Experimental Gerontology 224 (2026) 113283

Contents lists available at ScienceDirect

Experimental Gerontology

journal homepage: www.elsevier.com/locate/expgero

Nonlinear associations between exposure to natural environments and biological aging: A cohort study of middle-aged and older adults in China

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ARTICLE INFO

Section Editor: Yang Cao

Keywords:
Natural environment
Biological aging
Nonlinear association
Health equity

ABSTRACT

Objective: To examine nonlinear associations between natural environments (green and blue spaces) and biological aging in middle-aged and older Chinese adults.
Methods: We analyzed longitudinal data from the China Health and Retirement Longitudinal Study (CHARLS). Environmental exposures were assessed using satellite-derived indicators, normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), green space coverage ratio, and blue space coverage ratio. Biological aging was quantified by frailty index (FI) and KDM-biological age acceleration (KDM-BAacc). Generalized additive mixed models (GAMMs) were employed to model nonlinear relationships; beneficial exposure ranges and optimal level were derived by differentiating the curves. Subgroup analyses examined effect modification by socioeconomic status, sex, and age.
Results: Significant nonlinear associations were observed between environmental indicators and biological aging. For FI, the maximum protective effect of green space occurred at 66.6% coverage, reducing FI by 0.006 (95% *CI*: −0.009, −0.004), the protective effect interval was (0.466, 0.784). Blue space showed maximum FI reduction of 0.014 (95% *CI*: −0.021, −0.008) at 10.9% coverage, with protective interval of (0.013, 0.140). When the blue space ratio was 10.9%, the protective effect on FI was the largest. For KDM-BAacc, optimal NDVI was 0.663, and optimal blue space proportion was 10.8%. Subgroup analyses revealed stronger protective effects among individuals with low socioeconomic status, women, and those aged 45–65 years.
Conclusion: Moderate levels of green and blue spaces were associated with lower levels of biological aging. Nonlinear associations were stronger in socially vulnerable groups, suggesting that equitable nature-based planning could be a strategic public health intervention to promote healthy aging.

1. Introduction

As the global aging process accelerates (WHO, 2025), healthy aging has become an essential challenge for public health (Gianfredi et al., 2025). Traditional researches had identified several genetic and lifestyle factors of aging (Cao et al., 2022; Liu et al., 2019; Yang et al., 2022). However, the natural environment surrounding the residence, as a common and modifiable external exposure, is increasingly drawing scientific attention for its influence on healthy aging (Cushing et al., 2025; Mena et al., 2025).

The World Health Organization (WHO) considers green space (such as parks and forests) and blue space (such as rivers and lakes) around residential areas as important and modifiable health resources (Twohig-Bennett and Jones, 2018), which may help maintain physiological

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https://doi.org/10.1016/j.exger.2026.113283
Received 28 March 2026; Received in revised form 22 July 2026; Accepted 11 August 2026
Available online 14 August 2026
0531-5565/

functions and slow down the rate of aging (Alcock et al., 2014; Kondo et al., 2018; Li et al., 2025; Rojas-Rueda et al., 2019). Aging is essentially a state of progressive decline in multi-system physiological function (Kroemer et al., 2025; López-Otín et al., 2013), which is not only reflected in the clinical phenotype of frailty, but also quantified by biomarkers, including Klemera-Doubal biological age (KDM-BA) (Klemera and Doubal, 2006) and frailty index (FI) (Mitnitski et al., 2017). These indicators can reveal the status of individual aging earlier and more objectively.

In recent years, increasing attention has been paid to the potential benefits of natural environmental exposures on biological aging. Studies have shown that urban blue-green spaces (UGBS) can have a positive impact on public health by providing physical activity and social opportunities (Remme et al., 2021), and regulating ecosystems (for example, vegetation improves air quality by removing pollutants) (van den Bosch and Ode Sang, 2017). Other studies highlight that measures such as increasing tree cover in cities can help reduce the risk of death (Iungman et al., 2023). Compared with urban areas, rural areas have a higher degree of exposure to the natural environment, and residents in rural areas have more direct contact with nature through gardening and agricultural work, which may bring more obvious health benefits (Azul et al., 2021). A longitudinal study showed that proximity to natural environments was more advantageous for maintaining physical function in areas with higher levels of deprivation (de Keijzer et al., 2019). However, the evidence based on the impact of green-blue space, whether urban or rural, on sustainable development in low- and middle-income countries (LMICs) is relatively weak (Hunter et al., 2023; Rasolofoson, 2024). What is more, most of the existing studies were cross-sectional in design, which made it difficult to establish causality (Mena et al., 2025; Mora et al., 2025; Palteki, 2025). On the other hand, most studies assume a linear association between exposure and outcome, which may mask a true dose-response relationship. Although studies suggested that there may have been complex and nonlinear associations between natural environmental exposures and health outcomes (Li et al., 2025; Soncini et al., 2025), the protective effect interval and the optimal exposure threshold of natural environmental exposure remain unidentified, which has weakened the operability of public health interventions. In addition, most current studies focused on a single environmental indicator (Yu et al., 2024) or a single aging dimension (Lin and Wu, 2021), and there has been a lack of systematic discussion on the basis of multi-dimensional exposure assessment and multi-level quantification of aging. More importantly, whether the effect of green-blue space on biological aging differs across sociodemographic groups and whether there is a specific health-compensation effect for disadvantaged groups remains to be verified using large-scale longitudinal data.

Therefore, this study used longitudinal data from the China Health and Retirement Longitudinal Study (CHARLS) to explore nonlinear associations between natural environment exposure (including green and blue spaces) and biological aging in middle-aged and older Chinese adults. We adopted multi-dimensional exposure assessment, including normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and green/blue space coverage ratio, together with multi-dimensional indicators of biological aging, including the frailty index (FI) and KDM biological age acceleration (KDM-BAacc). Generalized additive mixed models were employed to characterize potential nonlinear dose-response relationships. This study aims to identify the beneficial exposure range and optimal exposure point of the natural environment on biological aging. At the same time, the differences in the association among sex, age, and socioeconomic status were further explored to provide a scientific basis for examining the impact of the natural environment on the aging process of middle-aged and elderly people and formulating relevant health promotion strategies.

2. Methods

2.1. Participants

We used data from the China Health and Retirement Longitudinal Study (CHARLS), which was approved by the Institutional Review Board of Peking University (IRB00001052-1015). All participants provided written informed consent (Zhao et al., 2014). The national baseline survey was conducted in 2011, covering 150 counties and districts. Follow-up surveys were subsequently conducted in 2013, 2015, and 2018. As a dynamic cohort, CHARLS not only tracked baseline participants but also recruited new participants in each wave. We integrated data from the 2011, 2013, 2015, and 2018 waves, with the time point when each subject first entered the cohort was taken as the baseline of the study. After excluding individuals younger than 45 years and those without FI, a total of 21,935 participants were included in the analysis with FI as the outcome. Furthermore, since blood samples in CHARLS were collected only at baseline (2011) and the third wave (2015), the analysis based on the KDM-BA included 9162 participants with complete blood biomarkers. The flow chart of the study is shown in Fig. 1.

2.2. Assessment of natural environmental exposures

Four environmental exposure indicators were used to assess exposure levels to green and blue spaces in the cities where the participants lived. First, the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and green space coverage ratio were used to assess green space exposure. NDVI data were acquired from the China regional 250 m normalized difference vegetation index data set provided by the National Tibetan Plateau/Third Pole Environment Data Center (http://data.tpdc.ac.cn) (Gao et al., 2023). EVI data were obtained from the monthly 1 km resolution Enhanced Vegetation Index (EVI) dataset for China by the National Earth System Science Data Center (https://www.geodata.cn) (Xu, 2025). To derive city-level exposure values from these raw raster products, we utilized ArcGIS 10.6 software to extract pixel values from the original GeoTIFF files. Notably, these raw datasets are provided as monthly maximum-value composites. For each city, we extracted all pixels falling within its administrative boundaries and calculated the city's monthly NDVI and EVI as the mean of these extracted pixel values. The NDVI theoretically ranges from −1 to 1, with −1 indicating non-vegetated features, 0 representing barren land, and positive values approaching 1 signifying denser green vegetation. The EVI, in contrast, offers better performance in high-biomass regions because it incorporates a blue band correction to minimize atmospheric and soil background influences, making it more sensitive than NDVI in densely vegetated areas (Matsushita et al., 2007). To reflect exposure during the period of vigorous vegetation growth, the average NDVI and EVI in summer (June to August) were used as the city's annual exposure values. The calculation of green space ratio and blue space ratio was based on the China Land Cover Dataset (Yang and H, 2024), which is the first annual Landsat-derived land cover product for China, developed on the Google Earth Engine platform and comprising nine land use types: cropland, forest, shrubland, grassland, water, snow and ice, barren, impervious surface, and wetland. Among these, forest, shrubland, and grassland were defined as green space, while water and wetlands were classified as blue space, and their area proportion was calculated, respectively. Using ArcGIS 10.6, we quantified the proportion of green and blue spaces within each city by tallying the number of pixels classified as specific land cover types and dividing this by the total pixel count for that city. It is important to note that while NDVI and EVI capture the spectral "greenness" intensity of vegetation, the green space coverage ratio derived from the CLCD measures the actual areal extent of green spaces. These two concepts reflect distinct dimensions of exposure to green environments (Klompmaker et al., 2018). Due to the right-skewed distribution of the blue space ratio variable, we restricted our analysis to the 98th

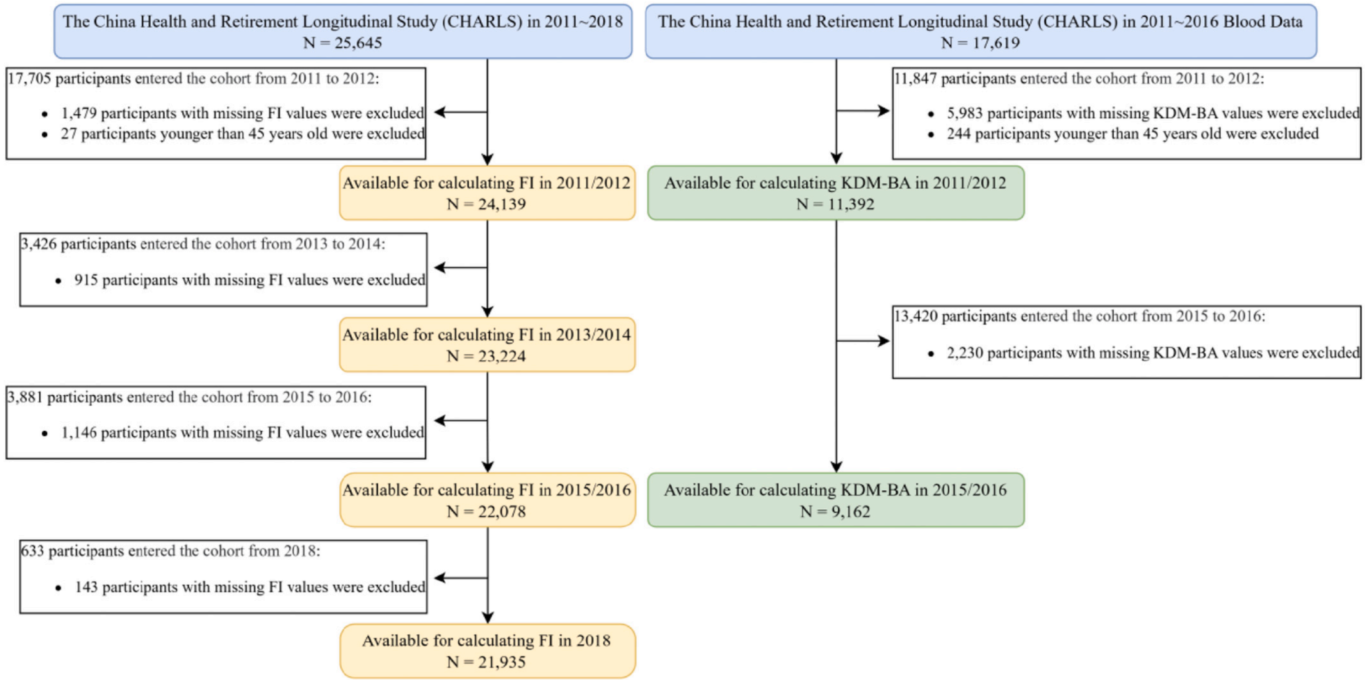

Fig. 1. Flow chart.
This study is a dynamic cohort study, with the time of each participant's enrollment defined as the baseline.

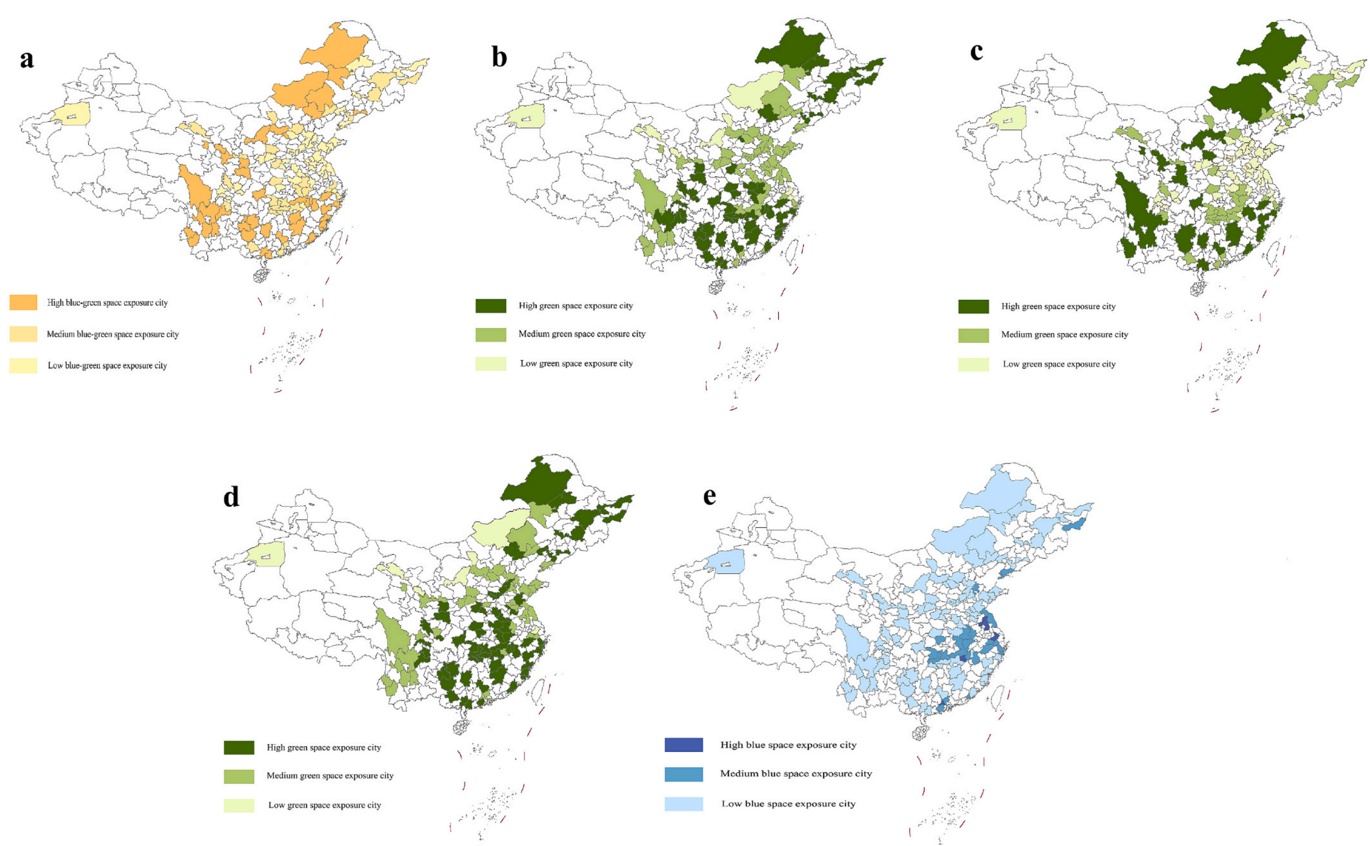

Fig. 2. Distribution of green and blue space proportions in cities of CHARLS participants.
The map displays the spatial distribution of green and blue space exposure across 122 cities included in this study, classified into high, medium, and low exposure levels based on DTW-based K-means clustering analysis. Panels show: (a) green-blue space exposure, (b) summer mean NDVI, (c) green space coverage ratio, (d) summer mean EVI, and (e) blue space coverage ratio. Color-filled areas represent cities categorized as high, medium, or low exposure for each variable. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

percentile, removing the top 2% of extreme values while retaining the vast majority of the sample. In addition, to account for the lagged effects of natural environmental factors on health, we used the environmental status from the year prior to each survey as the exposure indicator. Thus, the exposure for each survey was derived from the preceding year's data. The trajectories of natural environmental exposure in the cities where the subjects of CHARLS were located were divided into three categories by the K-Means clustering method based on Dynamic Time Warping (DTW). To characterize the dynamic patterns of environmental exposure over time, we performed trajectory clustering on the cities where the CHARLS participants resided. Dynamic Time Warping (DTW) was employed as the distance metric to measure the similarity between pairs of city-level time series. Unlike Euclidean distance, DTW optimally aligns sequences that may exhibit temporal shifts or varying rates of change, making it particularly suitable for capturing heterogeneous exposure trajectories across cities (Sardá-Espinosa, 2019). The K-Means algorithm was then applied to partition cities into distinct trajectory groups based on the DTW-derived distance matrix. The optimal number of clusters (K = 3) was determined using the elbow method in conjunction with silhouette coefficient analysis, which balanced within-cluster compactness against between-cluster separation. It should be noted that this approach identifies groups of cities with similar temporal patterns of environmental exposure, rather than classifying NDVI values at a single time point using fixed thresholds. Our trajectory-based clustering captures the dynamic evolution of green and blue space exposure over time. The blue-green space, green space (NDVI, EVI, green space coverage ratio), and blue space (Fig. 2) contributed to the formation of clusters. Supplementary Fig. 1 presented the specific clustering information.

2.3. Calculation of frailty index (FI)

The frailty index (FI) integrates multiple health deficits associated with aging. It has been widely used to assess biological aging and is considered a comprehensive and efficient indicator for quantifying frailty status (Sapp et al., 2023). In this study, 38 items were selected to construct FI, covering six aspects: activities of daily living (ADL), instrumental activities daily living (IADL), physical function, chronic disease, mental health, and subjective-rated health (see Supplementary Table 1 for details). Each deficit was dichotomized or mapped to 0–1 interval, with 0 indicating the absence of a deficit (the healthiest state) and 1 indicating the maximal expression of the deficit (the unhealthiest state). The frailty index was calculated for each participant as the number of deficits present divided by the maximum possible deficits score. FI was treated as a continuous variable ranging from 0 to 1, with higher scores indicating more severe frailty. Participants with at least 30 items were selected to calculate FI.

2.4. Calculation of KDM-BAacc

The classical Klemera-Doubal Method (KDM) was used to construct biological age, a validated method in both Chinese and British populations that demonstrated effective prediction of age-related health outcomes (Klemera and Doubal, 2006). Referencing previous studies (Hu et al., 2025; Liu, 2021), we trained the KDM-BA in the China Health and Nutrition Survey (CHNS) cohort aged 20–79 years using 12 selected candidate biomarkers, including total cholesterol (TC), triglycerides (TG), albumin, glycated hemoglobin (HbA1c), urea, creatinine, high-sensitivity C-reactive protein (hs-CRP), red blood cell count (RBC), platelet count (PLT), ferritin, transferrin, and systolic blood pressure (SBP), representing various aspects of physical function. Then, the trained KDM-BA is projected into the CHARLS. The coefficients for the biomarkers trained by on CHNS cohort are shown in Supplementary Table 2. Since CHARLS lacks four of these biomarkers (albumin, RBC, ferritin, and transferrin), the remaining eight biomarkers were used to calculate KDM-BA. This analytical strategy of employing a reduced biomarker set when full data are unavailable has been previously validated in the Chinese population. In the study that developed and validated KDM-BA in CHARLS (Liu, 2021), Liu et al. employed exactly the same eight-biomarker set (TC, TG, HbA1c, urea, creatinine, hs-CRP, PLT, and SBP) and demonstrated that this reduced set remained significantly predictive of all-cause mortality (OR = 1.05, 95% *CI* = 1.03, 1.07). Similarly, Hu et al. (2025) adopted this approach across multiple cohorts (CHARLS, UK Biobank, and HEHEC), applying different biomarker subsets contingent upon data availability, and confirmed the robustness of the KDM-BA estimates across varying biomarker compositions. It is also worth noting that while some earlier KDM applications have incorporated additional biomarkers such as FEV1 and alkaline phosphatase, these are not prerequisites for the KDM algorithm; the method's flexibility allows for adaptation to the biomarkers available in each specific cohort. The validity of our KDM-BA calculation is therefore supported by both the methodological foundations of the KDM framework and the empirical evidence from previous Chinese population-based studies that used the identical eight-biomarker set. To adjust for the effect of chronological age, KDM-BA acceleration (KDM-BAacc) was calculated as the residual of the linear regression of KDM-BA on chronological age.

2.5. Covariates

The main analyses of the study adjusted for covariates that included categorical and continuous variables: categorical variables included sex (male and female), smoking status (never smoked, ever smoked, or currently smoked), drinking status (never drank, less than once per month and more than once per month), education level (non-formal education, primary school, secondary school or above), and socioeconomic status (low SES: having received no education and living in rural areas; middle SES: primary school education level without considering urban or rural living areas, or no education but living in urban areas; high SES: secondary school education level or above, whether living in urban or rural areas). Continuous variables included age, body mass index (BMI), and nighttime sleep duration.

2.6. Statistical analysis

First, generalized additive mixed models (GAMM) were used to explore the nonlinear associations between the four environmental exposures and the two biological aging metrics. GAMM, as a mixed-effects model, is able to handle individuals with different numbers of follow-up visits and inconsistent follow-up time points. The smoothing term captures potential nonlinear effects of environmental factors. The smoothing term is estimated using thin-plate regression splines. For the primary analysis, the number of knots was set to k = 5, which provides a parsimonious starting point for detecting moderate nonlinear patterns while preventing overfitting. To further examine whether the identified nonlinear associations were sensitive to the complexity of the smoothing term, we conducted a sensitivity analysis with k = 15, allowing the splines to capture more complex nonlinear patterns (the first sensitivity analyses below).Given the longitudinal structure of the data with repeated observations nested within each participant, we included a random intercept for each individual to account for within-subject correlation and to capture inter-individual heterogeneity. Three models were constructed for analysis: Model 1 was crude model; Model 2 adjusted for sex and age; and Model 3 additionally adjusted for smoking, drinking status, BMI, and nighttime sleep duration. Then, we quantified the nonlinear association results. Specifically, the beneficial exposure interval of natural environmental factors on aging was determined at the point of zero smoothing effect. The derivative was used to pinpoint the optimal exposure point and the maximum protective effect. Subgroup analyses were also conducted, stratified by sex, age, and socioeconomic status. In the analysis of blue space proportion and biological aging, we further used the NDVI trajectory as a stratification variable for stratified analysis. K-Means clustering based on DTW was used to classify NDVI trajectories. Additionally, sensitivity analyses were performed to: 1) test the robustness of the results to the complexity of the smoothing term by setting the number of knots of the thin-plate regression splines at k = 15, allowing the splines to capture more complex nonlinear patterns; 2) participants who were already frail at baseline were excluded, with frailty defined as an FI ≥ 0.25; 3) excluding subjects with missing covariates at baseline; 4) only the population with 4 complete follow-up waves was analyzed; 5) distributed lag non-linear models (DLNM) were fitted to explore the cumulative effect of 2-year lag to reveal a more complex lag pattern, to examine whether the observed associations were robust to alternative lag specifications and to explore the potential cumulative effect of environmental exposure over a longer time frame; and 6) The exposure time window for the natural environment in the GAMM model was defined as two years prior to the start of the survey.

All statistical analyses were performed in R software (version 4.2.0) using the "dtwclust", "BioAge", and "gamm4" packages. The significance level for all statistical tests was $P \leq 0.05$ (two-tailed). In the GAMM analysis using the "gamm4" package, the EDF of effective degrees of freedom was used to access the nonlinear association between variables and outcomes. EDF = 1 corresponded to a linear relationship, and EDF > 1 indicated the existence of a nonlinear association. Missing data were present only in a limited number of covariates, the FI and all environmental exposure indicators (NDVI, EVI, green space coverage ratio, and blue space coverage ratio) had no missing values. Furthermore, to assess the potential impact of excluding participants with missing data, we conducted a sensitivity analysis by repeating the primary analyses after excluding individuals with missing baseline covariate data.

3. Results

This study found that exposure to the natural environment was associated with lower frailty and a slower pace of biological aging, with a nonlinear association. The effect was more pronounced in lower SES, women and people aged 45–65 years. Among 21,935 CHARLS participants, the mean follow-up was 3.6 years (median, 3 years). The baseline characteristics of the participants are shown in Table 1; the mean age was 61 years (SD = 10.3), and 57.8% were women. A total of 19,691 subjects (89.8%) did not have frailty at the baseline survey.

3.1. Nonlinear associations between natural environmental factors and biological aging metrics in GAMMs

In the GAMMs, all natural environmental factors exhibited statistically significant nonlinear associations with biological aging metrics. Tables 2 and 3 present the EDFs and *p*-values for the GAMM smoothing terms for natural environmental factors and FI and KDM-BAacc, respectively. For example, the mean summer NDVI had a significant nonlinear effect on FI (EDF = 3.493, $p < 0.001$). The coefficients (β) and significance of the nonlinear terms in each GAMM are shown in Supplementary Tables 3–10. From Figs. 2 and 3, it can be seen that the smoothing term of this model exhibits a complex nonlinear association, indicating that biological aging indicators exhibit nonlinear variations across the range of natural environmental exposures.

Table 1
Baseline characteristics of 21,935 CHARLS participants stratified by frailty status.

Variables	Total (n = 21,935)	Non-frail (n = 19,691)	Frail (n = 2244)	*P*
Sex				
Male	4728 (42.2)	4047 (42.9)	681 (38.6)	0.001
Female	6474 (57.8)	5390 (57.1)	1084 (61.4)	
Age	61.3 (10.3)	60.3 (9.8)	66.9 (10.8)	<0.001
Educational level				
Illiterate	4955 (23.0)	4032 (20.8)	923 (41.8)	<0.001
Primary school and below	7646 (35.4)	6895 (35.6)	751 (34.0)	
Middle school and above	8977 (41.6)	8444 (43.6)	533 (24.2)	
Marriage				
Married	19,105 (87.1)	17,421 (88.5)	1684 (75.1)	<0.001
Unmarried	2829 (12.9)	2270 (11.5)	559 (24.9)	
Residence				
Urban	1469 (21.8)	1269 (22.3)	200 (18.8)	0.011
Rural	5280 (78.2)	4414 (77.7)	866 (81.2)	
Smoke				
Never smoking	12,177 (65.4)	10,833 (65.5)	1344 (64.5)	0.377
Ever smoking	6447 (34.6)	5707 (34.5)	740 (35.5)	
Alcohol consumption				
Not drinking	14,633 (66.7)	12,798 (65.0)	1835 (81.8)	<0.001
Drinking less than once per month	1792 (8.2)	1701 (8.6)	91 (4.1)	
Drinking more than once per month	5502 (25.1)	5185 (26.3)	317 (14.1)	
BMI	23.53 (3.6)	23.53 (3.6)	23.51 (4.0)	0.793
Socioeconomic status				
Low SES	4258 (53.9)	3485 (52.0)	773 (65.0)	<0.001
Middle SES	3464 (43.9)	3064 (45.7)	400 (33.6)	
High SES	176 (2.2)	159 (2.4)	17 (1.4)	
Diabetes				
Yes	1183 (5.5)	848 (4.4)	335 (15.3)	<0.001
No	20,246 (94.5)	18,389 (95.6)	1857 (84.7)	
Hypertension				
Yes	4332 (21.4)	3333 (18.3)	999 (47.8)	<0.001
No	15,938 (78.6)	14,849 (81.7)	1089 (52.2)	
Dyslipidemia				
Yes	1937 (9.2)	1480 (7.9)	457 (21.5)	<0.001
No	19,039 (90.8)	17,366 (92.1)	1673 (78.5)	

Age and BMI are continuous variables, presented as mean (sd). Other variables are categorical, with their values reported as frequency (%). BMI: body mass index; SES: socioeconomic status.

Table 2
Approximate significance of smooth terms in association with FI.

Smooth term	Model 1			Model 2			Model 3		
	edf	F	*P*	edf	F	*P*	edf	F	*P*
Formula: FI ~ s (summer mean NDVI, k = 5)									
Summer mean NDVI	3.493	18.680	<0.001	2.737	5.591	<0.001	2.835	6.839	<0.001
Formula: FI ~ s (summer mean EVI, k = 5)									
Summer mean EVI	3.052	6.563	<0.001	2.446	3.998	0.034	3.078	6.135	<0.001
Formula: FI ~ s (green space coverage ratio, k = 5)									
Green space coverage ratio	3.849	24.790	<0.001	3.822	19.400	<0.001	3.864	12.960	<0.001
Formula: FI ~ s (blue space coverage ratio, k = 5)									
Blue space coverage ratio	3.229	32.200	<0.001	3.526	31.090	<0.001	3.512	24.290	<0.001

Model 1 was not adjusted for any covariates; Model 2 was adjusted for sex and age; Model 3 was further adjusted for smoking status, alcohol consumption, BMI, and nighttime sleep duration. NDVI: normalized difference vegetation index; EVI: enhanced vegetation index; edf: effective degrees of freedom.

Table 3
Approximate significance of smooth terms in association with KDM-BAacc.

Smooth term	Model 1			Model 2			Model 3		
	edf	F	*P*	edf	F	*P*	edf	F	*P*
Formula: KDM-BAacc ~ s (summer mean NDVI, k = 5)									
Summer mean NDVI	3.935	26.470	<0.001	3.935	26.970	<0.001	3.893	20.010	<0.001
Formula: KDM-BAacc ~ s (summer mean EVI, k = 5)									
Summer mean EVI	3.952	25.960	<0.001	3.952	26.640	<0.001	3.912	20.180	<0.001
Formula: KDM-BAacc ~ s (green space coverage ratio, k = 5)									
Green space coverage ratio	3.344	6.077	<0.001	3.351	6.257	<0.001	3.549	24.550	<0.001
Formula: KDM-BAacc ~ s (blue space coverage ratio, k = 5)									
Blue space coverage ratio	2.677	14.110	<0.001	2.908	13.970	<0.001	3.511	15.710	<0.001

Model 1 was not adjusted for any covariates; Model 2 was adjusted for sex and age; Model 3 was further adjusted for smoking status, alcohol consumption, BMI, and nighttime sleep duration. NDVI: normalized difference vegetation index; EVI: enhanced vegetation index; edf: effective degrees of freedom.

3.2. Optimal exposure windows and quantification of maximum protective effects

Figs. 2 and 3 suggest an "optimal window" for the beneficial association of natural environmental factors with aging. Therefore, we determined the beneficial exposure interval by calculating the point at which the smoothing effect was zero, and the optimal exposure point and the point of maximum benefit by taking derivatives (Table 4). Among the indicators measuring green space exposure, the green space ratio had the strongest protective association with FI. Among them, when the proportion of green space was 66.6%, the protective association with FI was the largest, reducing FI by 0.006 units (95% *CI*: −0.009, −0.004), with a protective effect interval of (0.466, 0.784). The beneficial association of blue space on FI was −0.014 (95% *CI*: −0.021, −0.008), and the interval of the protective association was (0.013, 0.140). When the blue space ratio was 10.9%, the protective association on FI was the largest. When NDVI in summer ranged from 0.598 to 0.722, it was beneficially associated with biological age acceleration. When NDVI was 0.663, the beneficial association was strongest, at −0.250 (95% *CI*: −0.308, −0.192). When the blue space ratio was in the range of (0.013, 0.140), it was beneficially associated with the biological age acceleration. When the proportion of blue space was 10.8%, the beneficial association was largest, at −0.545 (95% *CI*: −0.789, −0.301).

3.3. Enhanced protection in vulnerable subgroups: low SES, females, middle-aged adults, and areas with low NDVI exposure trajectory

The subgroup analysis showed that the strongest beneficial association of environmental factors on FI was more obvious among people with low socioeconomic status, women, and people aged 45 to 65 years (Figs. 4 and 5, Supplementary Figs. 2–16). The results of the protective effects of different natural environmental factors on the two biological aging indicators in the stratified analysis are shown in Supplementary Tables 11 and 12. In the high SES subgroup, the nonlinear association between natural environmental factors and FI was not significant (EDF = 1; supplementary Table 11). So, in the high SES subgroup, linear mixed models (LMM) were used to estimate the association between physical environment and FI, and the results showed that: β_{NDVI} = −0.079 (95%CI: −0.190, 0.031, P = 0.164), $\beta_{\text{Green Ratio}}$ = 0.019 (95%CI: −0.023, 0.061, P = 0.384), β_{EVI} = −0.120 (95%CI: −0.265, 0.025, P = 0.109). Similarly, in the high SES subgroup, the association between natural environmental factors and KDM-BAacc may also be nonlinear (Supplementary Table 12), with the estimated LMM of environmental factors and KDM-BAacc being β_{NDVI} = 0.392 (95%CI: −3.616, 4.401, P = 0.848), $\beta_{\text{Green Ratio}}$ = −1.091 (95%CI: −2.908, 0.725, P = 0.242), β_{EVI} = 2.170 (95%CI: −3.375, 7.715, P = 0.445) (Fig. 6). There was no statistical association between environment and aging measures in the high SES subgroup.

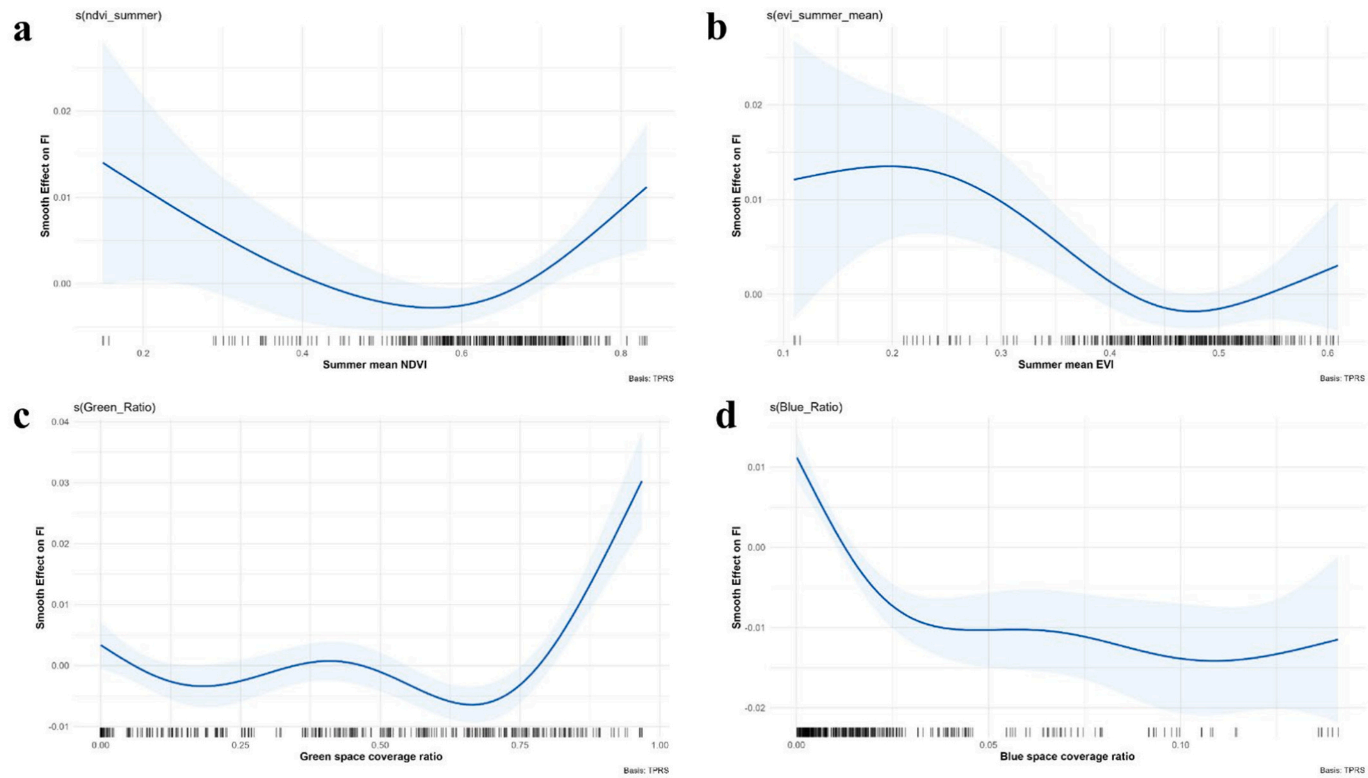

Fig. 3. Smooth effects of environmental exposures on frailty index (FI).
Associations were modeled using thin-plate regression splines (TPRS). In each panel: the dark blue curve represents the effect of smooth term; the light blue shaded denotes its 95% confidence interval; and the short black lines along the x-axis (rug plot) show the distribution of the observed exposure data. The specific exposures shown are: (a) summer mean NDVI, (b) summer mean EVI, (c) green space coverage ratio, and (d) blue space coverage ratio. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Protective effects of natural environmental exposures.

Variables	Protection effect interval	Optimal protection effect level	Effect at the point of optimal protection (95%*CI*)
FI ~ environmental exposure			
Summer mean NDVI	(0.423, 0.678)	0.562	−0.003 (−0.005, −0.001)
Summer mean EVI	(0.419, 0.544)	0.477	−0.002 (−0.003, −0.001)
Blue space coverage ratio	(0.013, 0.140)	0.109	−0.014 (−0.021, −0.008)
KDM-BAacc ~ environmental exposure			
Summer mean NDVI	(0.598, 0.722)	0.663	−0.250 (−0.308, −0.192)
Summer mean EVI	(0.442, 0.529)	0.489	−0.233 (−0.285, −0.180)
Green space coverage ratio	(0.000, 0.589)	0.439	−0.143 (−0.241, −0.045)
Blue space coverage ratio	(0.013, 0.140)	0.108	−0.545 (−0.789, −0.301)

The protection effect interval is the range in the GAMM model where the smooth term is negative. The optimal protective effect point denotes the lowest value of the smooth effect within this interval, corresponding to the optimal environmental exposure level. The effect at the optimal protection reflects the smooth effect when environmental exposure reaches its optimal level.

3.4. Sensitivity analyses

The results of the sensitivity analysis were similar to the primary analysis. When fitting a more complex nonlinear model, increasing the number of thin-plate regression spline knots to k = 15, there was also a significant nonlinear association, and the inflection point locations of the curves were similar, and the trend of nonlinearity was similar (Supplementary Table 13). Additionally, after excluding individuals who were already frail at baseline enrollment ($N = 19{,}691$) or those with missing baseline covariate data ($N = 8587$), the EDF values of the GAMMs remained statistically significant (Supplementary Tables 14 and 15). In the model that included only subjects at four follow-up waves ($N = 4934$), although the nonlinear association of NDVI with FI was not significant, the nonlinear association of other natural environmental factors with FI and KDM-BAacc remained (Supplementary Table 16). In sensitivity analysis 5, which fitted a distributed lag nonlinear model (DLNM) to explore the cumulative effect of environmental factors with a 2-year lag, we found nonlinear associations similar to those in the main analysis, with similar curve turning points (Supplementary Fig. 17). Notably, the estimated cumulative effect over the two-year period was not substantially stronger than the effect observed in the main analysis. This suggests that the contribution of exposure from the second prior year was minimal, indicating that our main analysis had already captured the predominant exposure effect within the first year. In sensitivity analysis 6, setting the exposure index in the GAMM model to the natural environment in the two years before the survey yielded results that were relatively robust. Consistently, the protective effect was decreased relative to the main analysis, which corroborated the findings from the DLNM and supported the rationality of the 1-year lag used in the main analysis. Although the associations of NDVI and EVI with FI with a lag of 2 years may be linear, significant beneficial associations

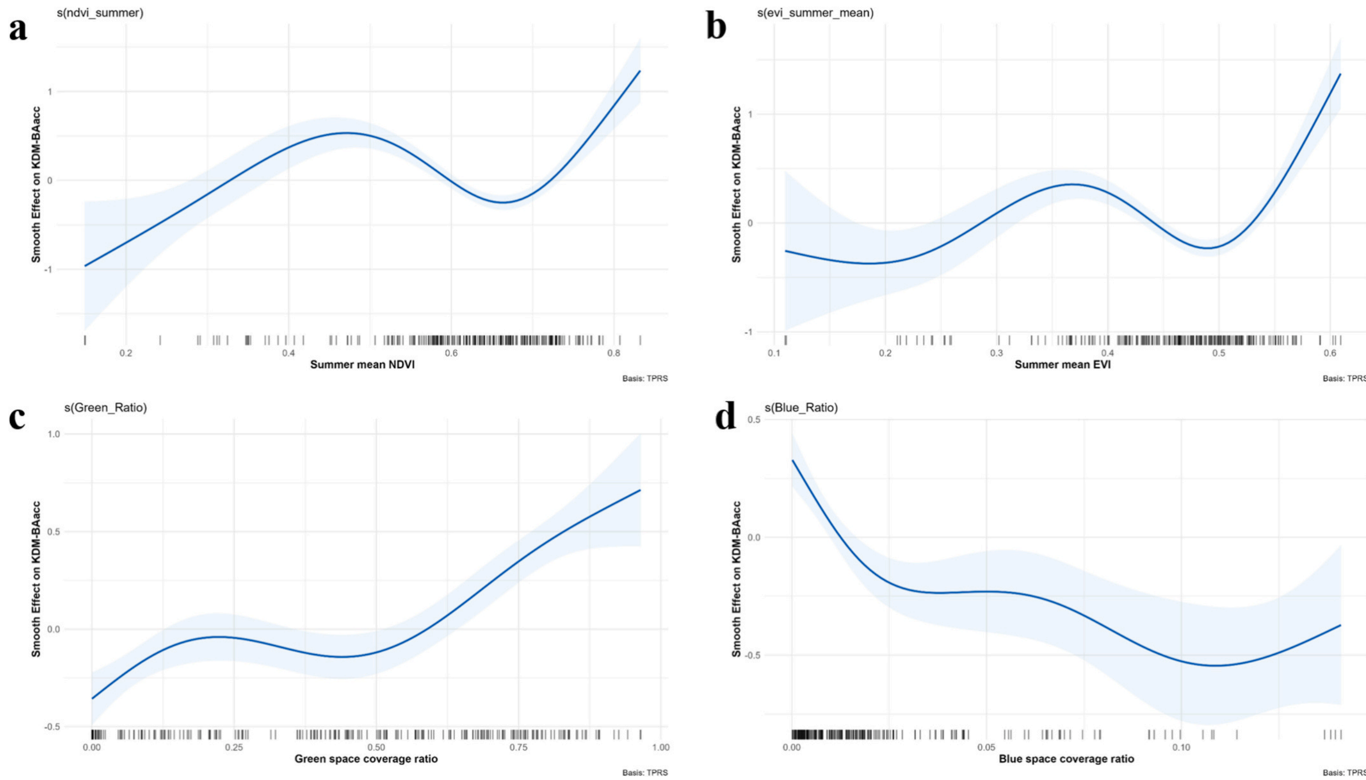

Fig. 4. Smooth effects of environmental exposures on KDM-BAacc.
Associations were modeled using thin-plate regression splines (TPRS). In each panel: the dark blue curve represents the effect of smooth term; the light blue shaded denotes its 95% confidence interval; and the short black lines along the x-axis (rug plot) show the distribution of the observed exposure data. The specific exposures shown are: (a) summer mean NDVI, (b) summer mean EVI, (c) green space coverage ratio, and (d) blue space coverage ratio. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

were still observed when NDVI exceeded 0.642, and EVI exceeded 0.465 (Supplementary Table 17, Supplementary Figs. 18 and 19). In addition, we fitted linear mixed models for variables without nonlinear associations: $\beta_{\mathrm{NDVI}} = -0.030$ (95%CI: -0.051, -0.008, $P = 0.008$) and $\beta_{\mathrm{Green\ Ratio}} = 0.003$ (95%CI: -0.005, 0.011, $P = 0.476$).

4. Discussion

This study analyzed large-scale cohort data and found that higher levels of natural environment exposure (NDVI, EVI, green space ratio, and blue space ratio) were significantly associated with lower KDM-BAacc and FI. This finding is consistent with the conclusions of previous studies. For instance, a large cohort study of middle-aged and older adults in the UK Biobank suggested a potential association between green and blue spaces and markers of aging (telomere length, the Klemera-Doubal method, and frailty) (Wang et al., 2025). Both cross-sectional and longitudinal studies have demonstrated that the greenness near the residence is associated with slowing epigenetic aging (Egorov et al., 2025; Kim et al., 2023). Our results were consistent with the above studies, and provided additional evidence regarding the optimal exposure range of the natural environment in relation to biological aging.

An important finding of this study is the nonlinear association between natural environment exposure and biological aging, and the beneficial associations of natural environment have an optimal range. This finding not only provides a new perspective on the dose-response relationship between natural environment and healthy aging but also may explain the inconsistent results in the previous linear model-based studies (He et al., 2022; Iyer et al., 2025; Lin and Wu, 2021; Wang et al., 2025; Zhu et al., 2020). For example, Zhu et al. (2020) found a weak association in rural residents, which might related to the high green environments exposure of the target population. Moreover, the average age of Zhu's research subjects was 83 years old, and our study also found that in the population over 65 years old, the natural environment has no protective effect on FI. This may suggest that middle-age may be a sensitive period for the natural environment to slow functional decline (Pescador Jimenez et al., 2024). Wang et al. also focused on the associations of green and blue spaces with aging (Wang et al., 2025). The study based on the UK Biobank, and found that urban green and blue space (UGBS) composite score within a 1000-m buffer zone of residential addresses was significantly associated with accelerated aging, and the outcome was measured in telomere length (LTL), KDM-BA, and FI. However, no significant association was observed between UGBS and KDM-BA. The inconsistency may due to the following reasons: First, Wang et al. used fine-scale measurements at the community scale, and their UGBS index integrated the proportions of green space, surrounding natural environments, home gardens and water, which made it easier to capture the complex interaction effects of blue and green space. In addition, there may be potentially complex effects of natural exposure at the local scale, such as dampness near water and garden mosquitoes (Medeiros-Sousa et al., 2015; Zhao et al., 2020), thus partially offsetting the positive contribution of green space. City-scale NDVI, EVI, and blue/green space ratios derived from remote sensing data might overlook local negative effects and highlight general ecological benefits. Consequently, the protective association may appear more pronounced. Compared with Wang's study which used KDM-BA as the outcome indicator, we used KDM-BAacc as the outcome indicator. KDM-BAacc reduced the influence of chronological age, and paid greater attention to the impact of the natural environment on the aging process.

It is worth noting that this presumption that the natural environment directly affects physical health has been supported by other studies. It has been shown that more green space, better accessibility, and higher

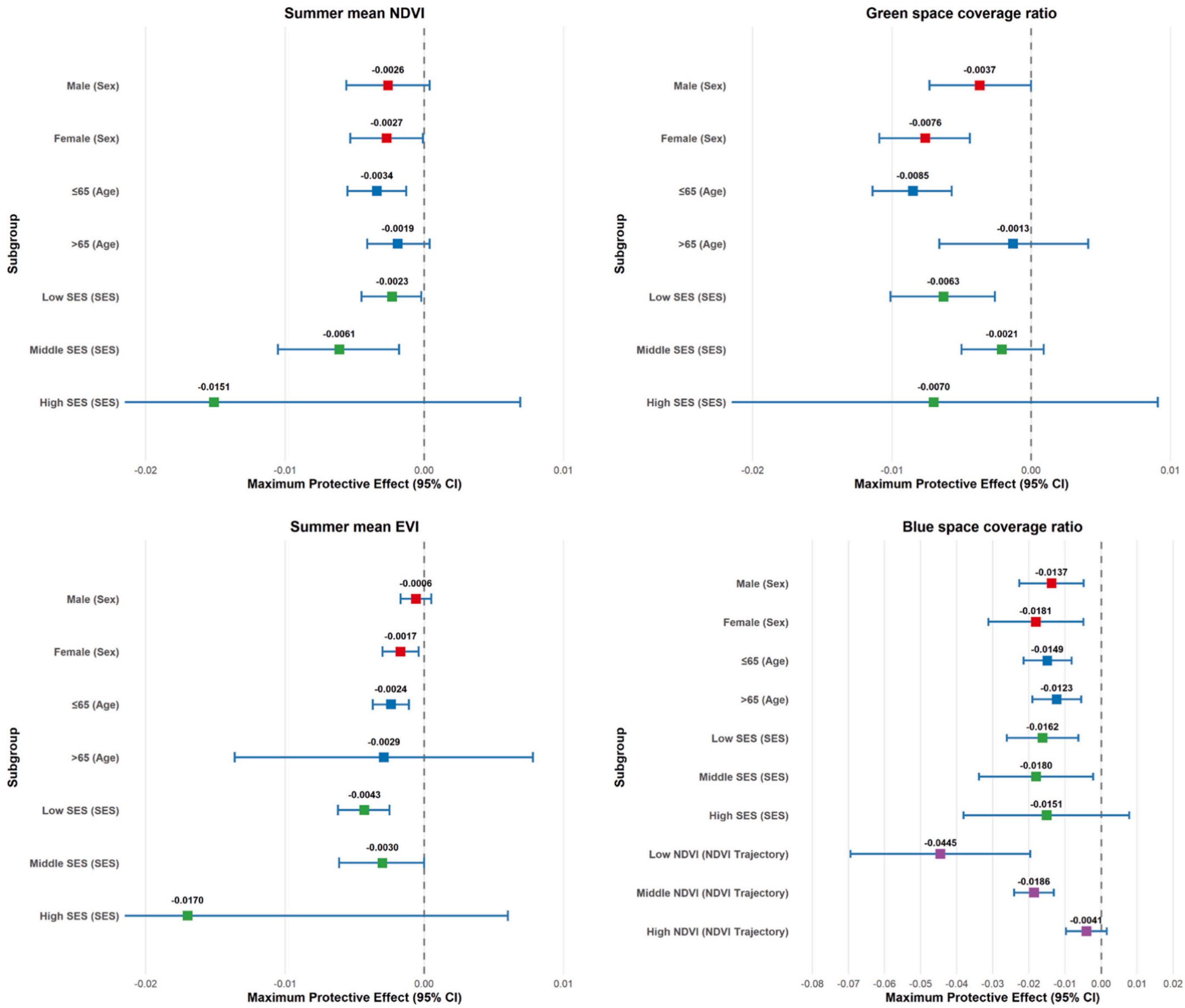

Fig. 5. Forest plots of maximum protective effects by environmental exposures on frailty index (FI).
The squares represent point estimates for each subgroup. The maximum protective effect of environmental exposure on FI: (a) summer mean NDVI, (b) green space coverage ratio, (c) summer mean EVI, and (d) blue space coverage ratio. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

vegetation quality directly promote physical health (Hong et al., 2025). The study by Hong et al. found that after controlling for individual behavior, lifestyle, socioeconomic factors, and built environment variables of green space use, the area of green space, NDVI, etc. still showed independent and statistically significant contributions to the health scores, the physical component summary (PCS) and the mental component summary (MCS). This contribution was treated as a "net effect" or "direct association" in the model. A more direct physio-psychological mechanism may not rely on the mediation of physical activity or social interaction, but rather on sensory contact (e.g., vision), attentional restoration and stress reduction (Kaplan and Kaplan, 1989; Ulrich, 1984), and immediate regulation of the microenvironment, which may not be fully measured. For example, abundant green space further enhances the microbial environment. Mycobacteria in soil and specific Gram-positive bacteria in the farming environments can directly stimulate the expansion of regulatory T cells (Tregs), enhance immune tolerance, and suppress excessive inflammation (Rook, 2013), which is one of the core mechanisms driving biological aging (Franceschi et al., 2000; Li and Ma, 2024; Zampino et al., 2020). Phytofungicides, volatile organic compounds with antibacterial properties released by trees, effectively reduce the levels of stress hormones such as cortisol by regulating the autonomic nervous system and the hypothalamic-pituitary-adrenal axis, which may explain the beneficial properties of "forest bathing" (Li et al., 2009; Tsunetsugu et al., 2010). Long-term psychological stress is another important pathway contributing to telomere shortening and accelerated epigenetic aging (Harvanek et al., 2021; Lin and Epel, 2022; Wu et al., 2024). As the CHARLS data used in this study did not measure biomarkers of specific biochemical pathways, future studies are still needed to confirm the direct biological pathways and their contributions at a finer resolution. In addition, in the study by Hong et al., park green space showed the strongest protective association even after adjustment for individual behaviors, lifestyle, socioeconomic factors, and variables related to green space utilization. This finding also suggested that the health benefits of the natural environments were not only dependent on promoting behavior change, but also had a direct impact on health.

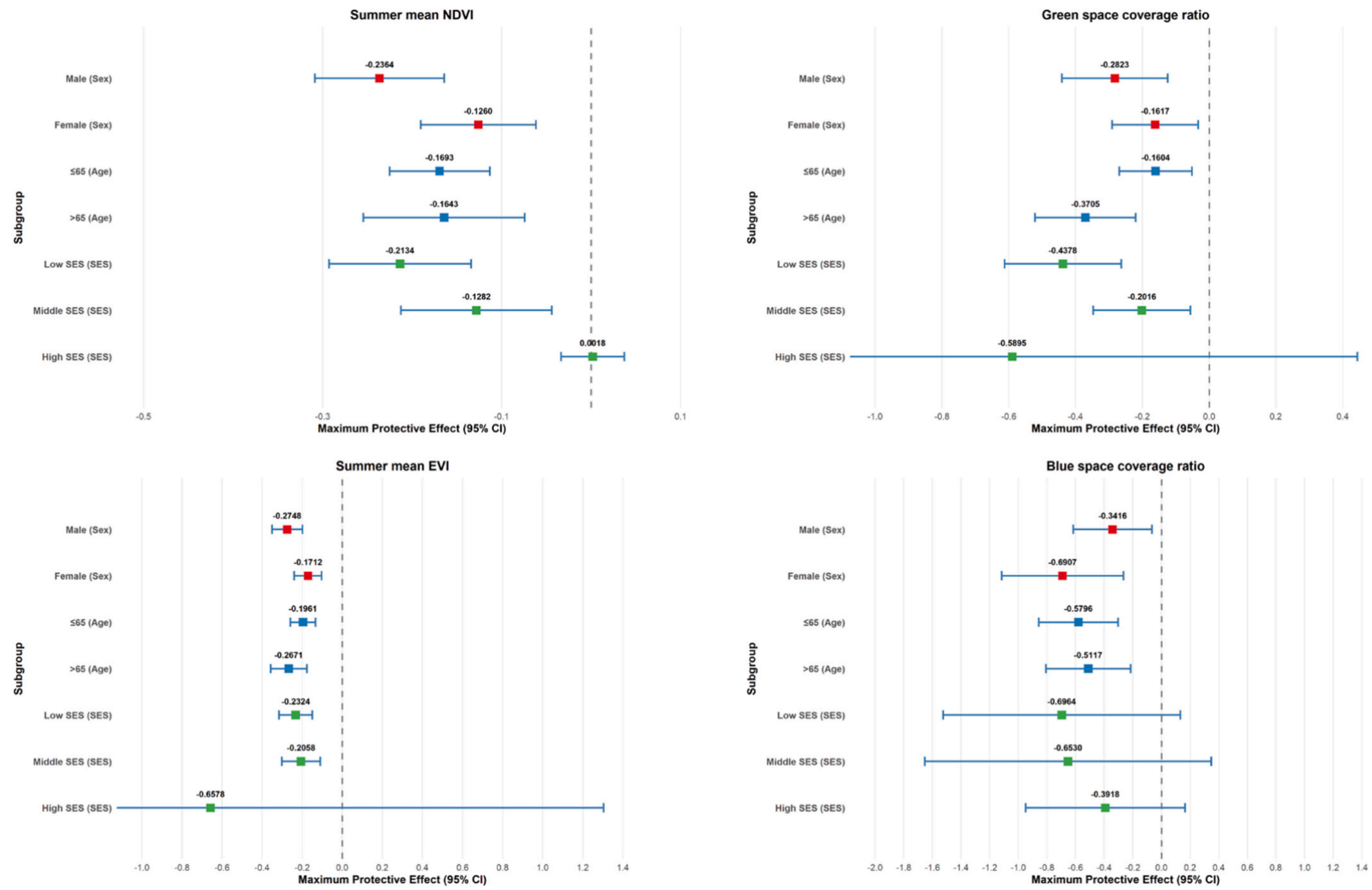

Fig. 6. Forest plots of maximum protective effects by environmental exposures on KDM-BAacc.
The squares represent point estimates for each subgroup. The maximum protective effect of environmental exposure on KDM-BAacc: (a) summer mean NDVI, (b) green space coverage ratio, (c) summer mean EVI, and (d) blue space coverage ratio. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The protective association observed in our study was more pronounced among individuals with low socioeconomic status (SES), women, and those aged 45–65, with significant public health implications. Our findings align with multinational evidence that urban and rural residents differ in the association between residential greenness and vulnerability, with individuals of lower SES tending to derive greater health benefits from greenspace exposure (Rigolon et al., 2021; Wei et al., 2023). This supports the "equigenesis hypothesis of greenspace" (Chen et al., 2024; Mitchell and Popham, 2008; Rigolon et al., 2021), which suggests that equitable provision of high-quality public natural environments to all, especially disadvantaged groups with limited resources, may partially compensate for the health disadvantages associated with low socioeconomic status, thereby reducing health disparities among populations. Additionally, we found that the association was stronger in women, consistent with studies showing that the association between green space and physical health was stronger in women than in men (He et al., 2022; Kim et al., 2023; Richardson and Mitchell, 2010; Sillman et al., 2022). However, some studies reported no gender differences (de Keijzer et al., 2019), which may be related to differences in study population, regional culture, or the type of green spaces measured. We revealed a particularly significant nonlinear association of natural environmental factors with FI among middle-aged individuals (aged 45–65). This phenomenon may stem from the uniqueness of midlife as a turning point for multiple biological processes (Ding et al., 2025; Shen et al., 2024). In contrast to the irreversible decline in old age, the plastic reserve of physiological function in midlife has not been exhausted (Lu et al., 2023). The elderly are less responsive to environmental exposure due to the decline of physiological function and chronic disease burden, which may explain why the association with FI was not significant. Nevertheless, the association with KDM-BAacc remained significant, suggesting that the natural environment may continue to modulate the pace of biological aging even when its effect on functional impairment is attenuated. In addition, the adaptive capacity and physical function of the elderly gradually decline with age, and they spend more time indoors, thereby limiting their effective exposure to outdoor blue-green spaces (Lee and Park, 2021). However, previous studies mostly focused on the elderly and ignored the unique effects of midlife (Zheng et al., 2025). Therefore, midlife may be a critical window for environmental exposures to influence the aging process. Intervention targeting the residential natural environment in one's middle age may be crucial for preventing frailty and disability in an old age. At the same time, future environmental intervention studies should pay greater attention to optimizing the indoor environment for the elderly through indoor biophilic design, such as introducing natural light, indoor plants, or natural elements.

The strengths of this study are as follows: Firstly, based on satellite remote sensing data, we used a multi-dimensional natural environment exposure assessment method, including NDVI, EVI, and green and blue space ratio. We considered both vegetation coverage and land use types to reduce the measurement error of a single index. In addition, we used the data in the peak vegetation period in summer (June to August), which improved the accuracy of exposure measurement, and took into account the lag of environmental exposure, which was more consistent with the time sequence of causal inference. Secondly, we used a combination of the clinical phenotype-based FI and the biomarker-based KDM-BAacc to represent aging. FI reflects the overall functional vulnerability and health defect state resulting from the cumulative decline of multiple physiological systems, with a focus on the clinical manifestations of aging. The KDM-BAacc estimates the deviation of biological age relative to chronological age through blood biomarkers and focuses more on revealing the rate of aging. The two factors reflect different dimensions of aging, corroborate and complement each other, thereby revealing biological aging more comprehensively. Thirdly, we applied GAMM to explore the nonlinear association, which broke through the assumption of the traditional linear model, identified the nonlinear protective effect of natural environmental exposure on biological aging in middle-aged and elderly people, and quantified the optimal exposure level and protective effect of natural environment.

Several limitations of this study should be acknowledged. First, the potential for exposure misclassification bias cannot be excluded. As detailed street-level residential addresses were unavailable, we used the city-level administrative area as the exposure assessment unit. In addition, we assumed that residents within the same administrative area had the same accessibility to and willingness to access blue and green space, which warrant further consideration in future research. Second, the exposures were measured based on satellite remote sensing data from municipal administrative units in this study. It assigned the same exposure value to all residents within the same administrative unit, which caused one of the most common sources of bias in geographic data analysis, called the modifiable areal unit problem (MAUP). On the one hand, this practice obscured the heterogeneity in the distribution of blue and green spaces and the actual accessibility of residents in the research unit. On the other hand, such macroscale assessments primarily focus on overall ecological benefits and fail to capture the complex effects in the local microenvironment. Future research should aim to analyze using finer spatial units, such as neighborhoods and streets, and try to incorporate individual-centered exposure assessment methods, such as buffer analysis, to mitigate the effects of MAUP. Third, we were unable to incorporate PhenoAge into our analysis, despite it being a widely used biological age measure derived from routine clinical biomarkers (Levine et al., 2018). PhenoAge calculation requires nine blood-based biomarkers: albumin, creatinine, glucose, C-reactive protein, lymphocyte percentage, mean cell volume, red blood cell distribution width, alkaline phosphatase, and white blood cell count, in addition to chronological age. However, several of these biomarkers, including lymphocyte percentage, red blood cell distribution width, and alkaline phosphatase, are not available in the CHARLS, rendering PhenoAge estimation infeasible in our study. By contrast, the KDM-BA approach adopted in this study requires only eight biomarkers (total cholesterol, triglycerides, glycated hemoglobin, urea, creatinine, high-sensitivity C-reactive protein, platelet count, and systolic blood pressure), all of which are measurable in CHARLS. Moreover, this reduced biomarker set has been previously validated in the Chinese population (Hu et al., 2025; Liu, 2021). Thus, while PhenoAge represents a valuable alternative for biological age estimation in other cohorts, its calculation was precluded by data availability constraints in our study. Fourth, the natural exposure was estimated based on objective geographic units rather than the actual visual or used exposure doses of individuals. Pleasant neighborhood views outside the window may be an important factor, especially among individuals with mobility problems (Finlay et al., 2015), and future public health researches should expand to explore the impact of the visual scenes accessible to the specific population on health. What is more, researches are still needed to develop a multidimensional exposure assessment system that integrates geographic information, residents' behavioral habits, and subjective feelings to accurately quantify the actual exposure dose. Fifth, as an observational study, unmeasured confounders such as genetic factors, early life experiences, and other environmental pollutants cannot be completely excluded. And the possibility of complex bidirectional causality affecting the results. Finally, participants were limited to middle-aged and elderly Chinese, the conclusions may not generalize to people in other countries or regions.

5. Conclusion

Utilizing longitudinal data from CHARLS, we found a nonlinear association between residential blue-green space exposure and biological aging in middle-aged and elderly people. Natural environmental factors showed protective associations with biological aging indicators within the beneficial exposure level. In particular, the protective association of the natural environment on biological aging was more pronounced among people with low socioeconomic status, women. Optimizing the allocation of urban green and blue spaces may serve as an inclusive public health intervention strategy, especially to support healthy biological aging among vulnerable groups, which may contribute to promoting health equity.

Abbreviations

ADL	activities of daily living
BMI	body mass index
CHNS	China Health and Nutrition Survey
CHARLS	China Health and Retirement Longitudinal Study
CI	confidence interval
DLNM	distributed lag nonlinear model
DTW	dynamic time warping
EVI	Enhanced Vegetation Index
FI	frailty index
GAMM	generalized additive mixed model
HbA1c	Glycated hemoglobin
hs-CRP	high-sensitivity C-reactive protein
IADL	instrumental activities of daily living
KDM	Klemera-Doubal method
KDM BAacc	Klemera-Doubal method biological age acceleration
LMIC	low- and middle-income countries
MAUP	modifiable areal unit problem
NDVI	normalized difference vegetation index
PLT	platelet count
RBC	red blood cell count
SBP	systolic blood pressure
SES	socioeconomic status
TC	total cholesterol
TG	triglyceride
UGBS	urban blue-green space
WHO	World Health Organization

CRediT authorship contribution statement

Yanan Sun: Writing – original draft, Visualization, Software, Formal analysis. **Boyu Qiao:** Writing – review & editing, Validation, Conceptualization. **Xue Meng:** Writing – review & editing, Supervision, Software. **Mohan Wang:** Writing – review & editing, Software. **Han Zhang:** Writing – review & editing, Supervision. **Zhengfang Wang:** Writing – review & editing, Supervision. **Shengzhi Sun:** Supervision, Software, Methodology. **Deqiang Zheng:** Supervision, Software, Methodology. **Yuxiang Yan:** Supervision, Methodology. **Lijuan Wu:** Supervision, Methodology. **Yinan Zhao:** Visualization, Supervision, Software. **Wenhui Dong:** Writing – review & editing, Supervision. **Kuo Liu:** Writing – review & editing, Validation, Supervision, Conceptualization.

Consent for publication

Not applicable.

Ethics approval and consent to participate

CHARLS was ethically approved by the Institutional Review Board at Peking University (IRB00001052-11015).

Funding

This work was supported by the National Natural Science Foundation of China [grant numbers 82273756].

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.

Acknowledgements

We would like to express our sincere gratitude to the China Health and Retirement Longitudinal Study (CHARLS) team for providing the cohort data utilized in this research. We are also grateful to the National Tibetan Plateau/Third Pole Environment Data Center (http://data.tpdc.ac.cn), the National Earth System Science Data Center (https://www.geodata.cn), and the China's Land-Use/Cover Datasets for data support to the NDVI, EVI, and land cover, respectively.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.exger.2026.113283.

Data availability

Data will be made available on request.

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