecosystems were significantly promoted. With the increase in vegetation factors and soil water content, the β decreased significantly. Vegetation factors (LAI and FVC) exhibited the highest direct effects (-0.42) on β , while climate factors (MAT, MAP, and VPD) had the highest indirect effects (-0.43). Soil water content



Fig. 7. The importance of factors affecting the Bowen ratio of terrestrial ecosystems in China (a) and their importance in different ecosystem types (b) and vegetation zones (c). The structural equation of β spatial variation (d) and the effects of each factor (e). In panel d, single-headed arrows indicate the hypothesized direction of causation. The arrow width is proportional to the strength of the relationship. Bidirectional arrows indicate the correlation between variables. The vertical arrow to the right of each variable indicates its correlation with β . Red and green arrows indicate positive and negative relationships, respectively. The numbers adjacent to arrows are standardized path coefficients, and the number in the upper right corner of each variable in the model represents the degree of explanation for each variable. Double-layer rectangles of Climate represent the first component from the PCA conducted for FVC and LAI. **P* < 0.05, ***P* < 0.01, ****P* < 0.001.

(SWC) showed the highest total effects (Fig. 7e).

4. Discussion

4.1. Statistical characteristics of β in terrestrial ecosystems in China

In this study, the significant differences in β between different ecosystem types and regions revealed the influence of climate, soil, and vegetation factors on β . We found that the β values of wetland, forest and cropland ecosystems with higher SWC, LAI and FVC were significantly lower than those of grassland and desert ecosystems (Fig. 2, Fig. A2a, b). This pattern may be attributed to the fact that ecosystems with high LAI and FVC favored vegetation consumption of energy through transpiration, and evapotranspiration had a large demand for water, which could be compensated for by high SWC, leading to increases in the partitioning of latent heat (Guo et al., 2020; Xu et al., 2020). Moreover, the increase in SWC promoted evaporation and thus increased the partitioning of latent heat, ultimately leading to a decrease in β . This also indicated the crucial role of vegetation and soil water content in regulating the partitioning of energy.

The variations in β among typical ecosystems in different regions highlight the indirect regulatory influence of climatic factors on β . The β values in Chinese forest ecosystems, which are widely distributed in tropical, subtropical, and warm-temperate regions at lower latitudes, were significantly lower than those in Europe, North America, and Oceania (Fig. 3, Fig. A3). Because of the elevated temperature and humidity, vegetation experiences longer growing seasons (Lian et al., 2022) and greater transpiration capabilities (Chen et al., 2019; Jin et al., 2020), enabling vegetation to allocate more energy toward latent heat. Although the vast majority of Oceania is in tropical and subtropical regions, the partitioning of latent heat of the ecosystems was still limited because more than half of the land was arid and the overall annual precipitation was low. More energy was partitioned into sensible heat, so the β of typical ecosystems in Oceania was significantly higher than that of China. Furthermore, the uneven spatial distribution of the sites used in this study influenced the differences in β values among different regions and introduced uncertainty. Collecting more β data from literature reports or combining site and satellite observations may reduce uncertainty.

4.2. Spatial variation in β of terrestrial ecosystems in China

Chinese terrestrial ecosystems exhibited an increasing trend in β with increasing latitude, a geographical distribution pattern that was previously observed in earlier studies (Huang et al., 2021). Previous research on the primary factors contributing to this latitudinal pattern has often emphasized the role of climate factors, such as precipitation, air temperature and vapor pressure deficit (Cho et al., 2012; Zhang et al., 2014; Huang et al., 2021). However, this study revealed that while climate factors did contribute to the β spatial variation to some extent, the majority of their impact was indirect, mediated through their influence on vegetation and soil factors. Climate and vegetation distribution are closely intertwined. Along latitudinal gradients, variations in temperature, uneven rainfall patterns, and changes in atmospheric aridity determine vegetation types. Simultaneously, changes in soil water content further influence vegetation structure and activity (Woodward and Williams, 1987; Peñuelas et al., 2009; Ge et al., 2021; Lian et al., 2022). Consequently, the latitudinal variation in vegetation and soil moisture conditions leads to shifts in ecosystem types along latitudinal gradients. Simultaneously, ecosystem evapotranspiration, which serves as a key regulator of surface energy partitioning processes, undergoes significant changes. With increasing latitude, there is a substantial reduction in ecosystem evapotranspiration (Zheng et al., 2016; Fan et al., 2022; Du et al., 2022). This reduction in latent heat allocation results in an increase in β .

In addition to the regulatory role of climate factors, changes in vegetation types along latitudinal gradients are a significant factor contributing to the latitudinal pattern of β . The transition in vegetation zones and site distributions from low to high latitudes revealed a gradual shift from more forested and farmland sites to an increasing number of grassland sites (Fig. 5f), resulting in a significant change in β values.

4.3. Vegetation dominates the direct effects to the spatial variation in the β of terrestrial ecosystems in China

Both climate and vegetation factors play an undeniable role in the spatial variation of β (Fig.7a, e). However, climate factors such as temperature, precipitation, and atmospheric aridity are closely coupled. In this relationship, climate factors exerted an indirect influence on $\boldsymbol{\beta}$ through vegetation and soil, as also evident in Fig. 7b. When vegetation types were consistent, the contributions of vegetation and soil factors decreased, while climate factors such as temperature and precipitation exhibited higher contributions (Fig. 7b). This implies that the vegetation characteristics of the ecosystem (LAI and FVC) play a crucial role in the surface energy partition. This is because the carbon, water, and energy balance processes of terrestrial ecosystems are highly interrelated, with plant leaves being a key mediator closely associated with these processes (Yu et al., 2013a; Yu et al., 2014). Therefore, with higher coverage and greenness, vegetation transpiration capacity increases, leading to higher latent heat partition (Forzieri et al., 2020; Yuan et al., 2021), resulting in lower β . Additionally, the impact of LAI and FVC on energy partition is also reflected in their influence on surface albedo. Higher LAI and FVC increased absorption of net shortwave radiation at the surface, leading to higher surface temperatures within the ecosystem and ultimately increasing latent heat partition, resulting in lower β (Bonan, 2008; Zeng et al., 2017; Piao et al., 2019).

This mechanism of climate-shaped vegetation affecting surface energy partition can also be found in Fig. 5f. Different biomes represent typical vegetation types formed under different climate and humidity conditions, and β exhibits significant variations among biomes.

This study highlights the critical role of vegetation in surface energy partitioning and the significance of the Bowen ratio within this context. However, there are still topics worthy of further investigation. For example, this study identified the crucial roles of FVC and LAI in surface energy partition, but the control exerted by stomata on energy distribution was not characterized. Further studies could delve into the impact of vegetation on surface energy partition by considering factors such as stomatal characteristics and even biomass variations. Furthermore, the impact of energy non-closure on β was not considered in this study. Although previous research has suggested its relatively small effect on β (Huang et al., 2021), the accurate correction of sensible and latent heat fluxes and the reduction of uncertainty in β still merit further investigation, thereby providing a more comprehensive understanding of surface energy balance processes.

5. Conclusions

Based on the long-term observation data of latent and sensible heat flux at 80 ChinaFLUX sites, this study calculated the β and analyzed the differences and dominant factors of the spatial variation in β . The results indicated that the β value for Chinese terrestrial ecosystems was 0.64 \pm 0.47, which was significantly lower than that of typical ecosystems in Europe, North America, and Oceania. The β showed a significant latitudinal pattern and increased linearly with increasing latitude, and the rate of increase was different among different ecosystems. The spatial variation in β was directly determined by vegetation and soil factors and

was dominated by climate-shaped vegetation factors, while climate factors indirectly affected the spatial variation in β by regulating vegetation and soil factors. The contribution of vegetation factors varied with the variation in climate and soil conditions, which showed that it gradually decreased from the hot and humid subtropical evergreen broad-leaved forest region to the low-temperature arid temperate desert region, while the contribution of SWC increased and even became the dominant factor affecting the spatial variation in β over the temperate desert zone and Qinghai-Tibet Plateau.

The results of this study advanced the understanding of the ecological meaning of the Bowen ratio, discovered the controlling role of vegetation in the process of surface energy partitioning, and revealed the law and mechanism of spatial variation in the energy balance and distribution over terrestrial ecosystems. In addition, this study emphasized the importance of the Bowen ratio as a key parameter to characterize the biophysical feedback effects of ecosystems on regional climate in the context of global climate change.

CRediT authorship contribution statement

Mingyu Sun: Conceptualization, Formal analysis, Visualization, Writing - original draft. Guirui Yu: Validation, Supervision, Writing review & editing. Zhi Chen: Software, Validation, Writing - original draft, Writing - review & editing. Tianxiang Hao: Investigation, Data curation. Meng Yang: Software, Investigation. Xianjin Zhu: Software, Methodology. Weikang Zhang: Software, Investigation, Data curation. Lang Han: Software, Investigation, Data curation. Zhaogang Liu: Software, Investigation, Data curation. Lexin Ma: Software, Investigation, Data curation. Xiaojun Dou: Software, Investigation, Data curation. Yuan Yao: Software, Investigation, Data curation. Jilong Wang: Software, Investigation, Data curation. Wenxing Luo: Software, Investigation, Data curation. Yong Lin: Software, Investigation, Data curation. Shiping Chen: Resources, Data curation. Zhengmiao Deng: Resources, Data curation. Gang Dong: Resources, Data curation. Hu Du: Resources, Data curation. Yanhong Gao: Resources, Data curation. Fengxue Gu: Resources, Data curation. Xiangxiang Hao: Resources, Data curation. Yanbin Hao: Resources, Data curation. Qihua He: Resources, Data curation. Yongtao He: Resources, Data curation. Jinsheng He: Resources, Data curation. Xibin Ji: Resources, Data curation. Shicheng Jiang: Resources, Data curation. Zhengde Jiang: Resources, Data curation. Xinhu Li: Resources, Data curation. Yingnian Li: Resources, Data curation. Yugiang Li: Resources, Data curation. Yuzhe Li: Resources, Data curation. Ran Liu: Resources, Data curation. Shaomin Liu: Resources, Data curation. Weijun Luo: Resources, Data curation. Xingguo Mo: Resources, Data curation. Liqing Sha: Resources, Data curation. Peili Shi: Resources, Data curation. Qinghai Song: Resources, Data curation. Dan Sun: Resources, Data curation. Junlei Tan: Resources, Data curation. Yakun Tang: Resources, Data curation. Fei Wang: Resources, Data curation. Huimin Wang: Resources, Data curation. Jianlin Wang: Resources, Data curation. Wenxue Wei: Resources, Data curation. Jiabing Wu: Resources, Data curation. Zhixiang Wu: Resources, Data curation. Xiaoping Xin: Resources, Data curation. Junhua Yan: Resources, Data curation. Fawei Zhang: Resources, Data curation. Yangjian Zhang: Resources, Data curation. Yiping Zhang: Resources, Data curation. Yucui Zhang: Resources, Data curation. Fenghua Zhao: Resources, Data curation. Liang Zhao: . Li Zhou: Resources, Data curation. Jiaojun Zhu: Resources, Data curation. Zhilin Zhu: Resources, Data curation.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

Acknowledgments

We are grateful to ecological stations and all monitors from the Chinese Ecosystem Research Network (CERN) and ChinaFLUX for sample collecting. This work was supported by the National Natural Science Foundation of China (31988102, 32222052, 42261144688, 42141005), Youth Innovation Promotion Association of Chinese Academy of Sciences (2022050), and Young Talents Project of Institute of Geographic Sciences and Natural Resources Research (2021RC004). The Global Land Surface Satellite (GLASS) data used in this work were obtained from http://www.glass.umd.edu/Download.html. ChinaFLUX published site observation data were obtained from http://www.china flux.org/.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2023.109816.

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