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Research Article

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Posted Date: September 8th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10829852/v1>

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Additional Declarations: No competing interests reported.

Geology-driven health suitability assessment using game theory-based combined weighting: a case study of Yongjia County, southeastern China

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Abstract: Geological Environmental Suitability Assessment (GESA) is shifting from single-medium assessments to multi-medium assessments. However, there is currently no unified and feasible model applicable to GESA in different regions. Focusing on Yongjia County, a region renowned for longevity, we develop a multi-medium suitability assessment framework spanning topography-vegetation, air, hydrology, and soil geochemistry. A game theory-based combined weighting (GTCW) method reconciles expert and data-driven weights, with performance validated through frequency ratio (FR) analyses. The GTCW method substantially outperformed single-weighting method: FR peaked at 6.05 and 1.85 in the top two suitability classes, capturing 85% of centenarian villages within 28% of the county area. Suitability follows a pronounced valley–highland gradient: high- and moderate-suitability zones occupy the Nanxi River alluvial–terrace belt, whereas lower-suitability zones dominate the rugged uplands and localized soil-metal anomaly pockets. Sensitivity analysis reveals a dual-driver hierarchy: environmental media such as water, soil and air are the primary determinants of habitability (cumulative contribution of 69.41%), while slope and aspect modulate fine-resolution heterogeneity through topographic filtering. The results of the FR validation indicate that the GESA framework using the GTCW method has practical application value in this region. The identification of the dual-driver hierarchy provides a basis for effectively mitigating geochemical exposure risks and for health-oriented land-use planning.

Keywords: Geological Environmental Suitability Assessment; Game theory-based combined weighting; Longevity Regions; Validation; Sensitivity analysis

1. INTRODUCTION

The geological environment forms the material basis for human survival and development; its elemental geochemical characteristics and topography configuration have a profound impact on regional population health and life expectancy patterns. A large body of research indicates that natural variations in the geological environment are the primary determinants of geographical disparities in human health outcomes (Selinus et al., 2013). This linkage is exemplified by the divergent spatial signatures of geogenically driven disease burdens versus longevity clusters. Endemic disorders display strong spatial fidelity to discrete geochemical provinces: Keshan disease is largely confined to a low-selenium belt extending from northeastern to central China (Tan et al., 2002; The Group of Environment and Endemic Disease, 1981), while Kaschin–Beck disease is predominantly endemic to selenium- and iodine-deficient plateau settings in Qinghai and Tibet (Moreno-Reyes, 2001; Zhang et al., 2011). Similarly, chronic fluorosis and arsenicism are closely tied to hydrogeochemical anomalies—exemplified by high-fluoride groundwaters in arid inland basins (e.g., the Datong Basin) (Guo et al., 2005; He et al., 2021) and by high-arsenic aquifers in the Bengal Basin, a globally recognized hotspot (Smedley and Kinniburgh, 2002). In contrast, world-renowned longevity regions, such as Bama (Guangxi) and Hotan (Xinjiang), owe their salubrious reputations to pristine air, clean water, and soils enriched with beneficial trace elements (Cai et al., 2021; Tang et al., 2025).

As an emerging interdisciplinary frontier integrating Earth sciences, environmental science, and public health, GeoHealth emphasizes the "double-edged sword" effect of the geological environment—acting both as a source of potential health hazards and as a vital provider of essential nutrients for sustaining life (Selinus et al., 2013; Finkelman, 2020). Contemporary research is increasingly focused on identifying and harnessing these positive health benefits, catalyzing a paradigm shift from unilateral risk mitigation toward a dual-objective framework that integrates risk control with health promotion (Finkelman, 2025).

However, no universally accepted theoretical framework or technical standards have yet been established for geological environmental suitability assessment (GESA). Current risk assessment practices are largely rooted in the site-specific health risk assessment paradigm originally developed for contaminated land, which primarily evaluates the potential health impacts of discrete chemical agents in air, soil, or water (USEPA, 1989, 2011). Although methodologically well-structured, this approach is inherently constrained to contaminated site contexts and typically addresses only a single environmental medium, making it inadequate for capturing the systemic complexity of geological environments or their

combined effects on human health. In recent years, the widespread adoption of the ‘One Health’ concept has catalyzed a paradigm shift in health geology research—moving from single-factor, single-medium assessments towards integrated, multi-factor, multi-medium coupled evaluation frameworks (Wang, 2020; Wen et al., 2025). Against this backdrop, numerous scholars have attempted to develop multi-dimensional evaluation systems for the suitability of the geological environment for human health. Recent research developments have gradually expanded the scope of Earth health assessment frameworks: from frameworks centred on land function, rock mass stability and air quality (Ju et al., 2020), to the Geological Health Index (GHI), which integrates climatic, geological, geochemical and anthropogenic factors (Jiao et al., 2021), and further to county-level applications combining multi-criteria weighting with GIS overlay techniques (Li et al., 2023).

Despite these studies having substantially broadened the scope of GESA, several deficiencies persist in the construction of a systematic and comprehensive assessment paradigm: (i) Evaluation systems largely adhere to environmental quality assessment frameworks, emphasizing "negative risk" indicators such as soil heavy metal contamination and water quality exceedances, while inadequately addressing the positive health values of the geological environment; (ii) Weighting methods are predominantly based on the AHP, which relies excessively on expert judgment and is susceptible to subjective cognitive biases; (iii) There is a lack of targeted spatial validation mechanisms—most models, once constructed, have not employed independent samples to verify the goodness-of-fit between assessment results and actual population health distributions (e.g., longevity areas, endemic disease regions), thereby casting doubt on model applicability and scientific robustness.

In view of these gaps, this study selects Yongjia County, Zhejiang Province, as the research area and constructs a four-dimensional GESA framework encompassing topography–vegetation, air quality, hydrology conditions, and soil geochemistry characteristics. A GTCW method is introduced to balance subjective and objective weight deviations, and the FR model is integrated for spatial validation. The findings aim to elucidate the driving mechanisms of health-geological suitability in longevous regions, thereby providing a scientific basis for regional wellness industry planning, distinctive agricultural land development, territorial spatial optimization, and resident health risk management.

2. STUDY AREA

Yongjia County (27°58′40″–28°36′54″N, 120°19′34″–120°59′19″E) is located in southeastern

Zhejiang Province, along the northern bank of the lower Ou River, covering a total area of approximately 2,677 km². The terrain is predominantly mountainous and hilly, descending in elevation from the northwest to the southeast. Shaped by the Kuacang and northern Yandang mountain ranges, the county exhibits a classic landscape pattern consisting of “80% mountains, 10% water, and 10% arable land” (Fig. 1).

The region experiences a subtropical monsoon climate, with mean annual temperatures ranging from 18.2 to 18.5 °C and mean annual precipitation of 1,718–1,743 mm, the bulk of which falls during the rainy season from May to September. Drainage is well developed, and the Nanxi River serves as the principal watercourse. Originating from Daqinggang in the northwest, this river has a main stem length of approximately 140 km and drains an area of 2,490 km², flowing southwards across the entire county before debouching into the Ou River.

Geologically, the area is structurally complex and underlain by widespread Jurassic–Cretaceous intermediate to felsic volcanic and intrusive rocks. Prolonged weathering and leaching under the humid subtropical climate have given rise to a soil system dominated by acidic red soils. This distinctive rock–soil geochemical framework not only underpins the regional biogeochemical cycles but also critically influences the population’s trace element exposure and homeostatic regulation, primarily through the soil–water–crop pathway.

Yongjia County, as the first “Longevity Township” in Zhejiang Province, has drawn growing research interest regarding the potential influence of its unique geological and geochemical environment on the longevity of its residents. As of 2024, the county was home to 113 centenarians distributed across 100 villages (Fig. 1). Preliminary baseline surveys conducted by the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (IGSNRR, CAS)—including regional environmental geochemical mapping and non-invasive hair sampling—have provided the empirical groundwork for investigating these geo-health associations. Human scalp hair serves as a reliable biological matrix for assessing systemic trace element status, as it integrates nutritional and internal exposure information over a retrospective window of several months (Xing et al., 2017; Wang et al., 2009).

Elemental analysis of hair samples from centenarians in Yongjia revealed significantly higher levels of essential trace elements (particularly selenium, zinc and manganese) than the reference values for long-lived populations in China. By contrast, the burden of toxic metals (lead and cadmium) was

exceptionally low (IGSNRR, CAS, 2017; Hao et al., 2016; Li et al., 2011). This characteristic of benign elemental homeostasis within the body provides strong biogeochemical evidence for the link between the regional geological context and populations with high life expectancy.

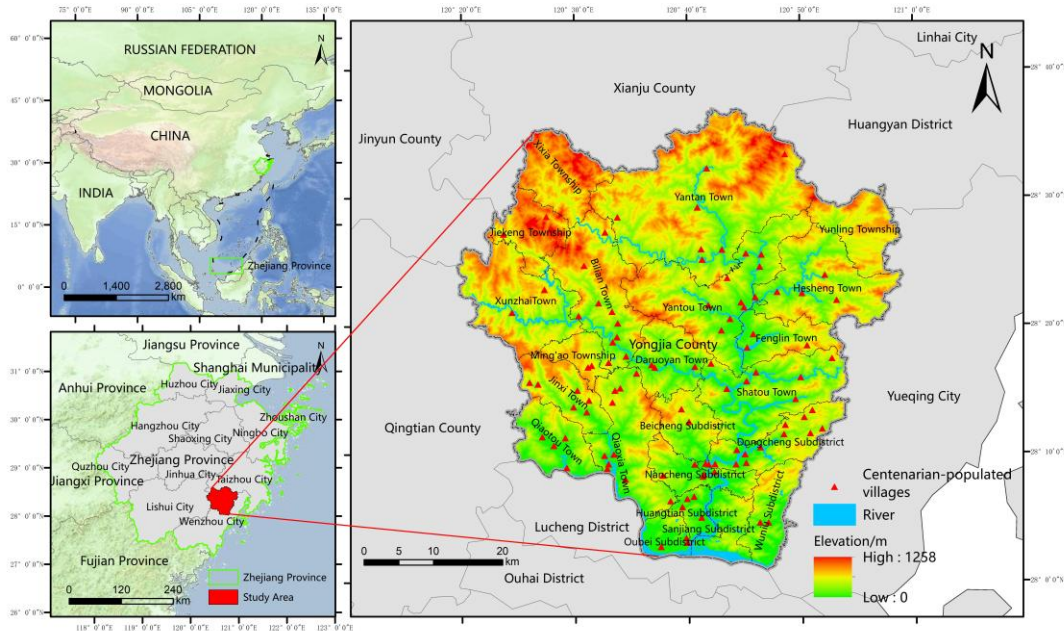


Fig 1 Study area and location

3. MATERIALS AND METHODS

3.1 Construction of the Assessment Framework

GESA is a comprehensive framework designed to quantify the capacity of regional geological environments to support human health. GESA goes beyond the scope of traditional environmental quality assessments by adopting an integrated modelling strategy that takes into account both risk exposure and health promotion. The selection of indicators adheres to the principles of health relevance, representativeness and data feasibility. In addition to general indicators such as altitude, slope, drinking water quality and ambient air quality, the framework explicitly incorporates region-specific health-promoting factors, such as beneficial elements in the soil and high concentrations of NAIs. The resulting framework comprises 11 indicators (Table 1), which not only enhance explanatory power but also improve sensitivity to the region's unique health-promoting geological characteristics.

3.1.1 Topography and vegetation

Five indicators were selected: elevation, slope, aspect, topographic relief, and vegetation cover. Elevation shapes human physiology primarily through reductions in barometric pressure and oxygen

availability; sustained residence at high altitude has been associated with accelerated biological ageing and elevated susceptibility to neuropsychiatric disorders (Wu et al., 2025). Steeper slopes and greater topographic relief impose persistent biomechanical stress on the spine, explaining the higher prevalence of lumbar degeneration observed in rugged terrain (Modgil et al., 2025). Slope aspect further regulates solar exposure: north-facing slopes intercept less direct radiation, a pattern linked to suboptimal vitamin D synthesis, increased osteoporosis risk, and circadian disruption mediated by altered melatonin secretion (Wacker & Holick, 2013; Rosenthal et al., 1984). Vegetation cover, used here as a proxy for bundled ecosystem services, reduces respiratory morbidity through particulate removal (James et al., 2015) and delivers ancillary health benefits—bolstered immunity and improved psychological well-being—via phytoncide emissions and access to outdoor recreation (Li et al., 2008; Markevych et al., 2017).

3.1.2 Air quality

Air quality was evaluated using PM_{2.5} and NAIs concentrations, representing adverse and salutogenic dimensions, respectively. Chronic PM_{2.5} exposure drives excess cardiopulmonary and all-cause mortality (Chen et al., 2020; Xia et al., 2026), while higher NAIs levels are associated with improved respiratory regulation, autonomic nervous system modulation, and mood states (Xiao et al., 2023; Perez & Alexander, 2013).

3.1.3 Hydrology conditions

Two water-related indicators were included: drinking water quality and proximity to rivers. Drinking water quality reflects a primary exposure pathway for waterborne pathogens and geochemical contaminants, directly shaping gastrointestinal and metabolic health (Li et al., 2026). River proximity, by contrast, serves as a proxy for the multidimensional benefits of blue spaces: a moderate distance secures domestic water access while supporting evaporative cooling, stabilising local microclimates, and alleviating respiratory dryness and heat stress (White et al., 2020).

3.1.4 Soil geochemistry characteristics

Soil indicators were grouped into two functional classes—potentially toxic heavy metals and beneficial elements—to disentangle food-chain hazard pathways from nutritional contributions. Heavy metals such as cadmium (Cd), arsenic (As) and lead (Pb) are recognised as priority pollutants whose chronic toxicity manifests across renal, carcinogenic, and neurological endpoints (Tchounwou et al., 2012). Among beneficial elements, Mn and Se were selected on two grounds: their concentrations

departed markedly from local geochemical baselines, and both underpin antioxidant defence and enzymatic homeostasis (Combs, 2001; Aschner & Aschner, 2005). Other candidate elements showing no consistent spatial enrichment against regional baselines were excluded from the indicator set.

3.2 Standardization of Assessment Indicators

Indicator standardisation is essential for cross-regional comparability in suitability assessments. We adopted an interval-based ordinal scoring scheme to rescale all variables onto a common 1–5 continuum. Guided by applicable environmental and industry standards, each continuous indicator was binned into five ordinal classes and scored from 5 (most favourable) to 1 (least favourable). This procedure fulfils two functions: it expresses heterogeneous indicators on a unified numeric basis, and it eliminates scale bias caused by incommensurable units in the composite evaluation.

1. Scoring for sub-dimension with a single indicator

For dimensions represented by a single indicator, scores were assigned directly from that variable's own classification rule (Table 1). Elevation was split into five tiers aligned with altitudinal decline in atmospheric O₂ partial pressure—<500 m, 500–1500 m, 1500–2500 m, 2500–3500 m, >3500 m. Topographic relief was binned by relative height into five geomorphic classes : <20 m (plain), 20–200 m (hill), 200–500 m (low mountain), 500–1000 m (medium mountain), >1000 m (high mountain). Slope gradient followed the Technical Regulations for the Third National Land Survey (TD/T 1055–2019), using <2°, 2–6°, 6–15°, 15–25°, >25°. Aspect was grouped by octant azimuth and ranked by solar access (north hemisphere convention) from most to least favourable: S/flat ground, SE/SW, E/W, NE/NW, N,. NDVI was divided into five equal-width intervals (0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, 0.8–1.0). PM_{2.5} was classified per GB 3095–2012 into 0–35, 36–75, 76–115, 116–150, >150 µg/m³, mapping onto the five AQI grades. NAI followed QX/T 380–2017: >2100, 1200–2100, 500–1200, 100–500, <100 ions cm⁻³. River distance used five buffers (<200, 200–500, 500–1000, 1000–2000, >2000 m) after Wang et al. (2024).

Table 1 Grading and Scoring of Indicators for GeoHealth Suitability Assessment

Criterion Layer	Indicator Layer	Evaluation Condition	Grading and Scoring				
			Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
			5	4	3	2	1
Topography and vegetation	Elevation	Elevation (m)	0~500	500~1500	1500~2500	2500~3500	>3500
	Topographic Relief	Topographic Relief (m)	0-20	20-200	200-500	500-1000	>1000
	Slope	Slope (°)	0-2	2-6	6-15	15-25	>25
	Aspect	Aspect	Flat, South	Southeast, Southwest	East, West	Northeast, Northwest	North
	Vegetation Cover	NDVI	0.8~1.0	0.6~0.8	0.4~0.6	0.2~0.4	0~0.2
Air quality	Air Quality	PM _{2.5} Concentration (µg/m ³)	0~35	36~75	76~115	116~150	>150
	Negative air ions (NAIs)	NAIs concentration (ind./cm ³)	>2100	1200~2100	500~1200	100~500	<100
Hydrology conditions	Drinking Water Quality	Cd, Hg, Pb, Cu, F, N, Se, Cr, Zn, etc.	Clean	Slight Pollution	Light Pollution	Moderate Pollution	Severe Pollution
	Proximity to River	Distance (m)	<200	200~500	500~1000	1000~2000	>2000
Soil geochemistry characteristics	Soil Heavy Metal Elements	As, Cr, Cd, Pb, Hg, Cu, Zn, Ni	Clean	Slight Pollution	Light Pollution	Moderate Pollution	Severe Pollution
	Soil Beneficial Elements	Se and Mn, other element contents	High	Moderate	Marginal	Deficient	Excessive

2. Scoring for sub-dimensions with multiple indicators

When a sub-dimension contained multiple evaluation indicators, the composite score for that dimension was determined through the following calculation protocols:

(i) Soil Heavy Metal Pollution and Drinking Water Quality

A single-factor pollution index was computed for each constituent:

$$P_i = C_i / S_i \quad (1)$$

where C_i is the measured concentration of pollutant i , and S_i is the corresponding regulatory threshold (soil: GB 15618–2018; drinking water: GB 5749–2022). Each P_i was then mapped to an ordinal score (5–1) using the breakpoints in Table 2. The sub-dimension score followed a critical limiting factor rule: the worst ordinal score among all constituents was adopted as the sub-dimension score.

Table 2 Pollution Grade Classification Based on Single-Factor Evaluation

Grade	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Range of P_i values	$P_i \leq 1$	$1 < P_i \leq 2$	$2 < P_i \leq 3$	$3 < P_i \leq 5$	$P_i \geq 5$
Pollution degree	Clean	Slight Pollution	Light Pollution	Moderate Pollution	Severe Pollution

(ii) Soil Beneficial Elements

According to DZ/T 0295–2016, soil Mn and Se concentrations were first classified into graded abundance tiers (Table 3) and converted to 5–1 scores. A weighted average of the two element scores yielded the beneficial-element sub-score; weights were set to 0.5 each unless regional sensitivity analysis suggested otherwise

Table 3 Classification of soil selenium and manganese abundances (Unit: mg/kg)

Grade	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Elemental Abundance	High	Adequate	Marginal	Deficient	Excessive
Se	0.4-3.0	0.175-0.4	0.125-0.175	≤ 0.125	> 3.0
Mn	600-1500	500-600	375-500	≤ 375	> 1500

3.3 Game Theory-Based Combined Weighting Method

To reconcile expert judgement with data-driven signal, we adopted a GTCW method. Subjective weights were obtained by analytic hierarchy process (AHP). A three-tier hierarchy—objective, criterion, indicator—was constructed; expert pairwise comparisons formed the judgment matrices, whose principal eigenvectors gave initial weights. Consistency was accepted when $CR < 0.10$. Objective weights used

the independence weight coefficient (IWC) method, in which an indicator's weight is inversely related to its total absolute correlation with the remaining indicators, thereby down-weighting redundant variables. The correlation structure for IWC was estimated from a random subset of 66 out of 100 centenarian-inhabited villages in the study area, treated as a reference cohort representing favourable health-geology conditions. Finally, the AHP and IWC weight vectors were embedded in a game-theoretic framework and reconciled at the Nash equilibrium that minimises their divergence, yielding the combined weights. The procedure is as follows.

1. Construction of the Basic Weight Vector Set

Assume there are m evaluation indicators and k weighting methods ($k \geq 2$). Each method j yields a weight vector $w^{(j)} = (w_1^{(j)}, w_2^{(j)}, \dots, w_m^{(j)})^T$, satisfying $\sum_{i=1}^m w_i^{(j)} = 1$. These vectors are compiled into a matrix W , where rows represent indicators and columns represent different methods:

$$W = \begin{bmatrix} w_1^{(1)} & w_1^{(2)} & \dots & w_1^{(k)} \\ w_2^{(1)} & w_2^{(2)} & \dots & w_2^{(k)} \\ \vdots & \vdots & \ddots & \vdots \\ w_m^{(1)} & w_m^{(2)} & \dots & w_m^{(k)} \end{bmatrix} \quad (2)$$

2. Construction of the Coefficient Matrix A and Right-hand Vector B

Define the coefficient matrix $A = (a_{ij})_{k \times k}$, where a_{ij} is the inner product of the i -th and j -th weight vectors:

$$a_{ij} = w^{(i)T} w^{(j)} = \sum_{t=1}^m w_t^{(i)} w_t^{(j)} \quad (3)$$

Define the right-hand vector $B = (b_1, b_2, \dots, b_k)^T$, where b_i is the self-inner product of the i -th weight vector:

$$b_i = w^{(i)T} w^{(i)} = \sum_{t=1}^m (w_t^{(i)})^2 \quad (4)$$

3. Solving the System of Linear Equations

Establish the linear system:

$$A\alpha = B \quad (5)$$

Where $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_k)^T$ is the vector of unknown combination coefficients. Solve this system (using a generalized inverse if A is singular) to obtain the initial combination coefficients.

4. Coefficient Processing and Normalization

To ensure the non-negativity of the combined weights, take the absolute value of the initial coefficients:

$$\alpha_i^{abs} = |\alpha_i|, \quad i = 1, 2, \dots, k \quad (6)$$

Normalize these absolute values to obtain the final combination coefficients:

$$\alpha_i^* = \frac{\alpha_i^{abs}}{\sum_{j=1}^k \alpha_j^{abs}}, \quad i = 1, 2, \dots, k \quad (7)$$

5. Calculation of Comprehensive Weights

Compute the weighted sum of the original weight vectors using the combination coefficients:

$$w^{comb} = \sum_{i=1}^k \alpha_i^* w^{(i)} \quad (8)$$

Finally, normalize the comprehensive weights to ensure they sum to unity:

$$w_i^{final} = \frac{w_i^{comb}}{\sum_{j=1}^m w_j^{comb}}, \quad i = 1, 2, \dots, m \quad (9)$$

3.4 Geological Environmental Suitability Assessment and Zonation

The formula for calculating the GESA score is as follows:

$$S = \sum_{i=1}^n W_i D_i \quad (10)$$

where S is the integrated suitability score, n is the number of indicators, W_i is the combined weight of indicator i , and D_i is its standardised score (range 1–5).

Based on Eq. (10), a suitability value was generated for each sampling unit. Scores were then classified into five ordinal zones using the Jenks natural breaks optimisation method in ArcGIS, balancing statistical homogeneity with cartographic interpretability: Highly suitable, Moderately suitable, Marginally suitable, Less suitable, and Unsuitable.

3.5 Model Validation Methods

The FR is a bivariate spatial statistic quantifying the association between a categorical environmental factor and a set of point occurrences. Here, FR was used to test the spatial correspondence between GESA suitability zones and centenarian-inhabited villages. For a given zone, FR expresses how many times more (or fewer) centenarian villages occur there than would be expected by chance:

$$FR_i = (N_i/N_t)/(S_i/S_t) \quad (11)$$

where N_i and N_t are the number of validation villages in zone i and the total validation set size, respectively, and S_i and S_t are the corresponding zone area and total study area. An $FR > 1$ indicates over-representation; $FR < 1$ implies under-representation. In a robust GESA zonation, FR should rise monotonically with suitability grade, peaking in the Highly Suitable zone—evidence that higher model scores align with actual longevity settlement patterns.

The 100 centenarian-inhabited villages were split into a training subset ($n=66$) for IWC weight calibration and an independent validation subset ($n=34$). FR values were calculated exclusively from

the latter. A clear monotonic increase, especially a pronounced FR peak in the Highly Suitable zone, would substantiate the external validity of the GESA framework.

3.6 Sensitivity Analysis Methods

Although grounded in a unified evaluation framework, GESA outcomes commonly display marked spatial heterogeneity, reflecting region-specific shifts in the relative importance of driving factors. For example, pristine water environments can render water quality a dominant positive driver, whereas areas with elevated geogenic backgrounds may be constrained primarily by heavy metal risks (e.g., As, Cd). This underscores the need for context-sensitive sensitivity analyses tailored to local geological settings and typical exposure profiles, so as to pinpoint dominant constraints and inform differentiated health-management strategies.

Sensitivity was examined using the effective weight method. The effective weight quantifies an indicator's percentage contribution to the composite suitability score for a given region, calculated as the ratio of its weighted input to the total score:

$$W = (P_r \times P_w / S) \times 100\% \quad (12)$$

Where W represents the effective weight of a specific indicator; P_r denotes the standardized score of the indicator; P_w denotes the weight of the indicator; and S represents the comprehensive GESA score of the region.

3.7 Data Sources and Processing

Primary datasets were compiled from national geographic information repositories and authoritative survey reports. The Digital Elevation Model (DEM) was obtained from the Geospatial Data Cloud, while NDVI data were derived from NASA's MOD13A3 product. PM_{2.5} concentration, NAIs concentration, and drinking water quality records were extracted from the Survey and Assessment of Longevity Environments in Yongjia County (IGSNRR, CAS, 2017). Soil geochemical data were sourced from the Land Quality Geochemical Survey of Yongjia County (The 11th Geological Brigade of Zhejiang Province, 2020), and hydrographic vector data were acquired from the Resource and Environment Science Data Center, CAS.

All preprocessing and spatial analyses were performed using ArcGIS 10.8 (ESRI, Redlands, CA, USA). To ensure spatial consistency, all raster layers were reprojected to the CGCS2000 Gauss–Krüger 3° zone 40 (central meridian 120°E) and resampled to a uniform spatial resolution of 30 m. For point-based observations—including PM_{2.5}, NAIs, drinking water analytes, and soil geochemical elements—

spatial interpolation was conducted using inverse distance weighting (IDW) to generate continuous raster surfaces. To quantify river proximity, the Euclidean distance from each raster cell to the nearest river feature was calculated, producing a distance raster layer.

4. RESULTS

4.1 Determination of Indicator Weights

To reconcile expert judgement with the intrinsic structure of the data, combined weights were derived via a GTCW method integrating AHP subjective weights and IWC objective weights (Table 4). Final weights ranged from 0.0488 (elevation) to 0.1543 (drinking water quality).

The integration tempers pronounced mismatches between methodological perspectives. Drinking water quality received a high subjective weight (0.1680), reflecting its recognised health relevance, but a lower objective weight (0.1068) owing to limited spatial dispersion locally; GTCW returned a moderated value of 0.1543. Aspect showed the opposite pattern—an inflated objective weight (0.1416) versus a low subjective rating (0.0510)—largely because fine-scale topographic variability exaggerates statistical independence despite a comparatively weak mechanistic link to longevity. The integrated framework pulled the aspect weight down to 0.0713, thereby retaining expert-informed interpretability while avoiding dominance by purely variance-driven signals.

Table 4 Indicator weights derived from different weighting methods

Criterion Layer	Indicator Layer	AHP	IWC	GTCW
Topography and vegetation	Elevation	0.0450	0.0619	0.0488
	Topographic Relief	0.0660	0.0685	0.0666
	Slope	0.0870	0.0971	0.0893
	Aspect	0.0510	0.1416	0.0713
Air quality	Vegetation Cover	0.0510	0.0658	0.0543
	Air Quality	0.1200	0.1129	0.1184
	negative air ions (NAIs)	0.0800	0.1074	0.0861
	Drinking Water Quality	0.1680	0.1068	0.1543
Hydrology conditions	Proximity to River	0.0820	0.0661	0.0784
Soil geochemistry characteristics	Soil Heavy Metal Elements	0.1500	0.0927	0.1372
	Soil Beneficial Elements	0.1000	0.0792	0.0953

4.2 Zoning of suitability assessment

Integrated GESA scores across Yongjia County ranged from 2.97 to 4.83, with pronounced spatial clustering rather than random scatter (Fig. 2). Applying Jenks natural breaks to the continuous suitability surface, we partitioned the landscape into five ordinal zones—Highly Suitable, Moderately Suitable, Marginally Suitable, Less Suitable, and Unsuitable—which are mapped in Fig. 2b.

The Highly Suitable zone (208 km², 7.7%) occurs mainly as narrow belts along the middle–lower reaches of the Nanxi River (e.g., Shatou and Fenglin towns), flanked by the Moderately Suitable zone (552 km², 20.6%). Together, these two top-tier zones account for 28.3% of the county and coincide with fluvial terraces, gentle slopes, high water quality, and strong ecosystem service provision—conditions interpreted as optimal for long-term habitation.

The Marginally Suitable zone dominates the central–eastern sector (798 km², 29.8%). The remaining areas are split between the Less Suitable (753 km², 28.1%) and Unsuitable (366 km², 13.7%) zones, which are concentrated in the western low-mountain hills, the northern high-elevation tracts (e.g., Xunzhai, Jiekeng towns), and the peri-urban industrial corridors (e.g., Jinxi, Qiaotou, Qiaoxia towns).

Notably, the drivers of unsuitability are not uniform. The western and northern margins retain high vegetation cover but are limited by steep terrain; in contrast, the valley-floor pockets are constrained by soil heavy-metal enrichment or degraded drinking-water quality. This duality reveals that ecological intactness does not guarantee habitation suitability—rather, suitability emerges from the joint influence of terrain constraints and elemental environmental quality.

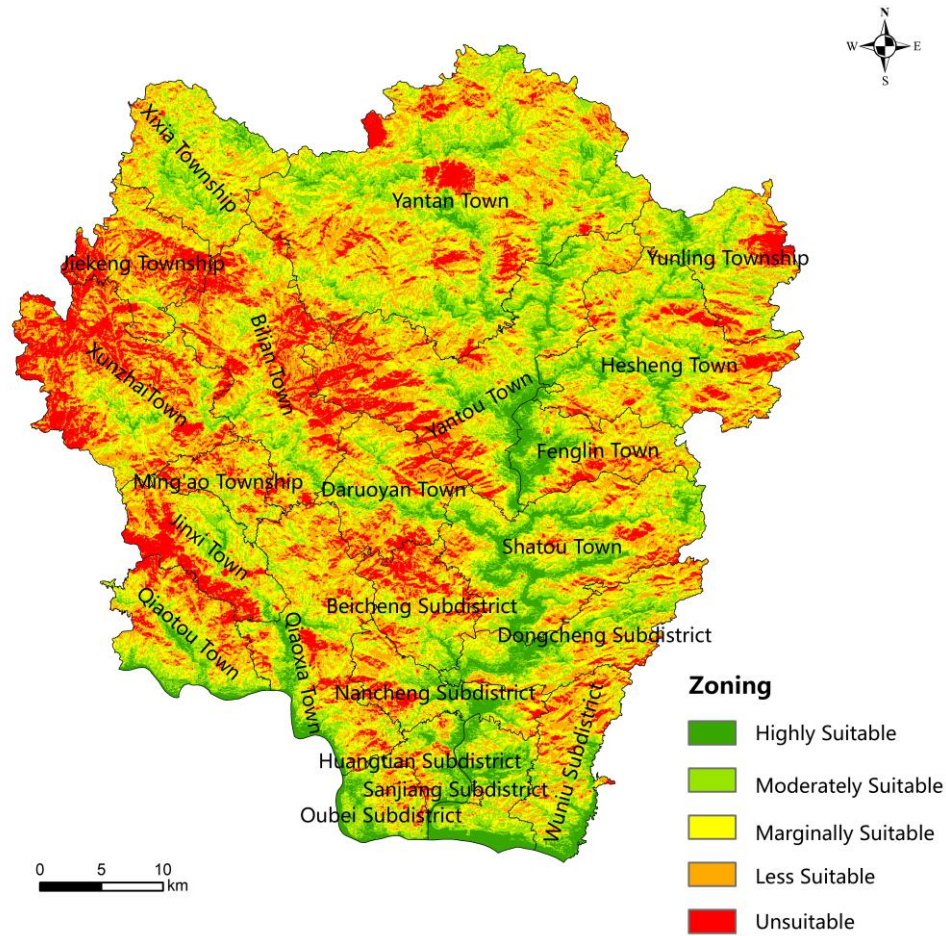


Fig 2 Zoning map of geological environmental suitability

4.3 Model Validation

Spatial agreement between modelled suitability and centenarian settlements was evaluated using the FR method across three weighting scenarios (Table 5). Under all schemes, FR decreased strictly and monotonically from the Highly Suitable to the Unsuitable class, with $FR > 1$ confined to the top two suitability grades—confirming basic discriminatory capacity.

The GTCW method delivered the strongest spatial coincidence. Its FR peaked at 6.05 in the Highly Suitable zone and 1.85 in the Moderately Suitable zone, versus sub-unity values in the Less Suitable (0.39) and Unsuitable (0.10) classes. Notably, the top two GTCW-derived zones occupied only 28.41% of the county yet contained 85.30% of the independent validation villages. By contrast, the AHP-based and IWC-based schemes captured 79.41% and 76.47% of the validation villages within their top two zones, while requiring 29.05% and 30.05% of the land area, respectively.

This comparison demonstrates that GTCW achieves superior targeting efficiency: it isolates longevity-linked settlements within a smaller areal footprint, outperforming purely subjective or purely

data-driven weighting approaches.

Table 5 FR Value Validation of Different Weighting Methods

Zoning	AHP			IWC			GTCW		
	Area (%)	Sample (%)	FR	Area (%)	Sample (%)	FR	Area (%)	Sample (%)	FR
Highly Suitable zone	8.16	41.18	5.05	7.84	44.12	5.63	7.78	47.06	6.05
Moderately Suitable zone	20.89	38.24	1.83	22.21	35.29	1.59	20.63	38.24	1.85
Marginally Suitable zone	31.07	17.65	0.57	28.69	14.71	0.51	29.8	11.76	0.39
Less suitable zone	27.7	2.94	0.11	25.08	5.88	0.23	28.12	2.94	0.10
Unsuitable zone	12.18	0.00	0.00	16.17	0.00	0.00	13.66	0.00	0.00

4.4 Sensitivity Analysis

Sensitivity analysis clarified the hierarchical driver structure underlying the GESA output (Table 6). Assigned combined weights ranged from 4.66% to 19.85%, revealing a clear tiering of influence. Drinking Water Quality (19.85%), Soil Heavy Metals (17.12%), Air Quality (13.26%), Negative Air Ions (10.37%), and Soil Beneficial Elements (8.81%) formed a dominant driver bundle, cumulative contribution 69.41%.

Spatially, Drinking Water Quality exhibited uniformly high realised contributions (high mean, low CV), reflecting the regionally pristine water baseline. Soil Heavy Metals showed a similar mean contribution but a far lower minimum, implying generally low geochemical loads punctuated by isolated exceedances that generate localised risk hotspots.

Classical terrain factors—Slope, Aspect, and Distance to River—carried modest mean contributions (<6%) yet the highest CV among all indicators. This signals a scale-dependent control: terrain exerts negligible aggregate leverage at the county scale but functions as a secondary modifier, sharpening or dampening suitability at fine spatial resolutions.

Table 6 Descriptive statistics of effective weights

Indicator Layer	Effective Weight (%)				
	Minimum	Maximum	Mean	Standard Deviation	Coefficient of Variation
Elevation	2.17	7.90	4.86	0.92	19
Topographic Relief	3.02	9.19	5.29	0.66	12
Slope	2.02	13.22	4.66	2.26	48

Aspect	1.57	11.08	5.67	2.32	41
Vegetation Cover	1.17	8.28	5.61	0.86	15
Air Quality	5.90	19.86	13.26	1.52	11
Negative air ions (NAIs)	5.59	14.48	10.37	1.28	12
Drinking Water Quality	8.57	25.94	19.85	1.39	7
Proximity to River	1.77	11.77	4.50	2.38	53
Soil Heavy Metal Elements	3.36	23.01	17.12	1.91	11
Soil Beneficial Elements	3.37	14.60	8.81	1.51	17

5. DISCUSSION

By reconciling subjective and objective weights via game theory, this study offers a transferable framework for GESA. The dominance of drinking water quality and soil heavy metals aligns with long-standing evidence that hydrochemical and pedogeochemical baselines govern endemic disease distributions (Pang et al., 2010; Lin et al., 2002; Shi et al., 2017).

Suitability in Yongjia County displays a clear valley–upland contrast. High-suitability cores track the Nanxi River floodplain, where fluvial terraces supply flat land, fertile sediment, and settlement amenity. Upland fringes (west/north) are instead constrained by relief and hypobaric stress rather than ecological degradation per se. This decoupling confirms that high ecosystem integrity—e.g., dense forest cover—does not automatically translate into high population-carrying capacity, underscoring the structural gatekeeping role of geological relief.

At the macro scale, environmental media (water, soil, air) behave as first-order determinants. Locally, drinking water retains uniformly high realised contributions, whereas soil metals show patchy exceedances, signalling manageable but spatially focal pollution risk.

At the micro scale, terrain attributes exert minor aggregate leverage but drive fine-resolution heterogeneity. Their high CVs imply a secondary-modifier role: aspect modulates insolation and moisture regimes, subtly shaping cutaneous vitamin D synthesis and humidity-linked morbidity, while micro-topographic gradients carve the “patchiness” of liveability within an otherwise benign geochemical envelope.

While this study provides a static snapshot of GESA, several limitations point to avenues for refinement. Going forward, coupling long-term environmental monitoring with longitudinal health records would enable dose–response relationships between key geochemical factors—such as soil Se—and health outcomes, advancing GESA from a descriptive baseline toward a predictive framework.

Beyond temporal extension, future work should address element interactions (e.g., Se–As/Cd antagonism) through chemometrics, replacing single-parameter scoring with a supply–constraint nexus that captures multi-element toxicity–benefit trade-offs. Crucially, spatial zoning has direct practical value: in the master plan for the study area, river terrace core zones with high suitability should be designated as protected areas, while differentiated intervention measures should be implemented in other areas. Specifically, targeted geochemical remediation should be carried out in areas where metal concentrations exceed standards, and development intensity should be regulated in rugged areas with high ecological net value, thereby directly incorporating geologically informed health priorities into land-use management.

6. CONCLUSIONS

This study develops a multi-criteria Geological Environment Suitability Assessment (GESA) framework for centenarian-dense regions. Methodologically, it employs a GTCW method that reconciles subjective AHP expert judgments with objective information-entropy weights, overcoming the limitations of single-weighting approaches. The GTCW–GESA model significantly outperforms single-weighting benchmarks in spatial discriminability: the top two suitability classes occupy only 28.4% of the county yet enclose 85.3% of centenarian villages ($FR = 6.05$ and 1.85), confirming that geological settings structurally filter habitation suitability. Spatially, suitability follows a valley–upland gradient, with high-value cores along Nanxi River terraces, where flat terrain and favorable hydrogeochemical conditions promote elemental balance, while poorer classes are confined to the heavily dissected western highlands and localized sites of heavy metal contamination. Sensitivity analysis reveals a media–terrain dual-driver hierarchy: water, soil and air quality contribute 69.41% at the macro scale, establishing the baseline suitability, whereas slope and aspect sculpt fine-scale patchiness via high spatial variance. The findings clarify how geological settings structurally filter habitation potential, albeit from a static baseline. Future work should couple long-term environmental monitoring with longitudinal health cohorts to establish quantitative dose–response relationships between specific geochemical exposures and healthy ageing indicators, and evolve toward process-based, dynamic GESA framework. Ultimately, this framework provides territorial planners with an evidence-based, spatially explicit tool for proactively identifying environments conducive to healthy longevity, moving geo-health research from retrospective correlation to prospective intervention.

ACKNOWLEDGMENTS

This research was financially supported by the Scientific Research Project of the 11th Geological Brigade of Zhejiang Province (Grant No. RD202404) and the Basic Scientific Research Project of Wenzhou Science and Technology Bureau (Grant No. SB20250004). The authors would like to express their sincere gratitude to the Civil Affairs Bureau of Yongjia County, the Yongjia Longevity Culture Research Association, and the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, for providing essential data and support for this study.

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