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Assessing Healthcare Facility Accessibility in High-Altitude Mountainous Regions of Western China

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Assessing Healthcare Facility Accessibility in High-Altitude Mountainous Regions of Western China

Xiangyu Dong

2025

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2025

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ABSTRACT

ABSTRACT

This dissertation investigates how population dynamics and healthcare accessibility interact in high-altitude mountainous regions of western China, where rugged terrain, sparse settlements, and fragile ecosystems pose persistent challenges to health equity. Building on a unified "population–health–space" coupling framework, the thesis links three empirical cases across multiple scales. First, county-level analysis of 42 high-altitude counties in Sichuan develops a Sustainable Population Migration Index (SPMI) based on geodetector-derived drivers, showing that healthcare accessibility is the dominant determinant of resident and rural population change, and that migration attractiveness generally deteriorated between 2010 and 2020. Second, a benchmark assessment of primary healthcare facilities in nine large-relief alpine counties in Tibet reveals severe shortfalls in 15-minute coverage, over-reliance on county hospitals, and pronounced inequities between townships and villages despite nominal improvements in supply. Third, the thesis proposes a Multi-Factor Integrated Mountain Walkability Model (MIMWM) embedded in a Two-Step Floating Catchment Area (2SFCA) framework for Diqing Prefecture, integrating slope-adjusted walking speeds, land-use resistance, and altitude-related physiological decline. Results show that conventional Euclidean and network methods systematically overestimate accessibility, that a critical threshold occurs around 30 minutes of walking time, and that most residents fall below national baseline standards when terrain constraints are fully considered. Synthesizing the three case studies, the dissertation demonstrates that terrain-sensitive, near-distance accessibility is central to stabilizing high-altitude populations, and that decentralized facility siting, micro-scale walking infrastructure, and digital-twin-based scenario tools are effective levers for improving rural health equity in mountainous environments.

Keywords: *High-altitude mountainous regions; Healthcare accessibility; Population dynamics; Sustainable Population Migration Index; Multi-Factor Integrated Mountain Walkability Model; Rural health equity*

Chapter 1

GENERAL INTRODUCTION

Chapter 1

General Introduction

1.1 Research Background

This study examines how terrain, altitude, and infrastructure jointly influence healthcare accessibility and population dynamics in the high-altitude regions of western China. Despite national efforts under the Rural Revitalization Strategy, these areas continue to face severe service deficits and spatial inequality. Integrating migration theory with spatial accessibility analysis, the research proposes a terrain-sensitive modeling framework that incorporates slope-adjusted walking speed, land-use resistance, and altitude-related mobility decline to correct the overestimation of traditional methods. It develops the Multi-Factor Integrated Mountain Walkability Model (MIMWM) and the Sustainable Population Migration Potential Index (SPMI), applying them to case studies in Sichuan, Yunnan (Diqing), and Tibet. Using GIS-based cost-surface analysis, the study identifies the relationship between limited healthcare coverage and population outmigration, providing a reproducible, equity-oriented framework to guide facility siting, workforce allocation, and infrastructure planning in high-altitude mountainous regions.

1.1.1 General Background

Globally, widening urban–rural disparities and the difficulty of achieving balanced regional development represent critical challenges for social progress. Residents in underdeveloped or topographically constrained regions often lack equal access to public services, resulting in lower living standards and inadequate health security (Guagliardo, 2004; Ouma et al., 2018; Peters et al., 2008). This challenge is not unique to China; similar issues have been documented in the Andes of Latin America and the Himalayas in South Asia, where infrastructure scarcity, poor transportation, and insufficient healthcare coverage make high-altitude regions persistent "bottlenecks" in sustainable development (MacKinnon & Derickson, 2012; Zimmerer, 2013).

As a major developing country with an exceptionally large population, China epitomizes the complexities of balancing rapid urbanization with equitable regional growth. Decades of accelerated urban expansion have driven economic progress but have simultaneously widened urban–rural gaps (Liu et al., 2014). In response, China has launched the Rural Revitalization Strategy, which emphasizes improving public services—particularly education, healthcare, and transportation—in rural and remote areas (Hualou et al., 2019). While the overall supply of medical resources has increased nationwide, empirical studies consistently reveal stark spatial disparities: healthcare accessibility and resource allocation efficiency in high-altitude and western mountainous regions remain far lower than in eastern coastal or metropolitan areas (Dong et al., 2025; Zhu et al., 2018).

High-altitude mountainous areas are both a priority and a persistent challenge within this strategy. Extreme terrain, fragile ecosystems, and limited transportation infrastructure hinder the construction and operation of healthcare facilities (Zhu et al., 2018). Poor accessibility to medical care not only exacerbates health risks but also accelerates population outmigration and undermines social stability (Fan, 2011). Compared with lowland populations, residents of high-altitude regions are more vulnerable to acute illness, insufficient management of chronic diseases, and heightened maternal health risks, all of which are magnified by systemic deficiencies in healthcare delivery (West et al., 2012).

From a global perspective, addressing healthcare accessibility in high-altitude mountainous regions is central to achieving multiple United Nations Sustainable Development Goals (SDGs), including "Good Health and Well-being," "Reduced Inequalities," and "Sustainable Cities and Communities" (United Nations, 2015). Enhancing medical service equity in these areas is therefore not only crucial for China's domestic regional development but also offers valuable insights for advancing the sustainability of human settlements in other mountainous regions worldwide.

1.1.2 Academic Background

（1）Migration theories and the role of healthcare accessibility

Migration and population redistribution have long been central issues in

human geography and regional development studies. Classical migration theories trace back to Ravenstein's "laws of migration" (Ravenstein, 1885) and Lee's push–pull framework (Lee, 1966), which describe migration as a process driven by negative "push" factors at the origin—such as unemployment and environmental constraints—and positive "pull" factors at the destination—such as better employment, infrastructure, and living conditions. However, such static models are limited in explaining multi-scalar and context-dependent migration dynamics. More recent frameworks, notably the aspirations–capabilities model, emphasize that migration arises from the interplay between individuals' life aspirations and their ability to realize them within structural constraints (de Haas, 2021). This perspective highlights that migration is not merely an economic response but also a socially embedded process shaped by institutional structures and access to public services (Massey et al., 1993).

Beyond macroeconomic determinants, public service facilities—including healthcare, education, and transportation—have emerged as critical factors influencing migration intentions and settlement behavior. Studies in both developed and developing contexts have shown that the accessibility and quality of public services substantially affect regional attractiveness and residents' well-being (Guagliardo, 2004; Peters et al., 2008). Regions endowed with comprehensive healthcare and educational systems tend to retain populations and attract newcomers, while deficiencies in such services may act as powerful "push" factors, particularly in rural and mountainous regions (Black et al., 2011; Vendryes, 2011). Moreover, the ability of individuals to utilize these services depends on mobility resources, income, and institutional constraints such as household registration systems, further reinforcing social inequality (Liu et al., 2014).

Within this context, spatial accessibility and social equity have become central analytical themes in the evaluation of public service provision. Accessibility, once measured using simple Euclidean distance or fixed service radii, has evolved toward more sophisticated spatial interaction models such as the Two-Step Floating Catchment Area (2SFCA) method and its enhanced variants (E2SFCA, SDA-2SFCA), which incorporate supply–demand balance and distance decay (Delamater, 2013; Luo & Wang, 2003). These approaches have been widely applied to healthcare accessibility studies, providing more realistic measures of service reachability in both urban and rural areas. In

parallel, scholars have highlighted the importance of fairness and spatial justice in facility distribution, emphasizing that accessibility disparities are manifestations of broader structural inequities (Apparicio et al., 2008; Fransen et al., 2015).

Among all categories of public services, healthcare facilities play a particularly vital role. Access to primary healthcare is widely recognized as a fundamental component of human welfare and a core pillar of universal health coverage (World Health Organization, 2022). Limited access to medical care is associated with delayed treatment, higher mortality, and increased spatial health inequalities (Ouma et al., 2018). In high-altitude or mountainous regions, healthcare accessibility is further constrained by topographic barriers, sparse settlement distribution, and insufficient transportation networks, producing spatial inequities that standard network models often fail to capture. Therefore, improving healthcare accessibility in such environments is not only a technical challenge of facility optimization but also a moral and policy imperative for advancing social equity and regional sustainability.

Building on these theoretical and empirical foundations, the present study seeks to bridge the gap between migration theory and healthcare accessibility analysis, particularly in high-altitude mountainous contexts. By integrating terrain-sensitive accessibility modeling with population mobility frameworks, this research aims to deepen understanding of how spatial equity in public services shapes sustainable demographic development in under-resourced regions.

（2）Evolution of Spatial Accessibility Methodologies

The concept and measurement of spatial accessibility have evolved remarkably, paralleling advances in geographic information science and public facility planning. Early accessibility assessments primarily relied on Euclidean distance or fixed-radius buffer approaches, which simply measured the straight-line distance between population centers and service locations. Although these models provided an intuitive proxy for proximity, they assumed isotropic surfaces and uniform travel conditions, overlooking barriers such as terrain, road hierarchy, and travel mode (Kwan, 1998; Talen & Anselin, 1998). Consequently, they tended to overestimate accessibility in areas with

poor transport infrastructure or complex topography, particularly in rural and mountainous settings.

The second phase of methodological development introduced network-based accessibility models, which leveraged advances in GIS and digital road data to simulate realistic travel paths. These approaches estimate accessibility along actual road or transit networks using algorithms such as Dijkstra or OD cost matrices, allowing for travel time to replace geometric distance as the key metric. Network-based analysis has become a foundational tool for urban and regional service planning because it incorporates road hierarchy, travel directionality, and mode-specific speeds (Dalvi & Martin, 1976; Neutens et al., 2010). However, the precision of such methods depends heavily on the completeness and spatial accuracy of network data, which remains inadequate in many developing or high-relief regions.

A major paradigm shift occurred with the development of floating catchment models, particularly the Two-Step Floating Catchment Area (2SFCA) method (Luo & Wang, 2003). Unlike traditional proximity or ratio indicators, the 2SFCA model accounts for both supply-to-demand ratios and distance-decay effects within variable service areas, thus integrating spatial interaction theory with health and social equity analysis. It captures overlapping service catchments and reflects the competition for limited resources among neighboring populations. This framework was further refined by the Enhanced 2SFCA (E2SFCA) (Luo & Qi, 2009), which applied continuous distance-decay weights, and by later multi-modal extensions that incorporated public transit, walking, and driving modes (Dai, 2010; Langford et al., 2012). These improvements shifted accessibility analysis from static spatial coverage to a more behavioral and equity-oriented perspective, enabling comparative studies across socioeconomic and demographic groups.

Recent years have witnessed a new generation of terrain-sensitive and multi-factor accessibility models, particularly in regions where elevation, slope, and environmental resistance significantly shape human mobility. These models integrate Digital Elevation Models (DEM), land-use friction coefficients, and slope-dependent walking speeds into cost-surface calculations to represent anisotropic movement across heterogeneous landscapes (Weiss et al., 2018). They enable the estimation of realistic travel times even in areas lacking dense

network data, such as high-altitude settlements or remote rural environments. The integration of these continuous cost surfaces within the 2SFCA or gravity-based frameworks has produced more reliable and policy-relevant evaluations of service accessibility, particularly for healthcare, education, and emergency response facilities.

The methodological trajectory from Euclidean simplicity to terrain-sensitive modeling underscores a broader epistemological transition in spatial accessibility research—from abstract geometry to contextualized, equity-centered modeling. Contemporary accessibility studies increasingly emphasize human–environment interactions, linking mobility behavior with physical constraints, institutional barriers, and social vulnerability. This shift not only refines measurement accuracy but also aligns spatial accessibility research with global policy agendas on health equity and sustainable development (United Nations, 2015; World Health Organization, 2022). Future methodological advancements are expected to integrate temporal dynamics, remote sensing, and machine learning, enabling multi-scalar and real-time assessments that bridge the gap between spatial modeling and policy implementation.

（3）China's research background

Since the onset of market reforms, internal migration has concentrated in the eastern coastal city-regions (Yangtze River Delta, Pearl River Delta, and the Beijing–Tianjin–Hebei corridor), reflecting persistent spatial polarization in employment, services, and institutional access (Chan & Zhang, 1999). Hukou institutions continue to condition migrants' access to welfare and urban public services, reinforcing population flows toward large metropolitan areas and complicating balanced development in inland and high-altitude regions (Chan & Zhang, 1999).

Pronounced inequalities in the distribution of health resources persist across China—between regions and between urban and rural areas—despite overall growth in service supply (Fang et al., 2010; Li et al., 2020). County- and province-level analyses repeatedly show lower densities of hospital beds and health professionals in western and rural jurisdictions relative to eastern urban cores. In planning practice, uniform service radii or walking-time thresholds

(e.g., the "15-minute life circle" derived from GB 50180-2018) are frequently referenced for siting neighborhood facilities; however, such one-size-fits-all benchmarks are poorly suited to low-density or topographically constrained settlements and risk overstating effective access in mountainous areas (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2018; Tao et al., 2018). Urban case studies further reveal strong clustering of accessibility in central districts with rapid decay toward peripheral neighborhoods (Tao et al., 2018).

In mountainous provinces such as Sichuan and Yunnan, GIS- and network-based studies consistently identify service shortfalls in minority and peripheral counties and a strong sensitivity of utilization to travel time (Wang & Pan, 2016). Most evaluations emphasize county-level and higher-tier hospitals, while township health centers and village clinics—crucial for first-contact care in rugged terrain—are less frequently centered in spatial analyses (Wang & Pan, 2016). Methodologically, reliance on Euclidean distance or road-only shortest paths can overestimate effective coverage where slope, land cover, and incomplete networks constrain movement. Global health-access work shows that friction-surface or least-cost travel-time models (with mode-specific speeds and terrain costs) more realistically capture accessibility under complex geography—a direction increasingly pertinent for China's high-altitude settings (Nelson et al., 2019; Weiss et al., 2020). Embedding such terrain-sensitive travel-time surfaces into 2SFCA-type frameworks used in China (Luo & Qi, 2009; Luo & Wang, 2003; Tao et al., 2018) would improve the validity and equity sensitivity of mountainous accessibility assessments.

（4）Research gaps

First, there is a clear lack of integrated, systematic research on high-altitude mountainous regions that explicitly links population dynamics (e.g., out-migration, aging, and changing settlement patterns) with healthcare accessibility. Existing studies from the Qinghai–Tibet Plateau demonstrate substantial travel times to county hospitals and physiology-related constraints at altitude, yet they typically treat accessibility as an isolated planning or transport problem rather than embedding it within demographic change and service-use behavior (e.g., hypoxia-adjusted "exercise efficiency" models report median travel times around two hours and large shares of residents beyond

one- or two-hour thresholds) (Wang et al., 2023). Parallel evidence on health status differences by altitude underscores the plausibility of compounded disadvantage but seldom couples these indicators to spatial access and migration trajectories (Dou et al., 2023). Together, these findings suggest a research gap: how high-altitude geography, physiological limits, and uneven service networks co-evolve with population redistribution gaps with direct implications for equitable service planning.

Second, there remains insufficient evidence on the coverage and equity of primary care (township health centers, community health centers, and village clinics)—the tier most relevant to first-contact care in dispersed mountainous settlements. The first national mapping of primary healthcare (PHC) accessibility shows pronounced inequality across mainland China and identifies large, underserved areas, but provides limited deep dives into plateau counties (Jia et al., 2022). Provincial and city-level studies confirm intra-provincial disparities and urban–suburban gradients in PHC access (e.g., Beijing ecological conservation districts; reform pilot provinces), and new work documents resource shortfalls in rural grassroots institutions relative to national averages (Xu et al., 2024; Zhang et al., 2021; Zhaoting Zhang, 2024). Policy syntheses likewise note that China's UHC agenda must pivot from hospital-centric growth to equitable PHC strengthening, especially in under-served regions (Yip et al., 2023). What is still scarce are systematic equity audits for primary care in high-altitude counties that join spatial access, staffing/capacity, and population need.

Third, methodological limitations continue to bias accessibility assessments in complex terrain. Euclidean distance and road-only shortest-path approaches can overestimate effective coverage where slope, land cover, and incomplete networks constrain movement; reviews have repeatedly called for equity-sensitive metrics and context-aware modeling (Delamater, 2013; Neutens, 2015). Terrain-sensitive, least-cost travel-time approaches—operationalized in tools such as WHO's AccessMod—allow anisotropic movement and capacity-aware coverage and are increasingly used in mountainous or data-sparse settings (Ray & Ebener, 2008). National-scale 1-km travel-time products further enable composite indicators that integrate travel impedance with supply–demand balance (Ye et al., 2024). Yet their systematic integration with PHC-specific equity targets (as opposed to hospital-only metrics) remains

limited in China's high-altitude contexts. This motivates the development of terrain-sensitive models and composite indices that combine (i) physiographic frictions (slope/altitude/land cover), (ii) multimodal or off-network mobility, and (iii) equity-oriented supply–demand weighting tailored to primary care.

（5）Positioning of research contributions

This study extends classic migration theory by explicitly situating the push–pull mechanism in high-altitude mountainous contexts, foregrounding healthcare access, terrain impedance, and infrastructural connectivity as distinctive migration drivers alongside economic opportunities. In doing so, it bridges Lee's (1966) structural push–pull logic with the aspirations–capabilities perspective (de Haas, 2021), arguing that altitude-related mobility frictions and uneven primary-care access constrain migrants' capabilities to act on their aspirations. It also resonates with environmental-migration scholarship that recognizes physical environment and accessibility as salient, place-specific factors shaping mobility decisions (Black et al., 2011). Together, these linkages clarify how health-service accessibility and topographic barriers jointly condition population redistribution in highlands.

Methodologically, we propose two complementary instruments. (i) The Multi-Factor Integrated Mountain Walkability Model (MIMWM) operationalizes terrain-sensitive travel cost by combining DEM-derived slope, land-cover friction, and altitude-adjusted walking speed into a continuous cost surface (Tobler, 1999; Weiss et al., 2018), which can be embedded in 2SFCA-type accessibility frameworks to avoid road-only bias (Luo & Qi, 2009; Luo & Wang, 2003). This design is consistent with least-cost travel-time practices widely used in health-access modeling (Ray & Ebener, 2008). (ii) The Sustainable Population Migration Potential Index (SPMI) integrates push/pull-capability factors (de Haas, 2021) with equity-oriented accessibility and data-driven attribution (Wang et al., 2016) to produce a composite, policy-legible indicator for high-altitude counties. Together, MIMWM and SPMI provide a replicable toolkit that links realistic mobility frictions with migration potential in data-sparse mountainous settings.

Empirically, we develop a multi-dimensional analysis framework for Sichuan and the eastern Qinghai–Tibet region, integrating DEM-based terrain

modeling, statistical yearbook indicators, and a digital-twin-inspired workflow for scenario exploration (Batty, 2018). The case evidence (Wang & Pan, 2016) demonstrates how terrain-sensitive accessibility alters equity diagnoses relative to Euclidean/network-only baselines, and how primary-care proximity can materially change migration-relevant service exposure. This integrated framework yields actionable insights for targeting township/village-level facilities and for stress-testing planning standards in complex topography.

1.1.3 Regional Background

The study area lies on the southeastern margin of the Qinghai–Tibet Plateau and encompasses the high-altitude mountainous belt spanning western Sichuan, northwestern Yunnan (notably Diqing Tibetan Autonomous Prefecture), and parts of the Tibet Autonomous Region. It is typified by extreme relief, deep incision along the upper Jinsha (Yangtze), Lancang (Mekong), and Nu (Salween) river corridors, and a dense ridge–valley mosaic. In China's physical regionalization, the combination of absolute elevation and the Relief Degree of Land Surface (RDLS) offers an operational basis for delineating mountainous zones; areas above ~2,000 m with high RDLS is commonly classified as high-altitude mountains (Feng et al., 2007).

Settlement patterns reflect this terrain. Populations are relatively sparse and ethnically diverse, with village and small-town clusters concentrated on valley floors and terraced benches, while numerous hamlets remain dispersed on slopes. Census statistics confirm a predominantly rural structure in these highlands compared with the eastern lowlands, implying stronger terrain-induced frictions to essential public services (National Bureau of Statistics of China, 2021).

Transport networks are tightly coupled with topography. National and provincial highways trace the main valleys, whereas village–township connectors are typically sinuous, discontinuous, and seasonally fragile. Differences in functional class translate into sharp contrasts in achievable speeds and reliability, and thus into uneven "effective catchments" for services. In many settlements, walking remains the default or fallback mode; yet steep grades, switchbacks, and frequent elevation changes depress walking speed relative to network-only or Euclidean assumptions (Tobler, 1999). High altitude compounds these frictions: aerobic capacity and submaximal performance

decline with elevation, narrowing realistic walking catchments even where straight-line distances appear short (West et al., 2012).

Healthcare delivery follows China's tiered system—village clinics and township health centers provide the primary interface, county hospitals serve as secondary hubs, and prefecture-level facilities act as higher-level providers. Mountainous prefectures in Southwest China lag the east in per-capita facility and workforce density, making the nearest primary-care point especially critical (Health Commission of Yunnan Province, 2021; National Health Commission of the PRC, 2022). Methodologically, neglecting terrain and anisotropic travel costs tends to overestimate access. The two-step floating catchment family (2SFCA/E2SFCA) and its derivatives (e.g., M2SFCA) balance supply, demand, and distance decay and can be coupled with cost-surface travel time models that incorporate slope-adjusted speeds, surface resistance, and road-class heterogeneity (Delamater, 2013; Luo & Qi, 2009; Luo & Wang, 2003; Ray & Ebener, 2008). Evidence from sub-Saharan Africa and global travel-time mapping further underscores the accuracy gains of such anisotropic approaches in remote and mountainous settings (Ouma et al., 2018; Weiss et al., 2018).

Policy benchmarks provide additional context. China's GB 50180-2018 Residential Area Planning and Design Standard operationalizes "15-minute living-circles" for daily services, including primary medical points. While appropriate for dense lowland cities, unadjusted thresholds risk overstating coverage in complex high-altitude terrain (Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2018). In practice, non-emergency primary care often exceeds 30 minutes on foot in rural highlands—consistent with terrain-sensitive cost-distance analyses (Esri, 2023; Weiss et al., 2018).

Taken together, the Sichuan–Diqing–Tibet belt is representative in three respects: (i) pronounced physical constraints (altitude, relief, discontinuous networks), (ii) low-density, valley-oriented yet slope-dispersed settlements that raise "last-mile" impedance, and (iii) reliance on primary care under conditions where nominal facility density diverges from "timely reachable" supply. This context is well suited to evaluate terrain-sensitive accessibility models that integrate slope-adjusted walking speed, altitude-related physiological decline, and surface resistance within a 2SFCA framework, and to calibrate

context-specific thresholds (e.g., identifying a pragmatic 30-minute walking benchmark) to guide micro-infrastructure, staffing, and mobile-service interventions in persistent deficit cells.

1.1.4 Problem Statement

Earthen In high-altitude mountainous regions of western China, the ability of residents to reach primary healthcare within clinically meaningful timeframes is systematically constrained by steep terrain, fragmented road networks, dispersed settlements, and altitude-related declines in walking capacity. Existing national planning practices often assume uniform service radii or fixed walking-time thresholds (e.g., 15 minutes), but these assumptions do not reflect actual mobility costs in complex highland environments. As a result, conventional Euclidean or network-based approaches tend to overestimate accessibility, masking service deficits that are critical to equity-oriented health planning.

At the same time, empirical evidence from county- and prefecture-level case areas shows that the effective 15-minute coverage of village and township facilities can be extremely limited in large-relief, >1,000 m settings, and that catchment gains diminish beyond short walking thresholds. These patterns indicate that "near-distance" access is the binding constraint in many settlements and that uniform benchmarks are insufficiently sensitive to topographic reality.

Methodologically, mainstream 2SFCA variants have advanced distance-decay and variable catchment ideas, yet applications in rugged mountains rarely integrate the full set of terrain and land-surface constraints, slope-dependent walking speeds, and altitude-related physiological penalties. Where online-map travel times are used, they typically presume slope-independent pedestrian speeds and complete networks, underrepresenting the informal paths that many rural residents rely on. Consequently, model outputs risk being non-transparent, non-reproducible, and biased toward optimism in mountainous settings.

Practically, these measurement gaps propagate into planning: facility siting, workforce deployment, and micro-infrastructure upgrades may be mis prioritized when terrain costs are not explicitly modeled. Villages falling just

outside short, realistic walking isochrones can be overcome despite being the locations where marginal investments (e.g., small clinics, outreach points, or path improvements) would yield the largest accessibility returns.

Conceptually, there is also a missing link between population dynamics in high-altitude counties and terrain-constrained access to primary care. Health service availability and reachability act as distinctive push–pull drivers in mountainous migration processes, yet decision frameworks have not consistently combined terrain-sensitive accessibility with population-oriented indices to assess sustainable settlement viability.

Therefore, the core problem addressed in this thesis is twofold:
(1) Measurement—how to produce auditable, reproducible, and equity-sensitive accessibility estimates that capture the dominant influence of terrain, land-surface resistance, and altitude-related walking capacity on short-range access to primary care; and
(2) Planning translation—how to convert terrain-aware accessibility diagnostics into actionable priorities for "last-mile" facility placement, workforce allocation, and micro-infrastructure in high-altitude counties.

To resolve these problems, we adopt and refine a terrain-sensitive, multi-factor distance accumulation approach embedded in the 2SFCA framework, explicitly modeling slope-adjusted walking speeds, land-use resistance, and altitude penalties to generate realistic pedestrian catchments. We then use these outputs to (i) benchmark the adequacy of existing short-range service thresholds, (ii) identify settlements with the largest near-distance access gaps, and (iii) provide a replicable evidence base for targeted interventions in topographically complex regions. Finally, by situating accessibility within a broader population-sustainability perspective for high-altitude counties, we seek to clarify how health access constraints shape spatial inequality and longer-term demographic resilience.

1.2 Literature Review

1.2.1 Study of Healthcare Facility Accessibility in the World

The spatial accessibility of primary healthcare services is a key dimension of health equity and a foundational indicator in global health system

evaluations. Over the past decade, there has been a substantial shift from purely distance-based measures toward more integrated models that account for travel time, supply-demand imbalances, and behavioral or structural constraints (Delamater, 2013; Guagliardo, 2004).

Early accessibility models often relied on static catchment radii (e.g., 5 km or 30 minutes) or Euclidean-distance buffers. However, such methods—while computationally simple—neglect actual road networks, topographic constraints, or dynamic user behaviors. In response, a family of gravity-based models and floating catchment area (FCA) techniques, especially the two-step floating catchment area (2SFCA) method and its enhancements, has gained prominence (Luo & Wang, 2003; Wan et al., 2012). The E2SFCA introduces distance-decay weighting, allowing a more realistic depiction of how service accessibility declines with distance or travel time. However, it still often assumes uniform travel behavior and neglects spatial heterogeneity such as terrain or land use resistance—factors that are particularly critical in remote and rural contexts.

Even with advanced modeling, substantial limitations remain. Aweke et al. found that in the Horn of Africa, rural children with malaria face critical treatment delays despite nominal proximity to clinics (Aweke et al., 2025). The root cause lies in poor path conditions, steep terrain, and long detours to cross physical barriers. Similarly, Tarekegn et al. noted that Ethiopia's Health Extension Program's outreach remains limited by unrealistic assumptions of flat-land accessibility (Tarekegn et al., 2025). Moreover, digital navigation systems and APIs (e.g., Google Maps) used in public planning often default to slope-insensitive pedestrian speeds (e.g., 4–5 km/h), overlooking vertical elevation and path quality. These assumptions severely distort accessibility evaluations in rugged or informal contexts.

Beyond physical constraints, social determinants of accessibility also deserve attention. Bolarinwa & Mohammed highlight how women with disabilities in sub-Saharan Africa face double exclusions: from transportation access and from social safety networks (Bolarinwa et al., 2025). Similarly, ethnic minorities and migrants in China's western provinces often face language, trust, and administrative barriers even when health posts are geographically close (Xu et al., 2021).

Recent literature calls for incorporating terrain cost surfaces, land-use friction coefficients, and slope-dependent pedestrian modeling into mainstream FCA-based methods. Iliadis et al have developed digital elevation model (DEM)-based tools that integrate physiographic features directly into accessibility calculations. Furthermore, spatial access metrics are now being linked with demographic resilience, particularly in regions facing aging populations, declining birth rates, or out-migration (Iliadis et al., 2023). Noor et al. stress that poor healthcare access is both a consequence and a driver of regional underdevelopment (Noor et al., 2003).

In summary, although global accessibility research has moved far beyond static metrics, it remains heavily biased toward data-rich, flat, or urban contexts. There is an urgent need for context-adaptive, terrain-sensitive, and population-informed models that reflect the reality of remote and mountainous settings.

1.2.2 Study of Healthcare Facility Accessibility in High-Altitude Mountainous

High-altitude mountainous regions represent a critical blind spot in mainstream healthcare accessibility research. These areas often exhibit extreme elevation gradients, highly fragmented settlements, and sparse infrastructure, all of which undermine the applicability of conventional models based on linear distance or travel time thresholds.

In large-relief environments—such as those found in western China, the Himalayas, and the Andes—the most binding constraint is often short-range, pedestrian-based access. The assumption that a 15-minute walk equates to ~1 km travel is rarely valid in these contexts. Recent studies confirm that walking speed declines notably with both increasing altitude and slope, especially among older adults or those with reduced cardiopulmonary capacity. Field and laboratory findings indicate that uphill gradients and hypoxic conditions at elevations above 3,000 meters greatly elevate fatigue and energy cost, leading to effective walking speeds often below 2 km/h. Specifically, walking on inclined terrain significantly reduces gait speed and increases fatigue among older adults (Abe et al., 2021). Age-related declines in aerobic capacity and walking energetics also contribute to slower speeds and higher perceived exertion (Garcia et al., 2024), while steep slopes further amplify metabolic and

mechanical demands even in healthy adults (Kafetzakis et al., 2024). Empirical evidence from urban areas in China indicates that the coverage of 15-minute community-level service areas remains limited. In Zhengzhou, only about 39.6% of residents can access community-level healthcare services within a 15-minute walk — substantially below the national target of 80% (Song et al., 2022). Elevation gain, seasonal path disruptions (snow, mud), and altitude-induced fatigue compound these limitations.

Modeling accessibility in complex mountainous terrain faces unique methodological challenges that are often overlooked by conventional spatial models. Standard two-step floating catchment area (2SFCA) and network-based approaches typically assume flat terrain, complete road networks, and uniform travel speed assumptions that collapse in high-slope, high-altitude environments. Empirical studies from western China reveal that when topographic factors such as slope, elevation, and incomplete road networks are integrated into accessibility modeling, service coverage is drastically reduced. For instance, in the Liangshan region of Sichuan, over 60% of the land area was classified as having poor transportation accessibility due to steep terrain and sparse infrastructure (Shili, 2011). Similarly, a modified 2SFCA analysis in Shizhu County, Chongqing, found pronounced inequalities in access to healthcare services, with high-altitude villages far more disadvantaged than lowland areas (Deng, 2015). In Wanyuan City, incorporating slope and walking speed into a spatial network model improved school site planning and revealed the inadequacy of flat-terrain assumptions in mountainous cities (Yang et al., 2017). Further, 3D urban modeling in Chongqing demonstrates that terrain and vertical built structures substantially reduce walking accessibility and visibility of public amenities (Gu et al., 2021). Likewise, in rural Nanjiang County, Sichuan, rugged topography was shown to exacerbate spatial inequities in access to primary schools (Zhu et al., 2023). Collectively, these studies underscore that terrain-sensitive, network-integrated, and elevation-adjusted models are essential for accurately representing accessibility and spatial equity in mountainous regions.

Exposure to high altitude creates substantial physiological barriers to human performance because of hypoxia, which restricts oxygen delivery to both muscles and the brain. Under hypoxic conditions, individuals experience amplified central and peripheral fatigue, as reduced neural drive and muscle

oxygenation impair endurance and strength (Goodall et al., 2012). Even after acclimatization, oxygen transport remains limited, and muscle fatigue persists during exercise at altitude (Amann et al., 2013). Reduced cerebral oxygenation further contributes to early exhaustion and diminished voluntary muscle activation (Fan & Kayser, 2016). Although acclimatization enhances blood oxygen-carrying capacity, overall aerobic performance remains compromised due to persistent arterial oxygen deficits (Fulco, 1988). Studies further show that respiratory muscle training can improve endurance under hypoxic conditions by reducing ventilatory fatigue (Helfer et al., 2016). Field experiments confirm that walking or load carrying at altitudes above 3,500 m significantly elevates energy expenditure and perceived exertion even at slow speeds (Chatterjee et al., 2017). Collectively, these findings show that hypoxia at high altitude imposes intertwined cardiovascular, muscular, and neural limitations, making sustained walking and physical work physiologically taxing despite adaptation.

Urban and regional planning in mountainous regions faces distinctive challenges that require a shift from spatial diagnosis to actionable, context-sensitive strategies. Studies emphasize that steep topography, limited land resources, and fragmented accessibility networks demand adaptive frameworks for sustainable urban growth. In western China, urban expansion in Chongqing and similar mountainous cities demonstrates unique leapfrog and edge-expansion patterns, driven by terrain constraints and evolving economic forces, underscoring the need for landscape-sensitive and GeoDesign-based planning models (Jia et al., 2020). Similarly, spatial growth modeling in mountainous western China shows that slope, accessibility, and land use jointly determine urban growth resistance and environmental vulnerability, providing critical tools for planners to forecast and manage ecological impacts (Guoping, 2017). Furthermore, adaptive land-use management approaches—emphasizing efficient land resource utilization and risk-based urban design—have been proposed to integrate ecological safety and development efficiency (Gao et al., 2021). Collectively, these findings highlight that effective planning in mountainous regions requires integrating topographic resistance, accessibility modeling, and socio-environmental resilience into decision-making, transitioning from descriptive spatial diagnosis to actionable, terrain-adaptive policy frameworks.

In conclusion, high-altitude mountainous regions require a paradigm shift

in healthcare accessibility modeling—from uniform benchmarks to terrain-sensitive, effort-based, and physiologically informed methods. Only such approaches can ensure that "15-minute access" reflects ground reality and leads to equitable, actionable planning in the world's most marginalized geographies.

1.3 Research Object

1.3.1 Regional Scope and Selection Basis

China's western mountainous regions are among the most complex human–environment systems in the world, characterized by steep topography, fragile ecosystems, sparse transport networks, and dispersed rural settlements. The present study focuses on the high-altitude mountain zones distributed across Sichuan Province, the Tibet Autonomous Region, Yunnan Province, and Guizhou Province, representing the eastern fringe of the Qinghai–Tibet Plateau. Average elevations generally exceed 2,000 m, and the terrain is deeply dissected by valleys and ridges, producing severe constraints on mobility, infrastructure construction, and service delivery.

The regional selection followed two complementary criteria—natural geographic representativeness and socio-economic comparability. First, physical parameters including mean elevation and the Relief Degree of Land Surface (RDLS=2–5) were used to delineate large-relief alpine counties, ensuring that each sample unit possessed typical highland geomorphological characteristics. Second, demographic density, gross domestic product (GDP), and accessibility to basic infrastructure were jointly considered to capture internal heterogeneity while maintaining analytical coherence. The selected regions thus encompass a full spectrum of topographic, demographic, and economic conditions typical of high-altitude China, enabling the assessment of spatial equity and service efficiency under diverse mountainous contexts.

1.3.2 Typical Study Areas

（1）High-Altitude Counties of Sichuan Province

Forty-two non-key counties with mean elevations above 2,000 m were selected within the transitional belt between the Qinghai–Tibet Plateau and the

Sichuan Basin (Figure 1-1.). This area exhibits pronounced vertical differentiation, sparse road connectivity, and uneven urban–rural development. The study analyzes the drivers of demographic change and develops the Sustainable Population Migration Potential Index (SPMI) to quantify push–pull dynamics under mountainous constraints. Using the Digital-Twin Spatial Decision Platform (DTSDP), multiple policy scenarios—reflecting variations in medical service coverage, industrial transformation, and transport investment—are simulated to evaluate how spatial accessibility and infrastructure jointly shape long-term population redistribution patterns.

（2）Nine Large-Relief Alpine Counties in the Tibet Autonomous Region

The second case covers nine counties located between 4,000 and 6,000 meters above sea level with RDLS values of 2–5, representing the most extreme topographical conditions in China. This region provides an empirical foundation for assessing the service efficiency of primary-level healthcare facilities—including village clinics, township health centers, and traditional Chinese medicine (TCM) hospitals—under severe terrain limitations. Using high-resolution Digital Elevation Model (DEM) data and multi-level road networks, 15-minute service-circle analyses were conducted to identify coverage gaps and evaluate the spatial equality of healthcare provision. The findings highlight the pronounced mismatch between population distribution and facility locations, providing quantitative evidence for optimizing rural healthcare layouts in high-altitude environments.

（3）Diqing Tibetan Autonomous Prefecture, Yunnan Province

Situated at the intersection of Yunnan, Tibet, and Sichuan, Diqing Prefecture is characterized by steep valleys and scattered settlements with average elevations exceeding 2,000 m. It serves as a representative case for modeling the realistic walkable catchments of healthcare facilities in mountainous terrain. Building on the Multi-Factor Integrated Mountain Walkability Model (MIMWM), the study incorporates slope-dependent walking speed, land-use resistance coefficients, and altitude-related physiological decline into the Two-Step Floating Catchment Area (2SFCA) framework. The resulting terrain-sensitive accessibility maps reveal substantial overestimation

by conventional Euclidean or network-based methods and establish a 30-minute threshold beyond which improvements in accessibility diminish. This model provides a replicable methodology for terrain-adjusted healthcare planning in other topographically constrained regions.

1.3.3 Research Object System

（1）Socio-Economic and Infrastructure System

This subsystem examines the foundational role of economic development and infrastructure provision in shaping population mobility and healthcare accessibility. Key indicators include GDP per capita, industrial structure, fiscal revenue, education resources, road density, and fixed-asset investment. Through spatial regression and geographic detector analysis, the study quantifies how socio-economic capacity and infrastructure connectivity support or hinder demographic stability and equitable service delivery in high-altitude counties.

（2）Population and Migration System

Population data—covering total, urban, and rural residents—are integrated to build a structural index of demographic dynamics. The SPMI framework quantifies the equilibrium between attraction and repulsion forces, capturing how healthcare accessibility, livelihood opportunities, and social-service quality interact within the broader push–pull mechanism of mountain migration. This subsystem emphasizes the spatial coupling between population redistribution and the provision of essential public services.

（3）Healthcare Facilities and Spatial Accessibility System

Medical institutions at the county, township, and community levels are treated as spatial supply nodes. Three methodological approaches—Euclidean buffer, network analysis, and multi-factor distance accumulation—are comparatively applied to evaluate accessibility differences. By linking terrain resistance with service coverage, the study establishes a quantitative framework for assessing spatial equity and optimizing the configuration of healthcare resources in mountainous regions.

（4）Natural Terrain and Environmental Constraint System

High-resolution DEM data provides the basis for extracting slope gradients, relief amplitude, and land-use resistance coefficients. An altitude-related physiological decay function is incorporated to simulate reductions in walking capacity with elevation gain. These factors are combined into a continuous mountain walkability surface, capturing the physical constraints of high-altitude environments on daily mobility, healthcare access, and migration behavior. This subsystem forms the physical foundation linking natural conditions with social outcomes in the integrated analytical framework.

In summary, the research object integrates multi-scale and multi-factor systems—spanning economic development, population dynamics, healthcare service networks, and physical terrain—to elucidate the mechanisms driving spatial inequality and sustainable development in high-altitude mountainous regions of western China.

1.4 Research Structure

This dissertation is organized into five closely interlinked chapters, each addressing a specific analytical scale within the overarching framework of population dynamics and healthcare accessibility in high-altitude mountainous regions of western China (Figure 1-1). The three core empirical studies—conducted in Sichuan, Tibet, and Yunnan—progressively build a multi-level analytical chain from population migration mechanisms to spatial efficiency evaluation and fine-scale accessibility modeling. Together, they provide a coherent theoretical and methodological system linking migration theory, public service accessibility, and health equity.

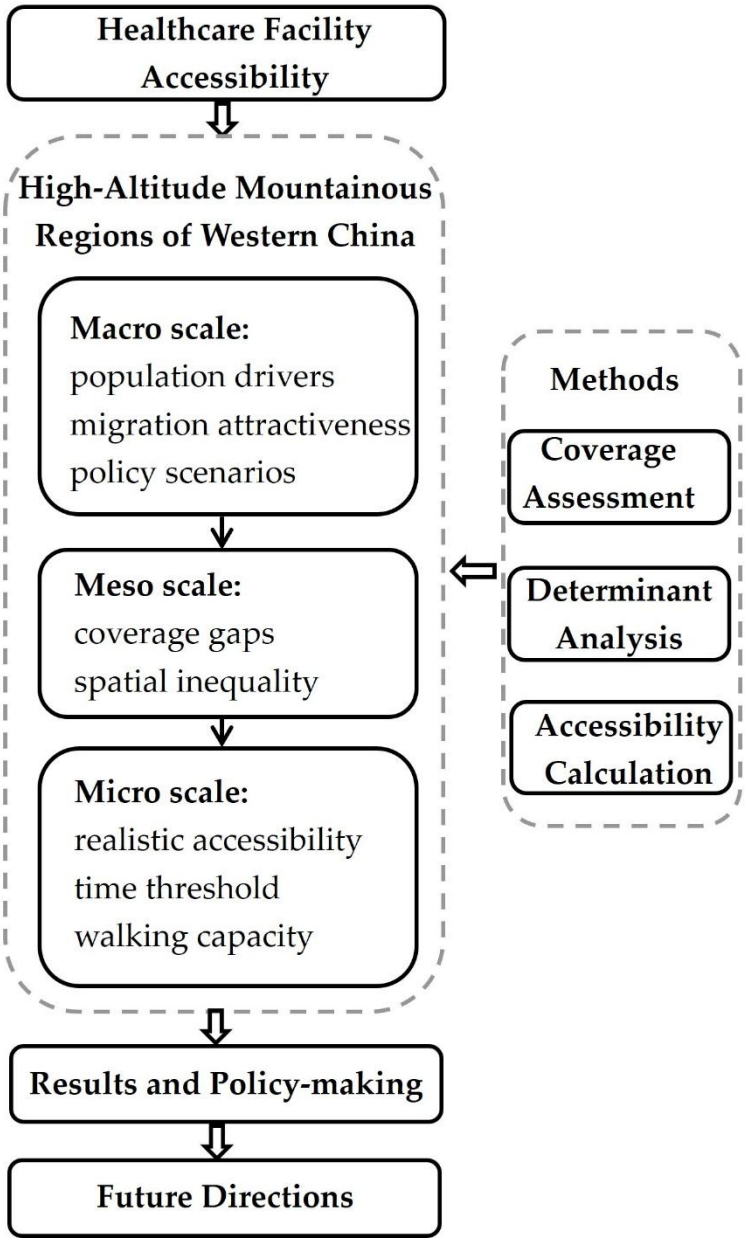


Figure 1-1. Research structure.

Chapter 1 – Introduction presents the overall background, theoretical framework, research objectives, and structure of the dissertation. It highlights the dual challenges of population sustainability and healthcare service provision in high-altitude mountainous regions, where rugged terrain, sparse infrastructure, and altitude-related physiological constraints limit both mobility and accessibility. The chapter reviews prior studies on migration theory, spatial accessibility, and health equity, identifying critical research gaps—especially the neglect of topographic and environmental factors in accessibility

evaluation—and clarifies the study's academic positioning, significance, and innovation.

Chapter 2 – Drivers of Population Dynamics in High-Altitude Regions represents the macro-scale analysis, focusing on the underlying drivers of population change. Based on empirical research across 42 high-altitude counties in Sichuan Province, this chapter applies the Geodetector model and develops the Sustainable Population Migration Index (SPMI) to quantify push–pull mechanisms related to environmental, infrastructural, and healthcare variables. The results demonstrate that public healthcare services and their spatial accessibility are the core determinants of population development in high-altitude mountainous regions, exerting stronger effects than economic or transportation factors. Healthcare accessibility not only shapes residents' well-being but also determines migration intentions and long-term demographic stability. A Digital Twin–based Simulation and Decision-support Platform (DTSDP) is further employed to visualize policy scenarios. However, one of the most critical mechanisms behind population dynamics lies in the accessibility of medical facilities themselves, which is explored in depth in the following Tibet case study.

Chapter 3 – Service Efficiency of Healthcare Facilities in High-Altitude Regions addresses the meso-scale dimension, examining the efficiency and spatial equity of primary medical facilities across nine counties in the Tibet Autonomous Region (elevation 4,000–6,000 m; RDLS 2–5). Integrating satellite imagery, POI data, DEM terrain indices, and road network data, this chapter evaluates township health centers and village clinics within the "15-minute living circle" framework. The findings reveal that healthcare accessibility in high-altitude mountainous regions is extremely poor, and that existing accessibility assessments suffer from significant distortion because Euclidean and network-based methods fail to account for topographic resistance. The analysis underscores the urgent need for a terrain-sensitive and dynamic modeling approach to capture real accessibility patterns. While this study identifies major deficiencies in healthcare coverage, it remains static in nature; the next chapter therefore introduces a dynamic, multi-factor model (MIMWM) to simulate true pedestrian accessibility under complex terrain conditions.

Chapter 4 – Multi Factor Assessment of Spatial Accessibility constitutes the

micro-scale methodological innovation of the dissertation. It introduces the Multi-Factor Integrated Mountain Walkability Model (MIMWM), which embeds high-resolution DEM data, slope-adjusted walking speed, land-use resistance, and altitude-induced physiological decline into the Two-Step Floating Catchment Area (2SFCA) framework. Applied to Diqing Prefecture in Yunnan Province, the model demonstrates that traditional Euclidean and network-based approaches overestimate accessibility by 40–60% in mountainous environments. The MIMWM identifies a 30-minute walking-time threshold, beyond which accessibility improvements diminish, indicating the inapplicability of uniform national standards in complex terrains. By integrating insights from the previous chapters on population dynamics and service efficiency, this study confirms that healthcare accessibility is the pivotal mechanism linking demographic sustainability and spatial equity in high-altitude regions, thereby establishing a methodological foundation for a comprehensive population–facility coupling framework.

Chapter 5 – Conclusions and Prospects summarizes the major theoretical, methodological, and empirical contributions of the dissertation. It proposes a multi-level population–health coupling framework linking population dynamics (SPMI), facility efficiency, and terrain-sensitive accessibility modeling (MIMWM). The policy implications highlight the need for prioritized healthcare investment, differentiated accessibility standards (15-minute vs. 30-minute thresholds), and digital twin systems for decision support in mountainous regions. Finally, the chapter discusses research limitations—such as cross-regional comparability, climate impacts, and lack of dynamic data integration—and suggests future directions involving seasonal and time-series modeling to support resilient and equitable healthcare planning in high-altitude contexts.

Collectively, the five chapters form a coherent analytical chain from population dynamics to service efficiency to accessibility modeling, constructing a comprehensive framework that captures the spatial mechanisms driving population sustainability in mountainous regions. By integrating the SPMI, efficiency evaluation, and MIMWM models, the dissertation provides both theoretical insight and methodological innovation for promoting health equity and sustainable development in high-altitude areas.

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Chapter 2

DRIVERS OF POPULATION DYNAMICS IN HIGH-ALTITUDE REGIONS

Chapter 2

Drivers of Population Dynamics in High-Altitude Regions

This chapter investigates the population dynamics of high-altitude mountainous areas, revealing how they are shaped by a complex interplay of socioeconomic and environmental drivers. The population dynamics of high-altitude mountainous areas are shaped by a complex interplay of socioeconomic and environmental drivers. Despite their significance, such regions have received limited scholarly attention. This research identifies and examines the principal determinants of population changes in the high-altitude mountainous zones of Sichuan Province, China. Utilizing a robust quantitative framework, we introduce the Sustainable Population Migration Index (SPMI) to systematically analyze the migration potential over two decades. The findings indicate healthcare accessibility as the most significant determinant influencing resident and rural population changes, while economic factors notably impact urban populations. The SPMI reveals a pronounced deterioration in migration attractiveness, decreasing by 0.27 units on average from 2010 to 2020. Furthermore, a fixed-effects panel regression confirmed the predictive capability of SPMI regarding population trends, emphasizing its value for demographic forecasting. We also develop a Digital Twin-based Simulation and Decision-support Platform (DTSDP) to visualize policy impacts effectively. Scenario simulations suggest that targeted enhancements in healthcare and infrastructure could significantly alleviate demographic pressures. This research contributes critical insights for sustainable regional development strategies and provides an effective tool for informed policymaking.

2.1 Introduction

Following the initiation of reform and opening-up policies in the 1980s, rapid economic development and urban expansion have contributed to growing

regional disparities in both population distribution and economic outcomes. These imbalances are primarily shaped by heterogeneous natural and geographical environments. These imbalances have further intensified the complex interdependence between demographic patterns and economic development, resulting in notable shifts in population structure and spatial distribution (He et al., 2016; Wang et al., 2019). The escalation of intercity mobility has been largely fueled by rising incomes, infrastructure improvements, and the expansion of the consumer economy, alongside increasing convenience and changing consumption behaviors. Beyond traditional economic disparities across cities, population mobility is increasingly shaped by the distribution of educational opportunities, the quality of public services, and the overall quality of life. This trend indicates an evolution toward more complex and multidimensional determinants of migration (H. Y. Gu et al., 2019; Liu et al., 2014).

Contemporary studies on population change have examined multiple aspects of population mobility, such as spatial distribution patterns (Li et al., 2019; Liang et al., 2014), transformation modes (Pan & Lai, 2019; Qi et al., 2016), underlying drivers (Liu et al., 2020; Wu et al., 2019), and associated effects. Globally, growing scholarly interest has been directed toward the internalization and regionalization trends of demographic shifts (Park & Lee, 2019). In the Chinese context—marked by a large-scale migrant population—research efforts have primarily concentrated on interprovincial migration and the dynamics of economically advanced urban agglomerations (J. J. Luo et al., 2018). According to the Seventh National Population Census, the new urbanization strategy, implemented since 2010, has spurred increased population movement, particularly with a growing share of interprovincial migration. However, uncertainties persist concerning the key driving forces, varying migration trends, and the underlying social dynamics (DING Jinhong, 2005).

Existing research has predominantly examined well-established urban regions, including the Yangtze River Delta, Pearl River Delta, and the Beijing-Tianjin-Hebei area, with less emphasis on the patterns of interprovincial migration in high-altitude zones and urban clusters in central and western China (Wang et al., 2012). Supported by national strategies and local governmental initiatives, the attractiveness of central-western urban clusters to

migrants has been gradually rising. To better understand regional demographic dynamics, future studies should investigate these diverse geographical settings—particularly those with a complex topography—to provide nuanced insights that can inform region-specific development policies (Wang & Xue, 2019).

Population change is commonly explained through the push-pull theory, where factors pushing people from their place of origin and those attracting them to a destination generate migration patterns. Migration motivation research is commonly divided into macro- and micro-level perspectives. Macro-level analyses focus on the interplay between population dynamics and regional economic development, incorporating factors such as spatial proximity, economic growth, and policy frameworks (Xinxian & Xiangdong, 2019). While these studies emphasize urban and lowland migration drivers, they overlook geographic constraints specific to mountainous contexts (Wang & Xue, 2019; Wang et al., 2012; Xinxian & Xiangdong, 2019). For instance, Liu et al. demonstrated that altitude-induced healthcare inaccessibility reduces population retention by 23% in Tibetan counties (Wang, 2024), while Liu and Li quantified a 40% higher infrastructure vulnerability in slopes >25° (Liu & Li, 2016). Such terrain-dependent barriers fundamentally reshape migration mechanics—whereas lowland models prioritize economic gradients (Stepus et al., 2025), which are central to our case. In contrast, micro-level studies center on individual attributes and decision-making rationales, exploring elements such as access to public services, infrastructure quality, family considerations, and life course stages (Black et al., 2022; Zhou & Chi-Man Hui, 2022).

Existing research on population dynamics has frequently integrated both qualitative and quantitative methodologies. Qualitative approaches—such as interviews, surveys, and case studies—draw upon established theoretical frameworks to explore change motivations at both individual and collective levels. Quantitative methods, including statistical analysis, spatial panel models, and econometric techniques, often harness big data to identify and measure key influencing factors. For example, Kraft examined demographic trajectories using mobile communication records and transportation network data (Kraft et al., 2022), whereas Zhang utilized location-based big data to analyze population mobility patterns across 328 cities (Zhang et al., 2020). Liu applied spatial analysis and the geodetector method to investigate the drivers and spatial

characteristics of population decline in mountainous areas. Moreover, mixed-methods research, which combines qualitative depth with quantitative rigor, provides a more comprehensive understanding of the complex mechanisms driving population movements (Liu et al., 2022).

This research investigates the high-altitude mountainous areas of Sichuan Province to identify the primary factors influencing population change, aiming to fill existing gaps in the scholarly literature. While the classical push–pull framework provides a foundational lens for understanding migration, its application in high-altitude mountainous contexts requires contextual adaptation. In such regions, environmental constraints—such as elevation-induced infrastructure costs, service delivery bottlenecks, and occupational rigidities in the primary sector—amplify both push pressures and barriers to in-migration. As a result, population decisions are shaped not only by conventional economic gradients but also by region-specific physical and institutional vulnerabilities. Recent empirical studies in China have underscored that mountainous zones exhibit structurally distinct migration drivers, where the loss of young labor is due more to deficits in healthcare access and educational continuity than to income alone. Therefore, this study reconceptualizes the push–pull logic to accommodate the dual role of terrain-dependent infrastructural disadvantage and policy-sensitive public service differentials. While prior research has considered the effects of economic, infrastructural, and healthcare factors, the unique geographical and socioeconomic characteristics of high-altitude areas remain underexplored. Pronounced elevation gradients and rugged topography—especially in areas exceeding 2000 m—introduce significant complexities into analyzing demographic dynamics. To uncover the mechanisms driving population shifts in these regions, this study applies the geodetector model based on 14 indicators related to the economy, infrastructure, and healthcare, derived from the Sichuan Statistical Yearbook. In addition, a novel Sustainable Population Migration Index (SPMI) is proposed to quantify migration potential by integrating attractive and push-pressure factors. A Digital Twin-based Simulation and Decision-support Platform (DTSDP) is also developed to visualize and simulate the spatial impacts of policy interventions. Together, these methods establish a comprehensive analytical framework for evaluating demographic changes in high-altitude regions and provide empirical insights for regional development and policy design.

2.2 Research Objects

This subsection examines population dynamics across 42 non-key high-altitude counties in Sichuan (average elevation >2000 m), a region spanning the Qinghai–Tibet Plateau, Hengduan Mountains, and Sichuan Basin. We assemble a standardized indicator system—economy, infrastructure, and healthcare—comprising 14 policy-relevant variables. To isolate intrinsic drivers, "key counties" designated for targeted poverty programs are excluded to avoid inflated health and economic metrics. Guided by the push–pull framework, indicators are classified as Attractive or Push-Pressure factors. Data are temporally harmonized to China's Five-Year Plan windows (10th–14th FYP); the 14th FYP currently includes 2021–2022 only. Limited missing values (<1%) are imputed by plan-window means. We acknowledge potential income–migration endogeneity (urban and rural disposable income) and address it via Geodetector-based weighting and robustness checks. This design provides a consistent, policy-oriented basis for subsequent spatial analysis and modeling.

2.2.1 Study Area

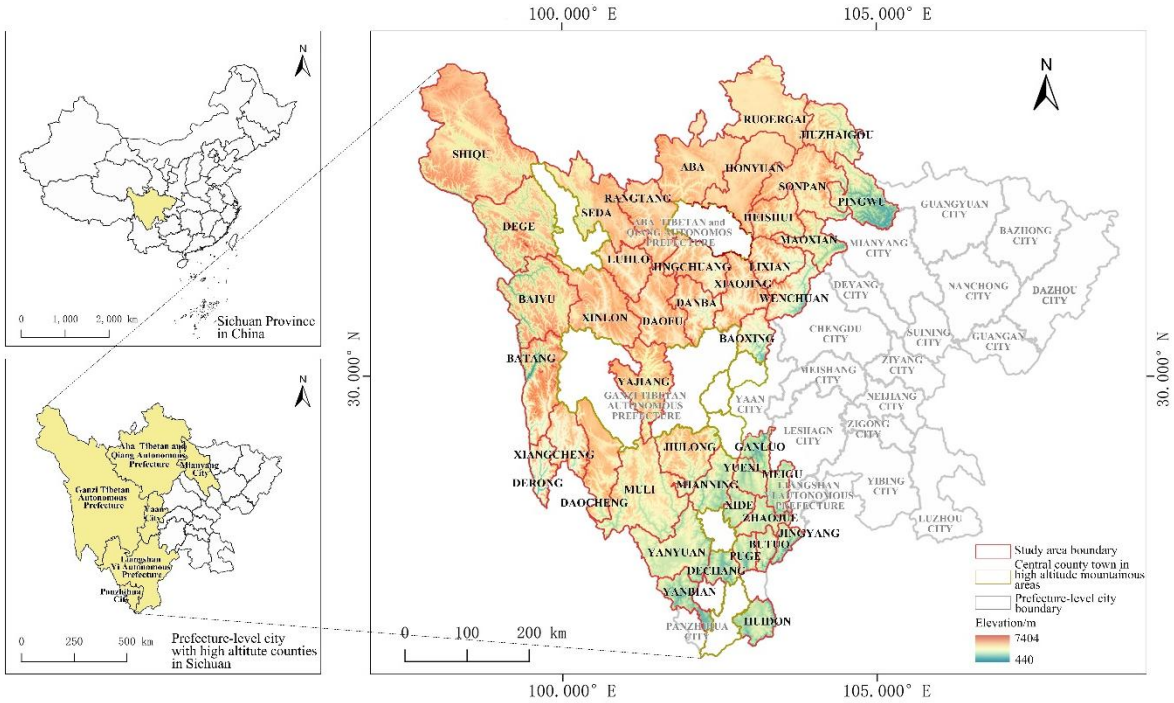


Figure 2-1. Altitude map of Sichuan counties in western China.

The This study focuses on 42 non-key high-altitude counties in Sichuan Province, China, each with an average elevation above 2000 m (Figure 2-1). The region includes sub-high and high-altitude zones. Sichuan features diverse geomorphological regions—such as the Qinghai-Tibet Plateau, Hengduan Mountains, and Sichuan Basin—with terrain descending from west to east. The average elevation is 2598 m, ranging from Mount Gongga's 7526-m peak to a low of 188 m in Yulin Town. These varied geographical conditions provide the essential context for the analysis.

2.2.2 Indicator System and Data Source

（1）Dependent Variables: Resident population, Urban population, Rural population

This study examines three distinct population categories: resident, urban, and rural populations. According to the Seventh National Population Census, the resident population encompasses individuals residing in a given township or sub-district, regardless of local hukou registration, including those temporarily abroad or absent from their registered location for more than six months. It reflects the actual number of people present and is key to assessing population distribution, labor supply, and resource allocation. According to national statistical standards, the urban population refers to individuals residing in cities or towns, while the rural population includes those living outside urban boundaries. This classification is based on residence and occupation. Urban population data help gauge urbanization, economic growth, and social change, whereas rural population figures are essential for rural planning, agricultural policy, and public service delivery. Together, these three metrics offer a comprehensive basis for evaluating demographic structure and guiding development policy.

（2）Independent Variables: Economy, Infrastructure, Healthcare

As shown in Table 2-1, this study evaluates how the economy, infrastructure, and healthcare influence population dynamics. Based on a literature review, 14 key indicators were identified across these dimensions, reflecting the multifactorial drivers of demographic change in high-altitude mountainous regions. To ensure study integrity and isolate intrinsic drivers, we

selected non-key counties. Al Abbasi et al. showed targeted poverty alleviation investments in "key counties" artificially inflate healthcare (e.g., hospital beds, doctor-patient ratio) and economic indicators (e.g., GDP per capita) by 18–35% based on 2015–2020 data, which could distort our analysis (Al Abbasi et al., 2025). Similarly, research focusing on the healthcare workforce in Western China by Duan et al. quantified a 22% overestimation in health personnel density attributable to temporary poverty alleviation subsidies in supported counties (Duan & Liu, 2025). Furthermore, analyses of economic data, such as those by Kang and Li examining counties in Yunnan province, reported GDP growth rates in neighboring key poverty counties that were inflated by approximately 18–23% due to concentrated policy interventions, potentially masking underlying economic fundamentals (Kang & Li, 2024). Including these designated counties would thus introduce substantial measurement bias and confound our analysis of intrinsic drivers.

Table 2-1. Variable definitions and data sources. (Data frequency: annual).

Indicator Type	Indicator	Units	Data Sources	Variable ID
Economy	Gross Regional Domestic Product	Ten thousand RMB	Provincial, city and county statistical yearbooks	E1
	Primary Industry Production Value	Ten thousand RMB	Provincial, city and county statistical yearbooks	E2
	Secondary Industry Production Value	Ten thousand RMB	Provincial, city and county statistical yearbooks	E3
	Tertiary Industry Production Value	Ten thousand RMB	Provincial, city and county statistical yearbooks	E4
	Local Public Finance Revenue	Ten thousand RMB	Provincial, city and county statistical yearbooks	E5
	Total Retail Sales of Consumer Goods	Ten thousand RMB	Provincial, city and county statistical yearbooks	E6
	Urban Residents Average Disposable Income	RMB	Provincial, city and county statistical yearbooks	E7
	Farmers and Herdsmen Average Disposable Income	RMB	Provincial, city and county statistical yearbooks	E8
Infrastructure	Investment in Fixed Assets of the Whole Society	Ten thousand RMB	Provincial, city and county statistical yearbooks	I1
	Number of Primary Schools	Number of schools	Provincial, city and county statistical yearbooks	I2
	Number of General Secondary Schools	Number of schools	Provincial, city and county statistical yearbooks	I3
Healthcare	Number of Hospitals and Health Centers	Number of Hospitals and Health Centers	Sichuan Provincial Health and Wellness Statistical Yearbook	H1
	Number of Beds in Hospitals and Health Centers	Number of Beds	Sichuan Provincial Health and Wellness Statistical Yearbook	H2
	Number of Health Personnel in Health Facilities	Person	Sichuan Provincial Health and Wellness Statistical Yearbook	H3

Note: This table presents descriptive indicator definitions only. No inferential statistics or significance testing were applied. Variable IDs (e.g., E1–E8, I1–I3, H1–H3) are assigned based on the initial letter of the indicator type (Economy, Infrastructure, Healthcare) followed by a numeric sequence for clarity and consistency with prior studies.

To ensure a comprehensive and systematic selection of independent variables, this study adopted a two-step screening process. Initially, potential determinants of population change were identified based on a thorough review of the relevant literature (China, 2021; Li et al., 2017; Ma & He, 2021; Zhu et al., 2018) and the official evaluation framework for urban development in China (China, 2021). Subsequently, the variable set was refined using criteria of scientific robustness and data availability, resulting in 14 measurable and policy-relevant indicators. Guided by the classical push–pull migration framework (de Haas, 2021), this study classified the 14 explanatory indicators into pull factors and push factors. Pull factors denote favorable conditions that augment a region's capacity to attract and retain residents (Niu, 2022), such as high-value-added industrial output, comprehensive public services, and high-quality healthcare resources. Push factors, in contrast, capture adverse conditions that erode population-retention capacity and propel labor out-migration (Mateus, 2023). Although the output value of the primary sector registers local economic activity, it is deemed a push factor for high-altitude counties. Heavy reliance on primary production typically signals limited economic diversification and short, fragile value chains that are highly vulnerable to market volatility and natural shocks. Such structural vulnerability constrains the availability of diverse, high-quality employment opportunities, diminishes the region's appeal to young labor, and ultimately generates net out-migration pressure in interregional competition. These indicators were classified into three categories: economic factors, including gross regional domestic product, output values of the primary, secondary, and tertiary industries, local public finance revenue, total retail sales of consumer goods, and average disposable incomes of both urban residents and rural populations (farmers and herdsmen); infrastructure factors, comprising total investment in fixed assets, number of primary schools and general secondary schools; and healthcare factors, including the number of hospitals and health centers, hospital beds, and health personnel. While statistical yearbooks provide standardized, county-level data, we acknowledged potential underreporting in remote areas. As mitigation, we cross-validated demographic trends with census data and provincial statistical bulletins where available. Furthermore,

qualitative drivers such as cultural attachment and place identity, though beyond the scope of this study's quantitative framework, were recognized as significant and warrant integration in future mixed-methods research. Furthermore, we recognize the potential endogeneity concerns associated with urban residents' average disposable income (E7) and farmers' and herdsmen's average disposable income (E8) (Mutlugün, 2022). This primarily stems from the well-established bidirectional relationship between income levels and migration patterns: higher income can attract migrants, while migration inflows (or outflows) can subsequently impact local income levels, as theorized by Todaro and supported by subsequent empirical work (Thomas & Vendryes, 2011). The Geographical Detector method (specifically the factor detector) (J. F. Wang et al., 2010; Yi et al., 2011), which confirmed that the explanatory power (q-statistic) of E7 and E8 did not exhibit significant overlap or dependence with other key drivers in the model. The results of these independence tests assured us that E7 and E8 could be meaningfully isolated and removed for robustness checks without fundamentally altering the structure of the remaining explanatory framework (Table A2-2). These steps collectively ensured that any potential inflation of explanatory power caused by income-migration feedback loops was effectively addressed.

（3）Temporal Harmonization of the Observation Framework

In China, macro-level statistical data are typically organized and published according to Five-Year Plan (FYP) cycles. Accordingly, this study aligned all annual observations with the relevant FYP periods: the 10th FYP (2001–2005), 11th FYP (2006–2010), 12th FYP (2011–2015), 13th FYP (2016–2020), and the currently ongoing 14th FYP. As of this study, only data from 2021 to 2022 are available for the 14th FYP, meaning that this window covers two years rather than a full five-year cycle. To ensure data continuity and comparability across counties and years, a small number of missing values—mainly due to rare omissions in individual yearbooks—were filled using mean values within the respective Five-Year Plan (FYP) windows. Notably, the proportion of missing values is extremely low, accounting for less than 1% of the total dataset. Given the window-based aggregation, this imputation had minimal impact on the robustness of the analysis.

2.3 Methods

Here I examine population dynamics in 42 non-key, high-altitude counties of Sichuan (>2000 m) using a standardized indicator system spanning economy, infrastructure, and healthcare, temporally harmonized to China's Five-Year Plan windows. I first characterize spatial patterns via global and local spatial autocorrelation (Moran's I, LISA). I then constructed a Sustainable Population Migration Index (SPMI) that integrates Attractive Indicators and Push-Pressure Indicators, with data-driven weights derived from Geodetector q-statistics. Robustness is assessed through correlation tests and fixed-effects panel models with lagged SPMI terms, complemented by a back-casting check against observed changes in a policy period. Finally, a Digital-Twin–based Simulation and Decision-support Platform (DTSDP) enable interactive scenario experiments—e.g., enhancing healthcare or infrastructure—and evaluates county-level SPMI shifts using paired tests, linking methodological outputs to policy-oriented insights.

2.3.1 Geodetector Method

Spatial autocorrelation is a statistical technique used to assess the spatial distribution patterns and relationships within geographic data (Getis, 2009). It is based on the premise that spatially adjacent or nearby locations may exhibit similar or correlated values and that this similarity tends to diminish or disappear as the distance between locations increases (Dale & Fortin, 2009).

Spatial autocorrelation is generally categorized into two types: global and local.

Global spatial autocorrelation provides an overall evaluation of spatial patterns within the entire study area. It helps determine whether the spatial data tend to cluster or disperse, as well as the intensity and statistical significance of such patterns (Ping et al., 2004). Among the various global measures, Moran's I is the most widely applied index (Tiefelsdorf, 1998), and its formula is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij(x_i-\overline{X})(x_J-\overline{X})}}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (2\text{-}1)$$

In this equation, n denotes the total number of spatial units, while $\overline{X}$ represents the mean value of all observations. X_i and X_j refer to the observed values for spatial units i and j, respectively. W_{ij} corresponds to the spatial weight matrix, which characterizes the spatial relationship between units i and j. A Moran's I value greater than 0 signifies positive spatial autocorrelation, meaning nearby areas tend to show similar values, either high-high or low-low clustering. A value less than 0 suggests negative spatial autocorrelation, where high values are surrounded by low values or vice versa. When Moran's I approaches 0, it implies a random spatial pattern with no discernible correlation.

In contrast, local spatial autocorrelation emphasizes the spatial characteristics of individual units within the study area. It assesses the degree and statistical significance of spatial heterogeneity by examining the relationship between each unit and its immediate neighbors. The most commonly employed metric for this purpose is the Local Moran's I index (Dale & Fortin, 2009), which is defined by the following formula:

$$I_i = \frac{(X_i - \overline{X})}{S^2} \sum_j W_{ij}(X_j - \overline{X}) \quad (2\text{-}2)$$

It serves as a tool for detecting various spatial clustering or dispersion patterns within a study area, including clusters of high values, clusters of low values, high-value outliers surrounded by low values, and low-value outliers surrounded by high values.

Spatial autocorrelation has been extensively applied to investigate spatial distribution patterns across various domains, including road traffic (Gedamu et al., 2024) and disease incidence (Tsai et al., 2009). For example, Zhu Mingfei (Zhu et al., 2024) employed spatial autocorrelation analysis to reveal the spatial clustering patterns and temporal evolution of COD (chemical oxygen demand) emissions across provinces in China. The findings provided important insights into the spatial distribution and underlying drivers of COD emissions.

The geodetector (Geodetector Software in Excel), developed by Jinfeng Wang and collaborators, is a statistical method designed to detect spatially stratified heterogeneity and to identify the dominant factors contributing to its formation (Jinfeng WANG 2017). One key advantage is its ability to analyze two core types of spatial variation: inter-factor interactions and intra-factor heterogeneity. Through this analysis, the geodetector provides a quantitative assessment of how well each factor explains variations in a target variable within spatial data.

The method includes four primary components: the factor detector, the interaction detector, the risk detector, and the ecological detector (Jinfeng WANG 2017). By computing and comparing the q-values of individual factors, the method evaluates their explanatory strength, where higher q-values indicate a stronger influence on spatial variation. The q-value is calculated using the following equation (J. Wang et al., 2010):

$$Q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{2-3}$$

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2, SST = N\sigma^2 \tag{2-4}$$

In this formula, $h = 1, \ldots, L$ indicates the stratification of variable Y or factor X, referring to the classification or segmentation of data. N_h and N represent the number of units in stratum h and the total number of units in the entire study area, respectively. σ_h^2 and σ^2 denote the variance of Y within stratum h and across the entire region. SSW (sum of squares within groups) and SST (total sum of squares) are used to measure internal and overall variability.

At present, the geodetector is widely applied across disciplines such as geography, environmental science, ecology, and social economics. It has become a key component of contemporary geographic information analysis (Li et al., 2013; Lou et al., 2016). For instance, Zhu Yaoyao utilized the geodetector to examine and quantify the multiple drivers influencing the transformation of urban open space in Shanghai, highlighting the predominant influence of socioeconomic factors (Zhu & Ling, 2024).

2.3.2 Construction of a Sustainable Population Migration Model

To enhance prediction accuracy and deepen understanding of population migration dynamics in mountainous regions, this study built on key driving factors identified via the geodetector model. Specifically, we reconstructed the Sustainable Population Migration Index (SPMI) using a bidirectional framework incorporating attractive and push–pressure dynamics; the SPMI quantifies the net migration potential of each spatial unit by integrating positive and negative drivers within a weighted structure. The index is calculated using the following formula:

$$SPMI_i = \sum w_j^{(AI)} \cdot Z_j - \sum w_k^{(PPI)} \cdot Z_k \quad (2\text{-}5)$$

where Z_j is the standardized score (Z-score) of the j-th Attractive Indicator (AI) in county i; Z_k is the standardized score of the k-th Push-Pressure Indicator (PPI) in county i; $w_j^{(AI)}$is the weight of the j-th AI, derived by normalizing its geodetector q-statistic:$\sum_{j=}1^{nAI} w_j^{(AI)} = 1$; $w_k^{(PPI)}$is the weight of the k-th PPI, similarly based on its q-statistic and normalized as: $\sum_{k=}1^{nPPI} w_k^{(PPI)} = 1$; n^{AI} and n^{PPI} denote the numbers of AI and PPI variables, respectively.

The Z-score Z_j is computed as$(x_j - \bar{x}_j)/\sigma_j$, where x_j is the raw indicator value, $\bar{x}_j$ is the county-wise mean of the indicator, and σ_j is its standard deviation. Positive SPMI values imply net pull effects (attraction > pressure), while negative values indicate net push effects (pressure > attraction), characterizing spatial migration dynamics.

We used geodetector-derived q-values as indicator weights in constructing the SPMI, as they directly reflect each variable's explanatory power for spatial population differences. Compared with entropy (unsupervised) or AHP (subjective) weighting, this approach is data-driven and outcome-specific. To test robustness, we recalculated SPMI values using equal and entropy weights, based on data from the 13th Five-Year Plan (2016–2020). The rankings remained largely consistent (Spearman ϱ = 0.70 vs. equal-weight; ϱ = 0.53 vs. entropy), confirming the stability of our method.

The push-pull model, originally proposed by Lee (1966), is a widely recognized theoretical framework for analyzing the motivations behind

population migration (Lee, 1966). First, a city's population size and economic scale (GDP) reflect its scale attractiveness (Chu et al., 2023). Second, the level of public services, represented by the proportion of the tertiary sector and education level, also significantly influences its advantages (Shen et al., 2023). Furthermore, average and minimum wage levels, as well as the unemployment rate, are important indicators of a city's employment environment, directly affecting labor mobility (Manning, 2021). Feng et al. focused on the population migration between Chinese cities, conducted an in-depth analysis using the push-pull theory, and clearly included the proportion of the primary industry and the income of rural residents in the empirical research of the "push" force factors, revealing the nonlinear and asymmetric characteristics of the push-pull factors in China's population migration (Shi et al., 2025). In addition, based on the push-pull theory, LI et al. empirically found with inter-provincial data from 1998 to 2012 that the output value of the primary industry and the average disposable income of farmers and herdsmen, which are indirectly related to agricultural technological progress, constitute a "push force" (Bin et al., 2015). Based on the above theoretical description, the selected variables were classified into two categories: Attractive Indicators (AIs), which reflect factors that potentially draw population inflows, such as Gross Regional Domestic Product, output values of the secondary and tertiary industries, the number of primary and general secondary schools, and the number of hospitals and health centers; and Push-Pressure Indicators (PPIs), which represent factors that may contribute to population outflows, including primary industry production value and the average disposable income of farmers and herdsmen.

All indicators were normalized using Z-score standardization to ensure comparability, with values reversed for those negatively correlated with migration potential prior to normalization.

Specifically, the geodetector method provided factor significance measures (q-values), reflecting the explanatory power of each indicator regarding spatial variation in population change. We standardized these q-values to compute weights (W_j), ensuring their sum equaled 1, as follows:

$$W_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{2-6}$$

The calculation of the SPMI involves the following steps: (1) standardizing all indicators using Z-score normalization; (2) deriving indicator weights directly from the q-values obtained via the geodetector model; (3) computing the SPMI score for each administrative unit based on the weighted combination of attractive and push-pressure factors; and (4) visualizing and analyzing the spatial distribution of SPMI results using Geographic Information System (GIS) software such as ArcGIS Pro3.5 (Environmental Systems Research Institute) .

2.3.3 Model Validation Strategy

To evaluate the robustness and explanatory power of the Sustainable Population Migration Index (SPMI) in modeling resident population dynamics, a two-step validation strategy was employed. First, Pearson correlation analysis was conducted to examine the bivariate association between SPMI values and annual population growth rates across all counties and years. Second, to account for potential time-lagged effects and unobserved heterogeneity, a fixed-effects panel regression model was constructed using lagged SPMI variables as predictors. The specification is as follows:

$$PG_{i,t} = \alpha + \beta_1 SPMI_{i,t-1} + \beta_2 SPMI_{i,t-2} + \delta_i + \gamma_t + \varepsilon_{i,t} \quad (2\text{-}7)$$

where $PG_{i,t}$ denotes the annual population growth rate of the county i in year t; $SPMI_{i,t-1}$ and $SPMI_{i,t-2}$ represent one- and two-year lagged values of SPMI, respectively; δ_i and γ_t capture county and year fixed effects; and $\varepsilon_{i,t}$ is the error term. Robust standard errors were clustered at the county level. Model performance was evaluated based on the signs and statistical significance of the estimated coefficients β_1 and β_2, as well as within-R^2 values, which indicate the proportion of variance explained. This approach enables a rigorous assessment of the SPMI's predictive power while addressing potential spatial and temporal confounding factors.

To enhance model validation, we adopted a back-casting approach by retrospectively comparing SPMI trends with observed demographic and sectoral changes during a known policy period. This enabled us to assess whether the model could reflect real-world population responses following policy-driven shifts in migration-related conditions.

2.3.4 Digital Twin-Based Simulation and Decision-Support Platform

To integrate and visualize the complex spatiotemporal dynamics of mountainous population migration, we developed a Digital Twin-based Simulation and Decision-support Platform (DTSDP). Combining digital twin technology, GIS, and scenario simulation, the DTSDP enables real-time modeling, visualization, and interactive decision-making. It functions as a virtual counterpart to real-world mountainous regions, dynamically reflecting migration drivers and outcomes based on socioeconomic, infrastructure, and healthcare factors. The platform bridges theoretical modeling and practical policymaking, allowing stakeholders to explore the spatial effects of various intervention scenarios.

The DTSDP features a three-tier architecture (data–model–interaction): (1) the data layer integrates standardized geospatial/statistical indicators (economy, healthcare, infrastructure); (2) the model layer computes migration potentials via the Sustainable Population Migration Index (SPMI) with geodetector-derived weights; and (3) the interaction layer enables real-time parameter adjustment and spatial visualization through an ArcGIS Pro interface.

The Digital Twin-based Simulation and Decision-support Platform (DTSDP) facilitates scenario-based analysis through a structured four-step methodology. First, a baseline scenario is established by calculating the Sustainable Population Migration Index (SPMI_baseline) without policy intervention, serving as a reference for comparison. Next, scenario design and parameter adjustment are conducted by defining hypothetical policy scenarios—such as increasing healthcare accessibility or infrastructure investment—and interactively modifying relevant input parameters within the platform. In the third step, the platform performs scenario simulations, recalculating migration potential (SPMI_scenario). The significance of scenario-specific SPMI gains was assessed using paired one-sample t-tests on county-level Δ values (n = 10 per scenario).

2.4 Population Dynamics and Migration Potential in High-Altitude Regions

This subsection uses the Digital Twin–based Simulation and Decision-support Platform (DTSDP) to evaluate how policy levers reshape county-level migration dynamics in 2022. Building on a baseline surface (SPMI_baseline) that reproduces existing spatial heterogeneity, we compare two counterfactuals: Scenario A uniformly increases basic healthcare capacity (facilities, beds, and medical staff) by 20%, and Scenario B uniformly increases fixed-asset investment and primary/secondary school capacity by 20%. DTSDP outputs show that healthcare strengthening yields the larger average SPMI gain (+0.11; e.g., +0.27 in Yanyuan) with statistically significant improvements (paired t-test, $p < 0.01$), forming pronounced hotspots in underserved western mountain corridors. Education-cum-investment upgrades also yield significant but smaller gains (+0.05; $p < 0.01$), smoothing deficits mainly along existing road axes and market towns. Together, the experiments demonstrate how DTSDP pinpoints where each policy lever delivers the highest marginal return, enabling mix-and-match interventions to convert "push-pressure" counties toward net migration attractiveness.

2.4.1 Identification of Driving Factors

（1）The Spatial Distribution Analysis of Population

As illustrated in Figure 2-2, the county-level population distribution in Sichuan Province in 2023 exhibited significant spatial disparity, with densely populated areas concentrated in the low-altitude central and eastern regions, while the high-altitude western regions remained sparsely inhabited. Central lowland areas had the highest populations (275,400–1,136,000), while northeastern and southern sub-high areas showed moderate levels (190,000–1,136,000). High-altitude zones had the lowest populations (25,000–190,000), highlighting altitude as a key factor influencing population distribution.

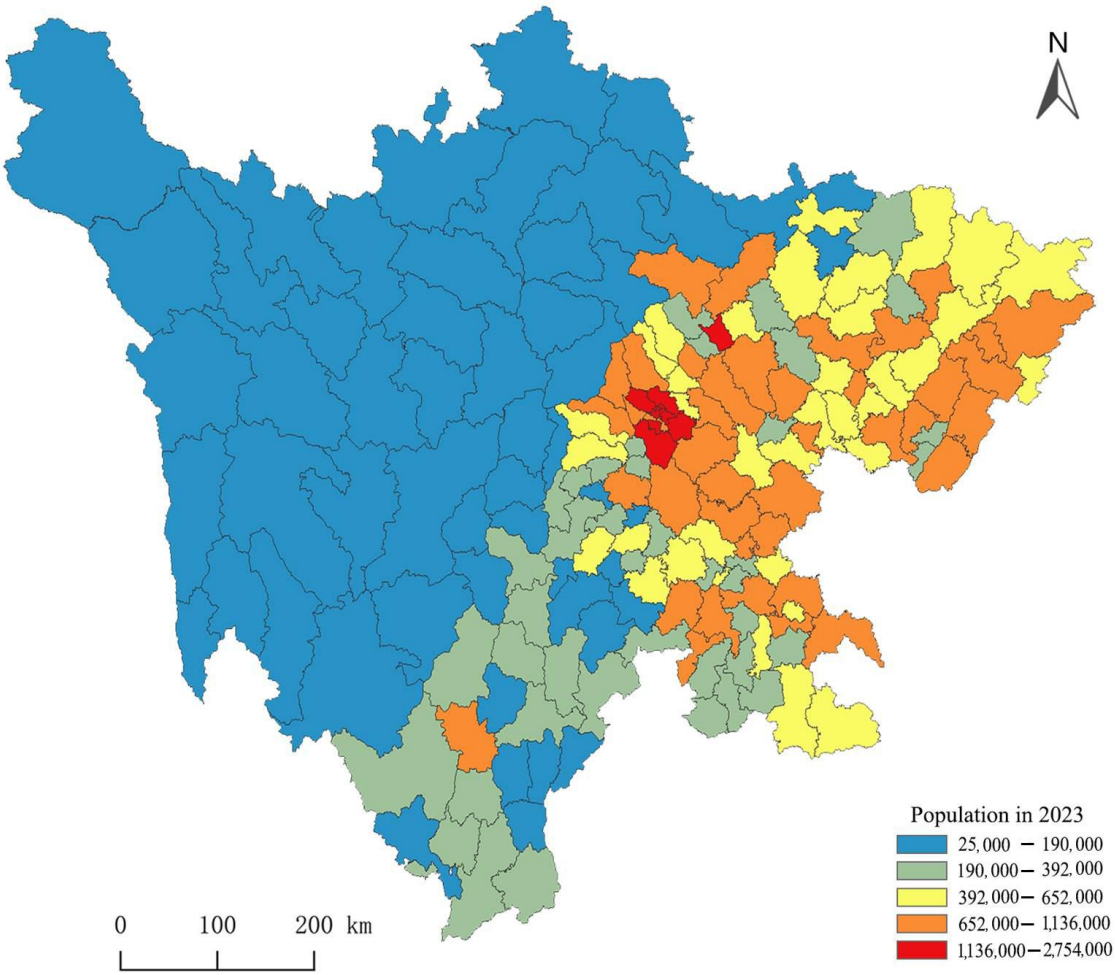


Figure 2-2. Spatial distribution of population in Sichuan Province.

A one-way analysis of variance (ANOVA) was conducted to examine the differences in average population growth rates between non-key counties located in high-altitude regions and those in middle- and low-altitude regions of Sichuan Province over the period 2012–2022. As shown in Table 2-2, the results revealed a statistically significant difference between the two groups, F

(1, 108) = 62.904, $p < 0.001$, $\eta^2 = 0.368$. The mean growth rate for non-key high-altitude counties was 0.01 ± 0.01, while that for middle- and low-altitude counterparts was–0.01 ± 0.01. These results indicate a substantially higher population growth rate in high-altitude areas compared to lower-altitude regions.

Table 2-2. Statistical significance of migration-related indicators.

Test Item	Comparative Group (Mean Difference ± Standard Deviation)		F-Value	*p*-Value
	Non-Key High-Altitude Counties (*n* = 42)	Non-Key Middle- and Low-Altitude Counties (*n* = 68)		
Population growth rate	0.01 ± 0 .01	−0.01 ± 0.01	62.904	0.000 **

Note: ** $p < 0.01$ (two-tailed *t*-test).

（2）Spatial Autocorrelation Analysis of Population

Spatial analysis of the 2023 county-level population distribution in Sichuan Province revealed a significant positive global spatial autocorrelation, with Moran's I = 0.535 ($p < 0.001$). As illustrated in Figure 2-3, the LISA cluster map demonstrates a distinct spatial structure: high–high clusters are predominantly located in the eastern region, whereas low–low clusters are concentrated in the western high-altitude areas. Additionally, high–low spatial outliers were identified in parts of the central and eastern regions, while low–high outliers appeared in the southern counties, indicating localized spatial heterogeneity. The analysis suggests that high–high clusters are located in the high-altitude western region, while low–low clusters are situated in the low-altitude eastern region of Sichuan.

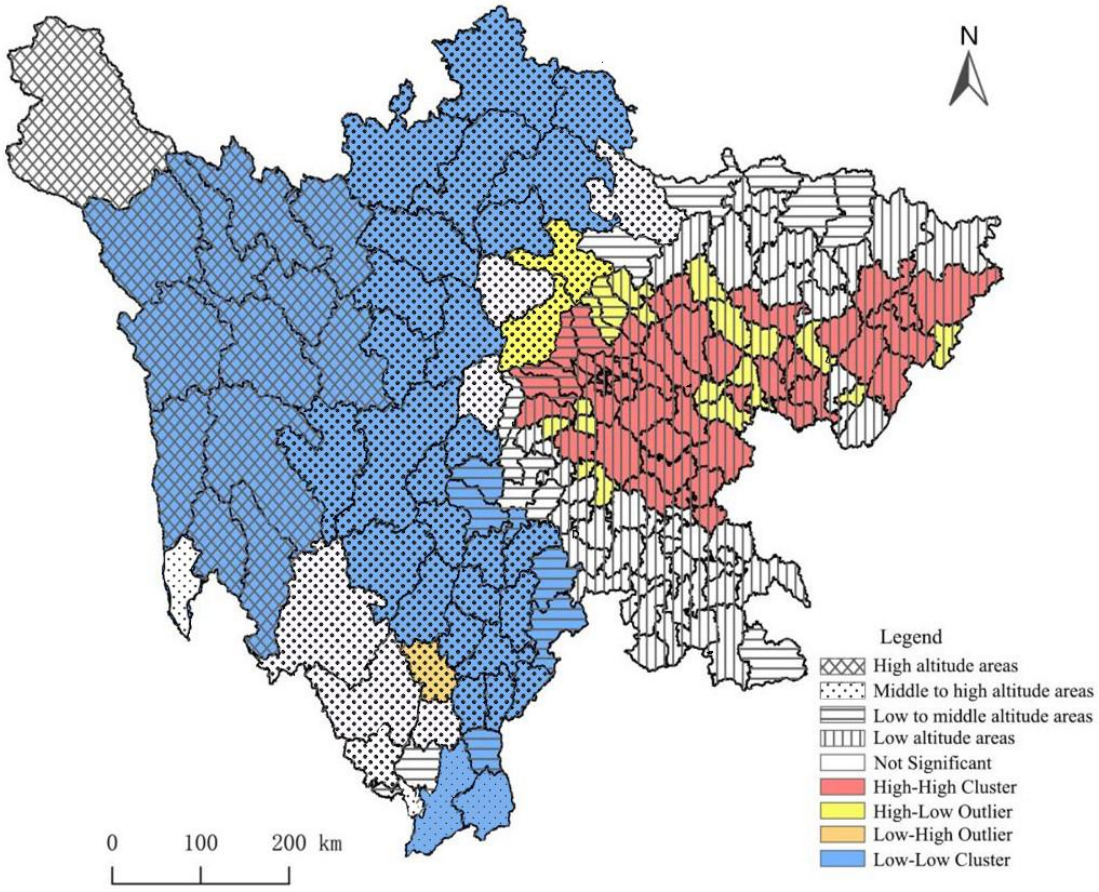


Figure 2-3. Autocorrelation of population spatial distribution.

（3）Identification of Driving Forces

As shown in Figure 2-4, in mountainous regions above 2000 m, healthcare is the dominant driver of resident and rural populations, while urban populations are influenced by both healthcare and economic factors. During the Tenth to Fourteenth Five-Year Plans, medical facilities consistently had the highest impact on resident populations (peak q = 0.86) and rural populations (peak q = 0.81). For urban populations, the economy was the main driver in early periods (peak q = 0.59), but medical facilities took precedence in later periods (average q = 0.79). These findings highlight healthcare and economic conditions as key determinants of population trends in high-altitude areas.

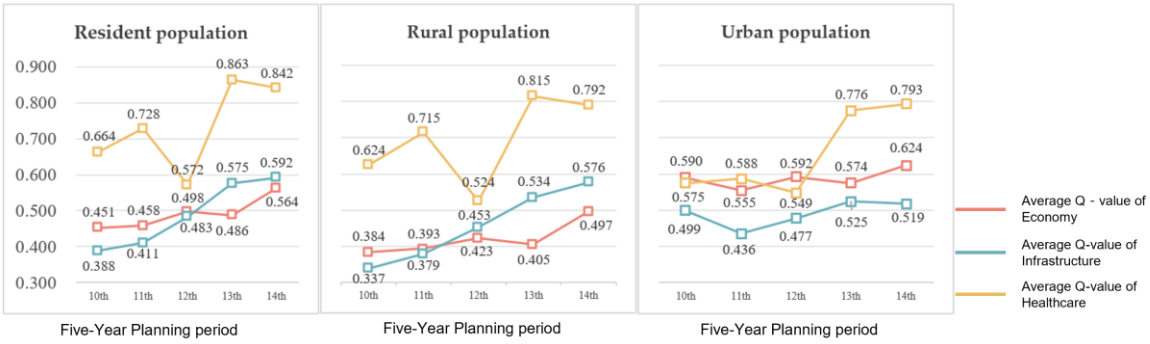


Figure 2-4. Driving factors and impacts on population dynamics. (a) Driving forces and impacts on the resident population; (b) Driving forces and impacts on the rural population; (c) Driving forces and impacts on the urban population.

The geodetector factor detection results indicate that all 14 selected indicators had a statistically significant impact on population distribution in counties situated above 2000 m ($p < 0.05$), with notable variation across different Five-Year Plan periods (see Figure 2-5 and Tables 2-3). In addition, based on the original p-values corresponding to 14 indicators in each period, totaling 70, corrections were made using the Benjamini-Hochberg FDR. Among the 14 indicators, 11 of their adjusted p-values remained below 0.05; see Table A2-1. During the Tenth to Twelfth Five-Year Plans, the primary industry production value emerged as the dominant driving factor for both resident and rural populations, with peak explanatory power reflected by q-values of 0.880 and 0.844, respectively. In the Thirteenth and Fourteenth Plans, this shifted to the number of hospital beds (resident $q = 0.937$; rural $q = 0.896$).



Figure 2-5. The q-values of factor detection for economy, infrastructure, and healthcare (2001—2022).

For rural populations, early drivers included health facility numbers (q = 0.804). Urban population drivers varied over time: retail sales led during the Tenth and Thirteenth Plans (peak q = 0.877), tertiary industry value in the Eleventh (q = 0.785), and health personnel in the Thirteenth and Fourteenth (peak q = 0.819). These results reflect the evolving population dynamics in high-altitude counties, driven by changes in economic and healthcare conditions (Table 2-3, Figure 2-6).



Figure 2-6. Evolution of driving factors across Five-Year Plans.

Table 2-3. The values of factor detection for economy, infrastructure, and healthcare (2001–2022).

Five Year Plan	Population	Result	Economy									Infrastructure			Healthcare	
			E1	E2	E3	E4	E5	E6	E7	E8	I1	I2	I3	H1	H2	H3
10th	Resident population	q	0.544	**0.789**	0.350	0.519	0.502	0.554	0.032	0.322	0.160	0.460	**0.544**	**0.779**	0.611	0.601
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.172	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Rural population	q	0.455	**0.768**	0.270	0.434	0.407	0.461	0.021	0.254	0.121	0.433	**0.458**	**0.804**	0.535	0.533
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.372	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Urban population	q	0.726	0.596	0.605	0.712	0.717	**0.751**	0.101	0.514	0.364	0.435	**0.698**	0.419	**0.674**	0.631
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
11th	Resident population	q	0.617	**0.819**	0.477	0.614	0.480	0.316	0.061	0.283	0.051	0.497	**0.686**	0.612	**0.813**	0.759
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.014	0.000	0.234	0.000	0.000	0.000	0.000	0.000
	Rural population	q	0.525	**0.804**	0.379	0.510	0.394	0.264	0.064	0.204	0.029	0.500	**0.606**	0.686	**0.769**	0.691
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.010	0.000	0.488	0.000	0.000	0.000	0.000	0.000
	Urban population	q	0.749	0.648	0.672	**0.785**	0.617	0.413	0.060	0.493	0.177	0.400	**0.729**	0.268	**0.762**	0.735
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.000	0.000	0.000	0.000	0.000	0.000	0.000
12th	Resident population	q	0.661	**0.880**	0.568	0.565	0.530	0.688	0.071	0.023	0.119	0.592	**0.738**	0.481	**0.774**	0.459
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.009	0.371	0.003	0.000	0.000	0.000	0.000	0.000
	Rural population	q	0.555	**0.844**	0.467	0.440	0.426	0.548	0.102	0.004	0.070	0.625	**0.663**	0.484	**0.708**	0.380
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.950	0.058	0.000	0.000	0.000	0.000	0.000
	Urban population	q	0.775	**0.813**	0.695	0.761	0.653	0.872	0.027	0.139	0.269	0.393	**0.769**	0.354	**0.756**	0.536
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.252	0.000	0.000	0.000	0.000	0.000	0.000	0.000
13th	Resident population	q	0.619	**0.805**	0.524	0.488	0.540	0.675	0.156	0.082	0.338	0.692	**0.695**	0.827	**0.900**	0.863
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.009	0.006	0.000	0.000	0.000	0.000	0.000	0.000
	Rural population	q	0.497	**0.744**	0.408	0.358	0.407	0.509	0.208	0.107	0.278	**0.714**	0.610	0.826	**0.861**	0.757
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Urban Population	q	0.737	0.800	0.658	0.656	0.683	**0.877**	0.060	0.125	0.367	0.519	**0.688**	0.618	0.831	**0.877**
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.020	0.000	0.000	0.000	0.000	0.000	0.000	0.000
14th	Resident population	q	0.696	**0.742**	0.518	0.736	0.387	0.616	0.401	0.414	0.306	**0.771**	0.698	0.719	**0.937**	0.869
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Rural population	q	0.611	**0.651**	0.415	0.610	0.312	0.463	0.507	0.404	0.280	**0.818**	0.629	0.700	**0.896**	0.780
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Urban Population	q	0.753	0.799	0.626	**0.861**	0.486	0.817	0.192	0.456	0.295	0.581	**0.680**	0.591	0.870	**0.919**
		p	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: q-values represent the explanatory power of each variable for population outcomes, with associated *p*-values indicating statistical significance (tested at α = 0.05). Units of the original variables are detailed in Table 2-1.

2.4.2 Application of Sustainable Population Migration Index

I applied the previously established SPMI to quantitatively analyze and visualize the spatial patterns of migration potential across the study area (Sichuan Province). Utilizing standardized indicator data and factor weights (Table 2-4) derived from geodetector analyses, we computed the SPMI and conducted spatial analyses to identify areas with high and low population migration potentials.

Figure 2-7 presents the spatial distribution of population migration potential, as indicated by the calculated SPMI values across all county-level administrative units within the study area. Results show clear spatial disparities in migration potential.

Table 2-4. Weights of AI and PPI indicators.

Population	Result	AI												PPI	
		E1	**E3**	**E4**	**E5**	**E6**	**E7**	**I1**	**I2**	**I3**	**H1**	**H2**	**H3**	**E2**	**E8**
Resident population	Mean q-value	0.627	0.487	0.584	0.488	0.570	0.172	0.231	0.602	0.672	0.684	0.807	0.710	0.807	0.275
	Weight	0.095	0.074	0.088	0.074	0.086	0.026	0.035	0.091	0.101	0.103	0.122	0.107	0.746	0.254

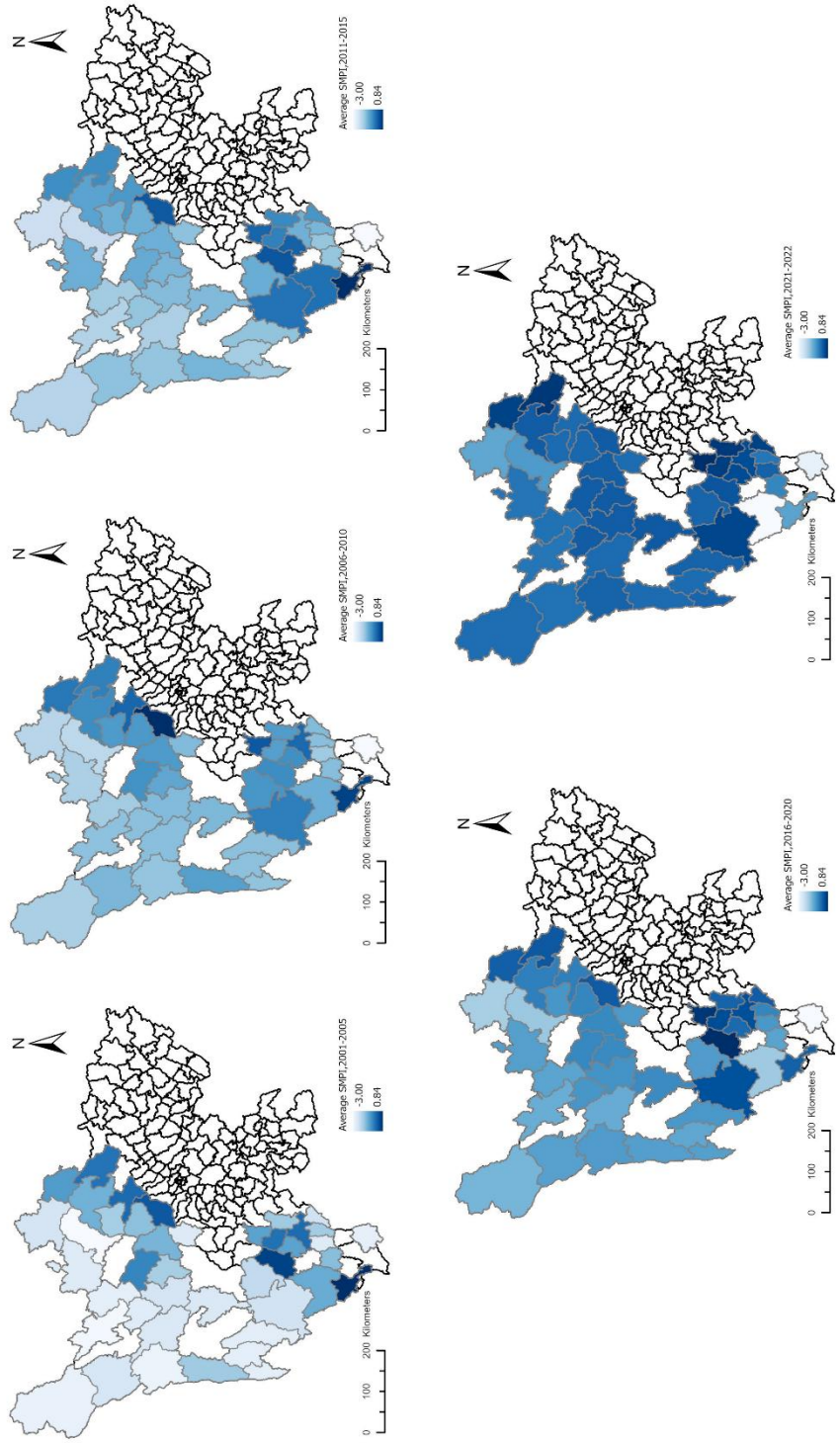


Figure 2-7. Evolution of the Sustainable Population Migration Index (SPMI), 2001–2022. Note: The segment "2021–2022" represents only the first two years of the Fourteenth Five-Year Plan (14th FYP).

Across the 42 ≥ 2000 m counties, the Sustainable Population Migration Index (SPMI) showed a clear, stepwise decline over the five evaluation periods. (1) Early 2000s strength: During 2001–2005, the mean SPMI was modestly positive (0.210 ± 0.193), and 95% of counties still offered net attractive conditions (SPMI > 0). The index spanned a narrow range (–0.034 to 0.662), indicating limited inter-county disparity. (2) Gradual erosion (2006–2015): The average potential fell to 0.104 in 2006–2010 and 0.067 in 2011–2015. Although most counties remained above zero (69% and 57%, respectively), growing variance (SD rising to 0.302) and deeper negative outliers (minimum–0.716) signaled emerging heterogeneity. (3) Inversion and acceleration (2016–2020): The index turned negative for the first time (mean–0.167), with barely 29% of counties retaining a positive SPMI. The mean year-on-year drop (–0.234 versus the previous interval) was more than six-fold that of 2006–2015, underscoring an inflection in migration dynamics. (5) Recent contraction (2021–2022): The latest window registered the sharpest deterioration (mean–0.532, SD 0.621). Only 9% of counties still displayed net pull effects, while the gap between the most and least attractive areas widened four-fold since 2001–2005 (range –3.001 to 0.227).

Overall, the results reveal a transition from broadly favorable to predominantly adverse migration potentials within two decades and an escalating spatial inequality whereby a shrinking cluster of resilient counties contrasts with a growing cohort experiencing pronounced push pressures. These findings highlight the urgency of targeted interventions—particularly in the post–2015 period—to counteract the accelerating loss of demographic attractiveness in high-altitude regions.

2.4.3 Validation Outcomes: Lagged Effects and Back-Casting Evidence

To quantify the temporal influence of migration potential on population dynamics, we estimated a two-lag fixed-effects panel model. The results (Table 2-5) indicate that the one-year lagged SPMI exhibited a positive and statistically significant association with population growth (β = 0.0024, p = 0.044). Substantively, a one-standard-deviation increase in SPMI in year t − 1 was associated with an average 0.24 percentage point rise in the population growth rate in year t. The two-year lag remained positive (β = 0.0022) but was only

marginally significant at the 10% level ($p = 0.090$), suggesting that the pull effect of SPMI attenuates over time yet persists beyond a single year.

Table 2-5. Lagged-effects panel regression between SPMI and population growth.

Variable	Coefficient (β)	Robust s.e.	t	95% CI	*p*-Value
SMPIt−1	0.0024	0.0012	2.02	0.0001–0.0047	0.04
SMPIt−2	0.0022	0.0013	1.70	–0.0003–0.0047	0.09

The model explained roughly one-third of the within-county variation in demographic change (within-R^2 = 0.33) after controlling for unobserved heterogeneity. A joint Wald test confirmed that the two lagged terms are jointly significant ($F = 5.61$, $p < 0.001$). These findings corroborate the hypothesis that counties with stronger short-term migration potential experience faster subsequent population gains, whereas the longer-term effect weakens but remains directionally consistent.

Sensitivity checks with alternative weighting schemes and balanced-panel specifications yielded comparable effect sizes, reinforcing the robustness of the estimated relationship. Although the within-R^2 (0.33) may seem modest, it is comparable to values reported in recent migration-related studies (e.g., 0.16 in Tong & Lo 2021 (Tong & Lo, 2021); 0.38–0.43 for conventional gravity models in Wang et al. 2023 (Wang et al., 2023)), underscoring the inherent stochasticity of population dynamics in complex mountain settings.

I conducted a historical backcasting analysis using county-level data from 2017 to 2020. This period was selected because it immediately followed the implementation of the "universal health insurance coverage" policy launched by Sichuan Province in 2016, which was expected to drive substantial improvements in local healthcare infrastructure and population retention. Specifically, we selected three representative high-altitude counties—Dechang, Zhaojue, and Puge—where the SPMI values exhibited substantial year-on-year increases. In Dechang County, for instance, the SPMI increased from −0.32 (2017) to +0.22 (2018), accompanied by a population growth from 221,700 to 225,000 and an increase of 216 in medical personnel. In Zhaojue County, the SPMI

peaked at 0.97 in 2018, while the number of hospital beds rose by 91 and the population grew by 6.3%. Puge County also saw a moderate SPMI increase (+0.097) and a 1.18% population rise in 2019, with parallel improvements in healthcare staffing (Figure 2-8).

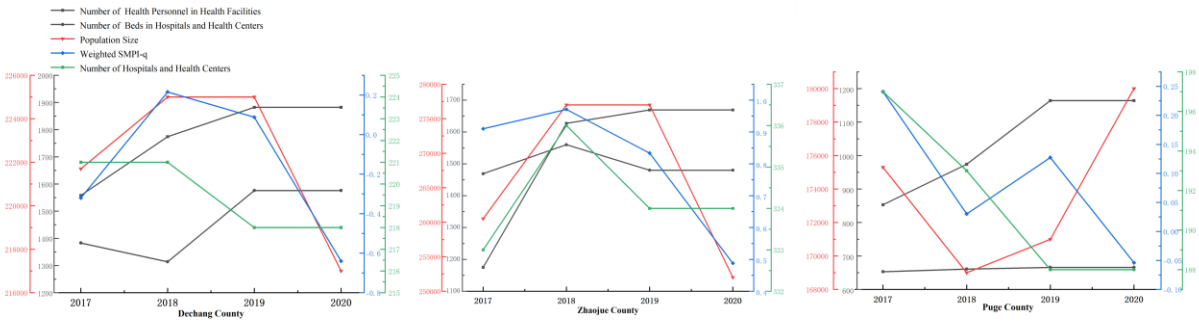


Figure 2-8. Trend chart of medical resources and population changes in Dechang, Zhaojue, and Puge counties with the SMPI from 2017 to 2020.

These cases demonstrate that the SPMI trends derived from our model closely track real-world policy interventions and subsequent demographic shifts, indicating that the digital twin platform has practical utility for reconstructing historical population responses to spatial policy stimuli.

2.4.4 Implementation of the Digital Twin Platform

To quantify how concrete policy packages reshape migration dynamics, we ran the Digital Twin-based Simulation and Decision-support Platform (DTSDP) under a baseline (no intervention) and two contrasted policy scenarios. The baseline (SPMI_baseline) reproduced the status quo spatial heterogeneity of the Sustainable Population Migration Index (SPMI) across all 2022 counties and therefore served as the reference surface.

When the supply of basic healthcare was uniformly increased by 20% (healthcare centers, hospital beds, and medical staff), the DTSDP calculated a mean SPMI uplift of +0.11 units across the ten randomly sampled counties (Table 2-6). The improvement ranged from +0.27 (salt-poor Yanyuan County) to +0.02 (already well-served Meitan County), translating into an average ≈6% gain relative to the counties' own baseline scores. Counties starting with the deepest medical deficits benefited the most, some turning their net "push-pressure"

status into a slightly positive migration potential. Raising fixed-asset investment, primary-school capacity, and general secondary-school capacity by 20% produced a smaller but still positive response, with a mean SPMI increase of +0.05 units (max +0.09 in Jinyang County; min +0.02 in Dege County). The relative gain (~3%) confirmed that education-cum-investment upgrades enhance migration attractiveness, yet their marginal effect is moderated when the county already possesses a basic educational and economic platform (Table 2-7). A paired two-tailed t-test confirmed that both policy scenarios produced statistically significant improvements in the SPMI (Scenario A: $t = 4.44$, $p = 0.0016$; Scenario B: $t = 5.17$, $p = 0.0006$).

The 20% increment assumption in healthcare and infrastructure capacity aligns with recent pilot upgrades in western China (e.g., the "Healthy Sichuan Initiative"), which targets annual growth rates of 15 – 20% in medical resources for mountainous counties (Cao et al., 2018). This magnitude is technically feasible, as evidenced by its effectiveness in reducing migration pressure through marginal improvements in public service accessibility (Dick et al., 2025). We acknowledge the fiscal constraints, and future iterations of the DTSDP will incorporate budget-sensitive scenarios based on county-level fiscal capacity data, following the phased implementation strategy recommended for underdeveloped regions (Mohmand et al., 2017).

Interactive rasters rendered by the DTSDP immediately highlighted these numerical shifts. Healthcare strengthening (Scenario A) generated the most pronounced hot spots in previously underserved western mountain corridors, whereas infrastructure spending (Scenario B) produced gradual, garden-wall improvements clustered around existing road axes and market towns. These layered visualizations allow planners to pinpoint where each policy lever delivers the highest marginal return, facilitating a mix-and-match approach.

Table 2-6. Scenario A—Effect of a 20% boost on the county-level SPMI (2022).

Name	SPMI_base	SPMI_scenA	Delta	Percentage (%)
Yanyuan	−3.340	−3.071	0.269	8.05
Yuexi	−0.080	0.141	0.221	276.25
Muli	−0.199	−0.082	0.118	59.30
Songpan	−0.367	−0.281	0.086	23.43
Luhuo	−0.318	−0.235	0.083	26.10
Jinchuan	−0.349	−0.267	0.082	23.50
Ruoergai	−1.308	−1.234	0.074	5.66
Batang	−0.491	−0.434	0.057	11.61
Li	−0.515	−0.470	0.046	8.93
Xiangcheng	−0.540	−0.500	0.040	7.41
Average value	−0.751	−0.643	0.108	14.33

Note: Δ = Scenario minus baseline SPMI. t values from paired one-sample tests against zero. Bold Δ values are significant at $p < 0.05$.

Table 2-7. Scenario B—Effect of a 20% increase on the county-level SPMI (2022).

Name	SPMI_base	SPMI_scenB	Delta	Percentage (%)
Jinyang	−0.014	0.078	0.092	657.14
Ganluo	0.187	0.264	0.077	41.18
Pingwu	0.107	0.181	0.074	69.16
Songpan	−0.367	−0.308	0.060	16.35
Aba	−0.665	−0.623	0.042	6.32
Mao	−0.566	−0.531	0.035	6.18
Rangtang	−0.606	−0.578	0.029	4.79
Heishui	−0.554	−0.534	0.020	3.61
Daocheng	−0.437	−0.418	0.018	4.12
Xiangcheng	−0.540	−0.529	0.012	2.22
Average value	−0.346	−0.300	0.047	13.29

Note: Δ = Scenario minus baseline SPMI. t values from paired one-sample tests against zero. Bold Δ values are significant at $p < 0.05$.

2.5 Discussion

2.5.1 Drivers of Migration Dynamics

This study investigated the primary drivers of population dynamics in high-altitude mountainous counties within Sichuan Province, China. Healthcare accessibility emerged as the most critical determinant of population changes, particularly for resident and rural populations. This aligns with prior findings that underscore the rising importance of quality-of-life factors in migration decisions (Liu et al., 2022; Mohmand et al., 2017; Wu et al., 2019; Xie et al., 2017; Yinhua & Yue, 2018). Economic conditions played a secondary yet notable role, especially influencing urban migration. During earlier periods, tertiary industry production and retail sales drove urban inflows, consistent with the literature on industrial clustering and regional competitiveness (J. Luo et al., 2018; Xinxian & Xiangdong, 2019; Zhang et al., 2023).

2.5.2 Predictive Validity of SPMI

The Sustainable Population Migration Index (SPMI) proposed herein provides a robust, composite framework for tracking migration potential over time. Its consistent decline across the Five-Year Plan windows reflects the growing demographic pressures in highland regions. Furthermore, the fixed-effects panel model confirmed that lagged SPMI scores are significant predictors of subsequent population changes, validating its utility in longitudinal migration forecasting (H. Gu et al., 2019; Pang & Wu, 2023). The ANOVA results indicating higher population growth in high-altitude counties reflect a horizontal comparison with lowland regions, many of which have faced sharper declines due to urban outmigration or demographic aging. In contrast, the SPMI measures longitudinal changes in migration potential within high-altitude counties. Its decline over time reveals a weakening structural capacity to attract or retain population, even as some counties still recorded short-term growth. This is further supported by our panel regression, which determined that population change often lags behind migration potential. Thus, the two findings reflect different dimensions and are not contradictory.

2.5.3 Policy Simulation Insights

The simulation results obtained from the Digital Twin-based Simulation and Decision-support Platform (DTSDP) highlighted the effectiveness of the

targeted interventions. Scenario A (healthcare upgrade) achieved a mean uplift of +0.12 in the SPMI, particularly benefiting the most underserved counties. Scenario B (education and investment boost) produced a more modest gain (+0.05), with limited effect in structurally weaker areas. These results suggest that foundational healthcare access remains the bottleneck for population retention in many counties. Accordingly, tiered healthcare reforms and region-specific economic diversification programs are essential. A high-altitude demographic sustainability transfer payment, benchmarked against SPMI performance, could further institutionalize equity and accountability in resource allocation.

2.5.4 Relative Impact and Cost Implications

Although fiscal costs vary across counties, our indicative calculations indicate that a 20% healthcare upgrade yields over twice the SPMI improvement per investment unit compared to infrastructure interventions—approximately 0.006 versus 0.0025. This finding underscores the strategic value of healthcare investment in constrained regions. Zhu and Fang (2018) (Zhu et al., 2018)demonstrated that economic development in high-altitude areas is often hindered by environmental and service accessibility barriers, rendering basic healthcare a key determinant of settlement viability. Similarly, Calero et al. (2009) found that, in low-income contexts (Calero et al., 2009), household-level investments in health and education are more effective than large-scale infrastructure in mitigating migration pressures. These studies support our conclusion that healthcare interventions offer higher marginal returns and may outperform relocation or infrastructure projects in moderately underperforming counties.

2.5.5 Theoretical Implications and Broader Significance

These findings extend classical migration theory by explicitly integrating both institutional and service-based constraints into the high-altitude context. Guo et al. (2007) highlighted that the out-migration of rural labor in China is largely driven by underdeveloped educational and healthcare systems (Guo et al., 2007), with basic service deficiencies functioning as critical “push” factors. Similarly, Fan and Ma (2011) emphasized that structural inequalities in public service provision—particularly in education and healthcare—have been central to China’s large-scale interregional migration flows (Fan & Ma, 2011). Building

on this, the present study advances the literature by quantifying the structural impact of basic healthcare provision on population retention through the SPMI metric, thereby empirically validating the claim that foundational service gaps undermine local settlement attractiveness. When essential needs such as healthcare remain unmet, traditional "pull" interventions—such as investment or education expansion—yield diminishing marginal returns. This underscores the theoretical imperative that sustainable migration governance must first address push-driven vulnerabilities. For peripheral counties in western China, these insights provide a policy rationale for prioritizing the closure of healthcare and basic service deficits, rather than relying solely on capital investment or educational improvements to curb out-migration.

2.5.6 Methodological Limitations and Future Directions

Despite the explanatory value of the fixed-effects panel model, the within-R^2 of 0.33 suggests that additional migration determinants remain overlooked. These may include social networks and kinship ties in origin communities, which significantly shape migration decisions and reduce mobility risks through information dissemination and mutual support mechanisms (Guo, 2025). Ethnic and religious affiliations also influence migration through shared community norms and spatial clustering patterns, as shown in recent studies on spatial heterogeneity in mobility outcomes (Xiao et al., 2021). Furthermore, land tenure security and rural land policy reforms have long been recognized as institutional drivers affecting rural residents' willingness and ability to migrate (Zhao et al., 2021). State-led resettlement programs, such as the Grain-to-Green ecological migration scheme, and temporally concentrated interventions like targeted poverty alleviation initiatives can create "policy window" effects (Feng & Liu, 2021). In addition, environmental shocks such as landslides or droughts may trigger involuntary migration. Owing to data limitations, such factors were not quantitatively incorporated, yet they likely contribute to regional migration heterogeneity. Moreover, given the spatial nature of the data, future research may benefit from applying spatial panel regression techniques (e.g., Spatial Durbin Model) to better capture interregional spillover effects and improve model robustness.

2.6 Summary

2.6.1 Core Findings in a Global Context

The analysis identified healthcare accessibility as the most critical driver of population changes, particularly for resident and rural populations, while economic factors exert a more pronounced influence on urban populations. This pattern aligns with broader global trends in high-altitude regions, where basic public services and quality-of-life factors increasingly outweigh traditional economic drivers in migration decisions. However, cross-regional comparisons reveal nuanced differences: unlike the Andes Mountains, where population dynamics are often dominated by extractive industry opportunities (Abad et al., 2025) or climate-induced displacement, or the Himalayan foothills, where environmental fragility (e.g., glacial melt) is a primary push factor (Kumar et al., 2025), Sichuan's high-altitude counties exhibit a unique interplay of state-led public service provision (e.g., healthcare infrastructure) and localized economic transitions. This highlights how institutional contexts—such as China's rural revitalization policies and regional development strategies—mediate the relative importance of demographic drivers in high-altitude settings.

Regarding transferability, the SPMI framework is structurally adaptable. Although this study focused on high-altitude counties in Sichuan, the underlying methodology—based on attractive and push–pressure dimensions, geodetector-derived weighting, and standardized scoring—can be recalibrated to fit other regions with distinct socio-geographic profiles. We encourage future researchers to apply and validate the SPMI in varied settings such as the Qinghai–Tibet Plateau, the Andes, or the Himalayas, where topographic constraints and public service disparities similarly influence migration potential.

2.6.2 Theoretical and Practical Contributions

Theoretically, this study advances understanding of population dynamics in high-altitude regions by introducing the SPMI: a framework that quantifies migration potential through integrating push–pull factors with spatially weighted indicators. While the fixed-effects panel model confirms that the SPMI exhibits a predictive value for short-term population trends (one-year lag: β = 0.0024, p = 0.044), its explanatory power (within-R^2 = 0.33) and weaker two-year

lag effect (p = 0.090) also highlight the complexity of demographic processes, emphasizing that migration decisions are shaped by both measurable factors and unobserved dynamics (e.g., cultural attachments or informal social networks). This modesty in predictive strength aligns with the inherently multifaceted nature of population mobility, reinforcing the need for complementary qualitative research to unpack residual variance.

Practically, DTSDP demonstrated how digital twin technology can bridge theoretical analysis and policy action. Scenario simulations revealed that targeted investments in healthcare (20% enhancement) and infrastructure (20% increase in fixed-asset investment and educational facilities) can significantly mitigate migration pressures, with the former yielding larger gains—particularly in counties with historically inadequate medical resources. This tool offers policymakers a visualized, evidence-based platform to prioritize interventions, addressing the longstanding challenge of translating demographic insights into actionable strategies in remote high-altitude regions.

2.6.3 Implications for Sustainable Development

High-altitude regions worldwide face the shared challenges of maintaining population stability while balancing ecological preservation and socioeconomic development. This study emphasizes that sustainable development in such areas requires tailored strategies: for rural and resident populations, prioritizing healthcare accessibility can strengthen community resilience; for urban centers, fostering economic opportunities—particularly in tertiary industries—remains critical to retaining talent. The SPMI, as a dynamic monitoring tool, can help in tracking the effectiveness of these strategies over time, while the DTSDP enables proactive scenario planning to avoid reactive policymaking.

Illuminating the interplay of healthcare, economy, and infrastructure in shaping population dynamics, this research not only enriches the literature on high-altitude demography but also provides a replicable analytical framework for studying other mountainous regions. Future work can extend this model by integrating climate change impacts and cross-border migration flows, further enhancing its utility for global sustainable development agendas in fragile high-altitude ecosystems.

Appendix A

Table A2-1. Summary table of Benjamini-Hochberg FDR correction results (FDR = 0.05).

Population Type	Independent Variable	Five-Year Plan	*p*-Value	Significance	The Adjusted *p*-Value	Note
Permanent resident population	E7	10th	0.1724	No	0.1775	
	E8	12th	0.3711	No	0.3711	
	E9	11th	0.2339	No	0.2373	
	other	All the others	0.000–0.0136	Yes	≤0.01423	67 significant results
Urban population	E7	12th	0.2516	No	0.2516	
	other	All the others	0.000–0.0069	Yes	≤0.0072	67 significant results
Rural population	E7	10th	0.3720	No	0.383	
	E8	12th	0.9503	No	0.9503	
	E9	11th	0.4882	No	0.495	
	E9	12th	0.0583	No	0.0609	
	other	All the others	0.000–0.0105	Yes	≤0.0110	66 significant results

Table A2-2. The q-values of economic, infrastructure, and healthcare factor tests.

Period	q value	E1	E2	E3	E4	E5	E6	E7	E8	I1	I2	I3	H1	H2	H3
10h	q_full	0.544	0.789	0.350	0.519	0.502	0.554	0.032	0.322	0.160	0.460	0.544	0.779	0.611	0.601
	q_noE	-	-	-	-	-	-	-	-	0.160	0.460	0.544	0.779	0.611	0.601
11h	q_full	0.617	0.819	0.477	0.614	0.480	0.316	0.061	0.283	0.051	0.497	0.686	0.612	0.813	0.759
	q_noE	-	-	-	-	-	-	-	-	0.051	0.497	0.686	0.612	0.813	0.759
12h	q_full	0.661	0.880	0.568	0.565	0.530	0.688	0.071	0.023	0.119	0.592	0.738	0.481	0.774	0.459
	q_noH)	0.661	0.880	0.568	0.565	0.530	0.688	0.071	0.023	0.119	0.592	0.738	-	-	-
13h	q_full	0.619	0.805	0.524	0.488	0.540	0.675	0.156	0.082	0.338	0.692	0.695	0.827	0.900	0.863
	q_noH	0.619	0.805	0.524	0.488	0.540	0.675	0.156	0.082	0.338	0.692	0.695	-	-	-
14h	q_full	0.696	0.742	0.518	0.736	0.387	0.616	0.401	0.414	0.306	0.771	0.698	0.719	0.937	0.869
	q_noH	0.696	0.742	0.518	0.736	0.387	0.616	0.401	0.414	0.306	0.771	0.698	-	-	-

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Chapter 3

SERVICE EFFICIENCY OF HEALTHCARE FACILITIES IN HIGH-ALTITUDE REGIONS

Chapter 3

Service Efficiency of Healthcare Facilities in High-Altitude Regions

To address the evidence gap on healthcare access in high-altitude mountains, we assess near-range pedestrian accessibility to primary care across nine "large undulating alpine" counties in Tibet (mean elevation >4,000 m; RDLS ≈2–5) within the Qinghai–Tibet Plateau. Fifteen-minute coverage is uniformly low (mean 6.3%, median 5.2%); Mainling is a relative outlier (12.5%), whereas Zuogong is the lowest (1.1%). Per-capita supply alone does not ensure short-range access: steep relief and dispersed valley settlements markedly compress effective catchments and weaken network connectivity. Policy directions include adopting terrain-sensitive service benchmarks (e.g., 15–30 min), decentralizing facility siting with micro-scale pedestrian infrastructure, and complementing fixed services with telemedicine and mobile clinics to enhance service resilience. The framework offers transferable support for health-equity planning in extreme mountain environments.

3.1 Introduction

China's vast mountainous terrain, particularly the western highlands encompassing the Qinghai–Tibet Plateau, Sichuan–Yunnan region, and Hengduan Mountains, poses profound challenges to achieving equitable healthcare accessibility. These areas, characterized by sparse populations, extreme topography, and fragile ecosystems, are often constrained by underdeveloped infrastructure and limited medical resources (Deng, 2015). Enhancing healthcare accessibility in such regions is crucial for realizing China's Healthy China 2030 initiative and promoting spatial equity in public health (Liu et al., 2024).

In recent years, a growing body of research has employed Geographic Information System (GIS)-based spatial analysis to evaluate healthcare accessibility in mountainous provinces such as Sichuan, Yunnan, and Chongqing. These studies have revealed significant spatial disparities in the distribution of medical resources, with lower accessibility observed in high-altitude and economically disadvantaged areas (Zhang et al., 2021). However, most existing studies have focused on county-level or public hospitals, while the accessibility of primary medical facilities—including township health centers and village clinics—remains insufficiently examined (Jin et al., 2015).

More critically, there remains a notable research gap concerning healthcare accessibility in high-altitude mountainous areas (typically above 3,000 meters). These regions, such as the Qinghai–Tibet Plateau, exhibit unique environmental and physiological challenges. The hypoxic climate, permafrost terrain, and extreme weather conditions substantially increase travel costs and restrict medical service delivery (Huang, 2014). Moreover, the limited road network and long travel times exacerbate healthcare inequities despite ongoing infrastructure improvements, such as the Qinghai–Tibet Railway and the Western Development Strategy (Yang et al., 2019).

Empirical research further indicates that high-altitude areas exhibit distinctive patterns of population distribution and settlement structure. Residential areas tend to cluster between 3,000–5,000 meters above sea level, aligning closely with transportation and water systems (Niu et al., 2022). Yet, this spatial concentration does not necessarily coincide with adequate access to medical services. Environmental constraints, such as permafrost degradation and snow disaster risks, further limit the sustainability of healthcare infrastructure in these areas (Liu et al., 2014).

Therefore, it is necessary to strengthen research that integrates topographic, climatic, and socio-economic factors into healthcare accessibility evaluation. This study focuses on primary medical facilities in high-altitude mountainous regions of western China, employing a terrain-sensitive spatial accessibility model that accounts for elevation, slope, and travel impedance. The goal is to generate a more realistic representation of medical accessibility in high-altitude environments and to provide decision-making support for optimizing

healthcare resource allocation under complex terrain conditions.

3.2 Mountainous Terrain and Health Care System in China

The natural and social environment of western China is characterized by extreme geographical complexity and diverse healthcare conditions. The region's mountainous terrain, dominated by high-altitude plateaus and deep valleys, poses significant challenges to infrastructure development and public service accessibility. In particular, the harsh topography and sparse population distribution have a profound impact on the spatial layout and accessibility of medical service facilities. Understanding both the geomorphological characteristics and the structure of the healthcare system is therefore essential for analyzing spatial disparities in healthcare accessibility. This section first introduces the geomorphological background of the study area, followed by an overview of the healthcare system and types of medical institutions that provide public health services in western China.

3.2.1 Mountainous Terrain

Based on a systematic review of existing geomorphological classification systems and their quantitative indicators, it is proposed that the basic landform types of China can be classified using two principal indices: altitude and relief amplitude. This dual-index system reflects the complex and multi-stepped characteristics of China's terrain (Li, 2009). Specifically, five altitude classes are suggested: low altitude (<1000 m), middle altitude (1000–2000 m), sub-high altitude (2000–4000 m), high altitude (4000–6000 m), and extremely high altitude (>6000 m). Combined with seven relief categories (plain, tableland, hill, low-relief mountain, moderate-relief mountain, high-relief mountain, and extremely high-relief mountain), a total of 28 fundamental landform types can be delineated, ranging from low-altitude plains to intensely undulating extremely high mountains (Bingyuan et al., 2013).

This classification system aligns with China's well-recognized three-step geomorphological framework, where terrain gradually descends from the Qinghai–Tibet Plateau in the west to the eastern coastal plains (Dan, 2007; Feng

et al., 2007). The Tibet Autonomous Region, Sichuan, Yunnan, and Guizhou are representative high-altitude, high-relief regions, characterized by significant vertical differentiation, strong tectonic activity, and complex mountain-valley systems (Chen et al., 2024). Among them, the Tibet Autonomous Region features the most extensive areas of extremely high mountains and alpine relief, resulting from prolonged uplift of the Qinghai–Tibet Plateau during the Cenozoic (Xiao et al., 2014).

For this study, the research area is defined as large- undulating alpine regions with an average altitude between 4000 m and 6000 m and an average relative digital terrain slope of 2–5. Based on these geomorphological criteria, nine counties in the Tibet Autonomous Region were selected as representative study sites. These regions exhibit typical features of high-relief alpine landforms, including extensive glacial valleys, periglacial geomorphology, and strong altitude stratification in ecological and human systems (Wei-Ming, 2007). The selected sites provide a scientifically sound spatial basis for analyzing healthcare accessibility under extreme geomorphological and environmental conditions.

3.2.2 Healthcare System

In China, the healthcare delivery system comprises a diverse range of medical service institutions that differ in ownership, administrative level, and service capacity. These institutions collectively form a three-tier healthcare system designed to ensure equitable access to health services across urban and rural populations (Zhang et al., 2013). The primary types of medical service institutions include public hospitals, community health service centers, township health centers, and Traditional Chinese Medicine (TCM) hospitals, each playing a distinct role in health service provision.

Public hospitals are the backbone of China's healthcare system, owned and managed by the central, provincial, municipal, or county-level governments. They provide comprehensive services ranging from general outpatient care to advanced specialty treatments. As major recipients of government investment and medical resources, public hospitals play a leading role in implementing national health reforms and public health initiatives (Zhang et al., 2013).

At the primary level, community health service centers (CHSCs) and

township health centers (THCs) form the fundamental service network. CHSCs, primarily located in urban neighborhoods, provide preventive healthcare, chronic disease management, maternal and child health services, vaccinations, and general medical consultations. These centers are critical for implementing China's basic public health service programs and achieving health equity in urban settings (Zhang, 2024).

In contrast, township health centers are the mainstay of healthcare provision in rural and mountainous areas. They offer broader medical functions—including basic inpatient services, diagnostic imaging, and limited specialist care—serving as both medical and referral institutions for surrounding villages. Studies in Tibet and western China indicate that township health centers provide better continuity and accessibility of care for rural residents, despite persistent shortages in human resources and medical infrastructure (Wang et al., 2015). However, inequities remain in the allocation of medical staff, facilities, and equipment, especially in minority and high-altitude regions (Jinghua, 2013) .

Traditional Chinese Medicine (TCM) hospitals constitute an integral component of the healthcare system, emphasizing preventive and holistic treatment through herbal medicine, acupuncture, and moxibustion. Many township and community health centers have established TCM service units in response to national policy promoting the integration of TCM and Western medicine in primary care (Manli, 2011).

According to the statistical data from the Tibet Autonomous Region Health Commission and relevant field studies, these four categories of medical institutions—public hospitals, CHSCs, THCs, and TCM hospitals—jointly represent the core framework of primary public medical services in the mountainous regions of western China (La, 2015). They provide essential medical care, preventive services, and emergency response in high-relief, sparsely populated areas where healthcare accessibility remains a critical issue (Wang et al., 2022).

Therefore, this study selects these four types of institutions as the main research objects to examine the spatial distribution and accessibility of public medical services in mountainous western China. During the data screening

process, medical institutions will be categorized according to their service content and healthcare delivery capacity.

3.3 Materials and Methods

This section characterizes the Tibetan study context and outlines the datasets and methods used to quantify terrain constraints and short-range healthcare access. We analyze counties on the Qinghai–Tibet Plateau (with Tibet as the focal area) within a four-province frame (Tibet, Sichuan, Yunnan, Guizhou) and use county units for all statistics. Public medical facility POIs were curated from Amap (2023); elevation came from SRTM (resampled to 1 km); land cover from Esri Living Atlas. We derived county-level median elevation and RDLS by 10 × 10 km relief grids with a non-flat land ratio, then identified nine representative "large undulating alpine" counties (>4,000 m mean elevation; RDLS ≈2–5). For accessibility, we built an anisotropic walking time-cost surface integrating slope, altitude penalties, road hierarchy, land-surface type, and hydrography, and ran ArcGIS Pro Distance Accumulation to obtain least-time rasters and 15-minute pedestrian isochrones; outputs were passed to 2SFCA for comparative metrics. All preprocessing, thresholds, and barrier rules were standardized in a single reproducible workflow.

3.3.1 Study Area

Tibet, located in the southwestern part of China, shares borders with Qinghai Province, Sichuan Province, and Yunnan Province to the east, and the Xinjiang Uygur Autonomous Region to the north. Geographically, Tibet constitutes the core area of the Qinghai–Tibet Plateau, which spans approximately 2.5 million square kilometers, accounting for nearly one-eighth of China's total land area, with an average elevation exceeding 4,000 meters. Known as the "Roof of the World", the plateau represents the highest and largest plateau on Earth, exerting significant influence on global climate and ecosystem patterns (Xiao, 2000). Its complex topography and harsh environment have shaped both the natural and human systems that exist there.

According to the Main Data Bulletin of the Seventh National Census of the Tibet Autonomous Region (2021), as of November 1, 2020, Tibet's permanent

population was 3.65 million, representing an increase of 645,934 persons (21.52%) since 2010, with an average annual growth rate of 1.97%. Among the total population, 1.30 million (35.73%) reside in urban areas, while 2.34 million (64.27%) live in rural areas, indicating that Tibet remains predominantly rural in demographic structure. Spatial population analyses confirm that settlement distribution is concentrated along river valleys and southern basins, reflecting the strong environmental constraints on habitation in the plateau region (Li et al., 2020).

In terms of healthcare infrastructure, by 2022, the Tibet Autonomous Region contained 1,655 medical and health institutions, including 182 hospitals. There were 674 township-level health centers, comprising 476 township health centers and 198 central township health centers, as well as 16 community health service centers (stations) and 648 clinics and infirmaries. The number of hospital beds per 1,000 population reached 5.49, indicating gradual improvement in healthcare accessibility and capacity despite geographical challenges. However, healthcare distribution remains spatially uneven, with significant disparities between urban centers such as Lhasa and rural or high-altitude counties, where accessibility continues to be constrained by terrain, transportation, and limited human resources (Tibet Autonomous Region Health Commission, 2022) .

Tibet's unique combination of vast area, extreme altitude, and sparse population presents profound challenges to healthcare delivery, infrastructure planning, and sustainable development. Understanding these demographic and geographical characteristics provides a critical foundation for analyzing the spatial distribution and accessibility of medical facilities in the region.

3.3.2 Data Sources

The data used in this study primarily consist of four categories. First, medical facility data for the Tibet Autonomous Region were obtained via the Gaode Map API, 2023 (Amap, 2023). Second, Digital Elevation Model (DEM) data were derived from the open-source SRTM DEM UTM 90 m dataset provided by NASA's Jet Propulsion Laboratory(NASA Jet Propulsion Laboratory, 2013). Finally, land cover data were obtained from Esri's Living Atlas of the World platform(Esri, 2023). These datasets collectively provide the spatial and environmental foundation for the subsequent analysis of healthcare accessibility in the Tibet Autonomous Region.

（1）Medical Facility Data

Medical service institutions in Tibet encompass multiple types, including both public and private facilities. Based on the objectives of this study, only public medical service institutions were selected for analysis, as they represent the primary providers of public healthcare services in the region. The selected categories include Public Hospitals, Community Health Service Centers, Township Health Centers, and Traditional Chinese Medicine (TCM) Hospitals.

The raw medical Point of Interest (POI) data obtained from the Gaode Map API contained numerous duplicate entries for the same institution (e.g., separate records for outpatient, inpatient, and emergency departments). To ensure data accuracy and consistency, all records were manually verified and consolidated, merging multiple points belonging to the same facility into a single entity. The resulting dataset thus reflects a refined and accurate spatial representation of public medical facilities across the Tibet Autonomous Region (Amap, 2023).

（2）Digital Elevation Model (DEM) Data

To support terrain-related analyses such as relief amplitude, slope calculation, and population density estimation, DEM data were obtained from the SRTM DEM UTM 90 m dataset (NASA Jet Propulsion Laboratory, 2013).The data were projected into the Albers Equal-Area Conic projection using ArcGIS software, ensuring spatial consistency across all datasets. Following projection, the DEM was resampled to a 1km grid resolution to harmonize spatial granularity with population and medical facility data. This processed DEM dataset was subsequently employed for terrain classification and elevation-based accessibility modeling.

3.3.3 Methods

（4）Altitude and RDLS Calculation

The processing of DEM elevation data covered four provinces in western China—Tibet Autonomous Region, Yunnan Province, Sichuan Province, and Guizhou Province. According to China's geomorphological classification standards, landform types are determined by two principal indicators: altitude

and relief amplitude. Considering that the county represents the basic administrative unit in China, this study adopts counties as the primary spatial analysis unit. The median elevation of counties classified as large undulating alpine terrain ranges between 4,000 m and 6,000 m, with a median Relative Digital Terrain Slope (RDLS) between 2 and 5.

Using ArcGIS software, the DEM data were processed at a grid resolution of 1 km × 1 km. The median elevation of each county was calculated based on the preprocessed DEM data, and the results were spatially aggregated within county administrative boundaries.

The RDLS was derived through raster-based terrain analysis using the Spatial Analyst tools in ArcGIS. Within the study area encompassing the four western provinces, a 10 km × 10 km grid was established as the analysis unit. For each grid cell, the maximum (Max(H)) and minimum (Min(H)) elevation values were extracted, and the difference [Max(H) – Min(H)] was computed to generate a new raster layer representing terrain relief. To calculate the non-flat land ratio [1 – P(A)/A], this study referred to the national standard for landform classification in China, defining flat terrain as areas where the maximum elevation difference within 25 km^2 ≤ 30 m. For each 5 km × 5 km analysis window, the maximum and minimum elevation values were extracted to compute the maximum height difference. Grids meeting the 30 m threshold were identified as flat areas, and the proportion of non-flat terrain in each 10 km × 10 km grid was calculated using the formula [1 – P(A)/A].

Finally, the terrain relief of each grid cell was obtained by multiplying the [Max(H) – Min(H)] layer by the non-flat land ratio layer, followed by dividing the resulting raster by 500 m, yielding the final terrain relief dataset. Based on the computed median elevation and RDLS, nine counties were identified as representative of large undulating alpine terrain.

（5）Accessibility Calculation

We constructed an anisotropic walking resistance surface from DEM- and land-cover–derived inputs and performed least-time accumulation from medical facility POIs. First, slope and elevation were derived from the DEM and integrated with road hierarchy, surface type, and hydrography layers under a

unified projection and resolution; each cell was assigned a time cost (min/cell). Impassable features (e.g., lakes, major rivers, cliffs) were encoded as barriers (NoData) and excluded from traversal. Slope-dependent speed adjustments and high-altitude walking-capacity penalties were then applied, and travel efficiencies across road classes and surface types were normalized to yield a continuous time-cost surface. Using ArcGIS Pro's Distance Accumulation framework, we computed least-accumulated travel time with travel direction oriented toward the nearest reachable facility. Fifteen-minute isochrones were extracted to delineate baseline pedestrian service areas, and the continuous travel-time raster was exported for subsequent accessibility metrics (e.g., 2SFCA). All preprocessing (clip, resample, mask) and modeling parameters (resolution, thresholds, barrier rules) were recorded within a single workflow for reproducibility.

3.4 Accessibility Coverage in Tibetan Counties

3.4.1 Spatial Patterns of Elevation and Terrain Relief

Spatial patterns of elevation and relief were highly heterogeneous across the four-province study area (Figures 3-1,3-2,3-3). As shown in Figures 3-1,3-2, land above 2,000 m is predominantly concentrated in western Sichuan, western Guizhou, and northern Yunnan, with extensive very-high-elevation belts (>4,000 m) spanning most of the Tibet Autonomous Region and continuing into western Sichuan. These highlands form broad, contiguous swaths rather than isolated peaks, indicating that a large share of settlement hinterlands lies at or above alpine thresholds. Consistent with this, Figure 3-3 shows that Relative Digital Terrain Slope (RDLS)—our proxy for local relief amplitude—is highest in central–western Sichuan, eastern Tibet, and the northwestern margin of Yunnan, delineating rugged mountain chains with steep vertical gradients and fragmented valley systems.

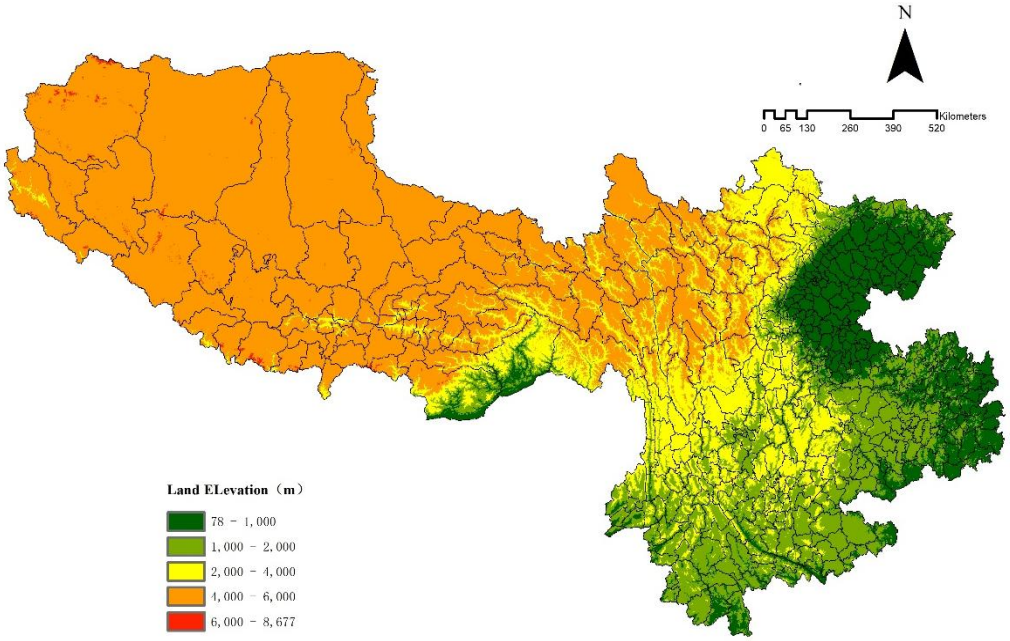


Figure 3-1. Elevation Map of Four Provinces in Western China.

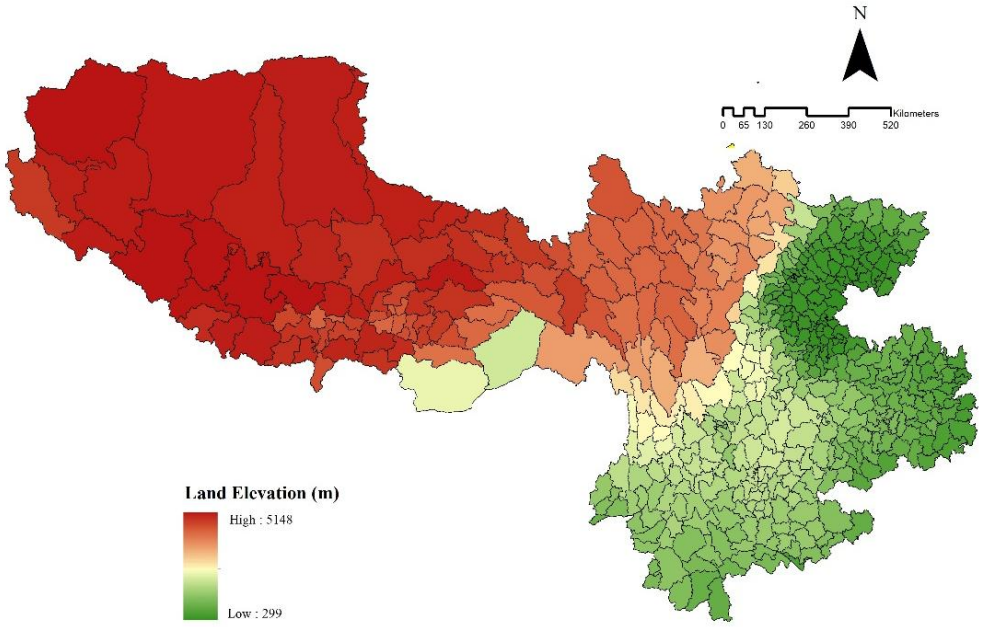


Figure 3-2. Mean Elevation Map of Four Provinces in Western China.

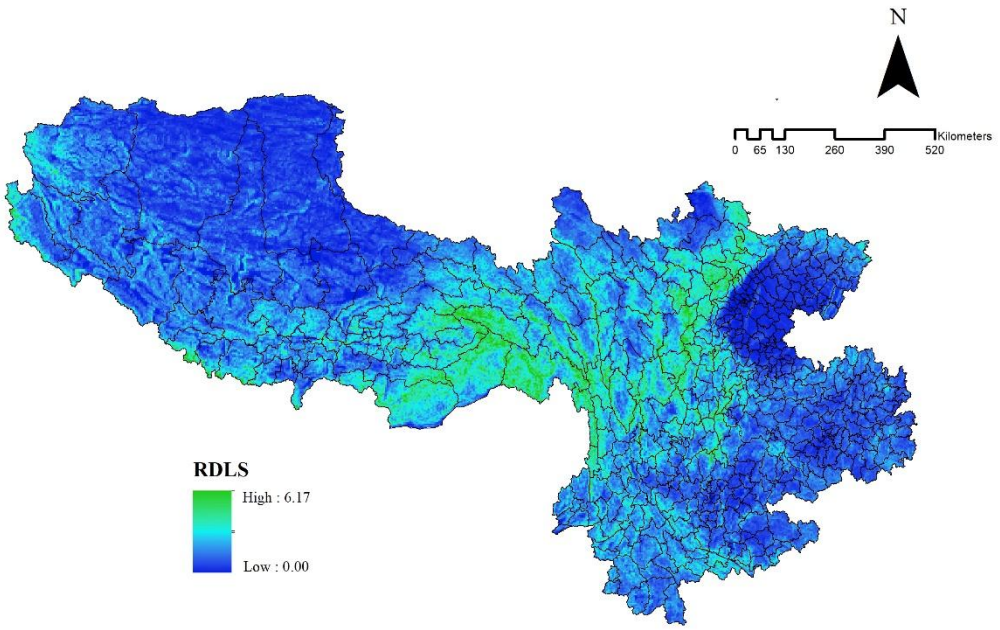


Figure 3-3. RDLS Map of Four Provinces in Western China.

Table 3-1. County-level Statistical Table of Large Undulating Alpine Terrain in Western China.

Province Name	County Name	Elevation Min	Elevation Max	Elevation Mean	RDLS Min	RDLS Max	RDLS Mean	Population
China's Tibet Autonomous Region	Bayi District	1370	6739	4177	0.69	5.17	2.33	84254
China's Tibet Autonomous Region	Banbar County	3422	6480	4780	0.87	4.67	2.00	44021
China's Tibet Autonomous Region	Bomê County	2019	6548	4413	0.65	5.56	2.85	32665
China's Tibet Autonomous Region	GongbujiangdaCounty	3199	6565	4815	0.59	4.83	2.15	32874
China's Tibet Autonomous Region	Nang County	3020	6013	4541	0.87	4.29	2.14	17648
China's Tibet Autonomous Region	Lhünzê County	354	6156	4130	0.44	4.55	2.18	33570
China's Tibet Autonomous Region	Lhozhag County	1759	7306	4827	0.00	3.95	2.04	19865
China's Tibet Autonomous Region	Mainling City	2378	6989	4231	0.86	6.17	2.24	26176
China's Tibet Autonomous Region	ZuogongCounty	2067	6188	4438	0.59	5.26	2.14	46608

Table 3-1 provides a quantitative profile of nine representative counties in Tibet; notably, the mean elevation of all nine exceeds 4,000 m. Mean elevations cluster around ~4,484 m (range: 4,130–4,827 m), while mean RDLS averages ~2.23 (range: 2.00–2.85), confirming jointly high altitude and relief as dominant physiographic constraints. Several counties illustrate extreme topographic contrasts: Lhozhag County spans from 1,759 m to 7,306 m (mean 4,827 m) and uniquely contains cells with RDLSmin = 0.00, indicating pockets of local flatness embedded within highly rugged terrain; Mainling City exhibits the highest RDLSmax (6.17) alongside a wide elevation range (2,378–6,989 m); Bomê County combines very high relief (RDLSmean = 2.85, the highest among the nine) with elevations up to 6,548 m; and Lhünzê County drops to just 354 m at its minimum yet reaches 6,156 m, evidencing deep incision and valley-gorge systems. Populations remain modest (≈17.6–84.3 k), implying sparse settlement exposure across these severe landforms. Taken together, the co-occurrence of high elevation and high RDLS outlines continuous corridors of extreme topographic constraint along the Hengduan-style ranges from western Sichuan into eastern Tibet and across the Yunnan–Sichuan borderlands—zones expected to impose the greatest penalties on pedestrian movement and network continuity, foreshadowing the lower accessibility estimates observed in subsequent analyses.

3.4.2 Fifteen-minute pedestrian accessibility

Table 2. Primary Healthcare Facility Service Rate

Province Name	County Name	Residential Areas Served	All Residential Areas	Rate	Medical Facilities	Population
China's Tibet Autonomous Region	Bayi District	6	74	8.1%	8	84254
China's Tibet Autonomous Region	Banbar County	2	58	3.4%	2	44021
China's Tibet Autonomous Region	Bomê County	4	84	4.8%	3	32665
China's Tibet Autonomous Region	GongbujiangdaCounty	4	77	5.2%	6	32874
China's Tibet Autonomous Region	Nang County	3	35	8.6%	3	17648
China's Tibet Autonomous Region	Lhünzê County	5	56	8.9%	5	33570
China's Tibet Autonomous Region	Lhozhag County	2	47	4.3%	3	19865
China's Tibet Autonomous Region	Mainling City	7	56	12.5%	7	26176
China's Tibet Autonomous Region	ZuogongCounty	1	91	1.1%	1	46608
	Mean	3.4	64.2	6.3%	4.2	34612

As shown in Table 3-2, at a 15-minute walking threshold, coverage is universally low across the nine Tibetan counties (mean rate = 6.3%; median =

5.2%), with 8/9 counties below 10%. On average, only 3.4 of 64.2 residential areas per county fall within service reach, underscoring sparse near-facility catchments. Mainling City is the only clear positive outlier (12.5%; 7 of 56 residential areas served), consistent with its relatively high supply intensity (~2.67 facilities per 10,000 people). By contrast, Zuogong County exhibits the most severe shortfall (1.1%; 1 of 91) alongside the lowest supply (~0.21/10,000). Intermediate cases illustrate how supply alone does not guarantee short-range access: Gongbujiangda County maintains a comparatively higher facility-per-capita level (~1.83/10,000) yet achieves only 5.2% coverage, implying that rugged terrain and dispersed settlement patterns reduce the effective 15-minute footprint of facilities. Overall, the pattern suggests a joint constraint of limited facility density and extreme topography/dispersion, with per-capita supply helping but insufficient to overcome relief-induced anisotropic travel costs in most counties.

3.5 Spatial Accessibility and Terrain Constraints Analysis

The findings of this study underscore the profound impact of topography and altitude on healthcare accessibility in high-altitude mountainous regions such as the Qinghai–Tibet Plateau. Across the nine analyzed Tibetan counties, pedestrian accessibility to primary medical facilities within a 15-minute threshold averaged only 6.3%, demonstrating significant spatial inequity. These results align with previous studies indicating that mountainous environments impose severe physical and infrastructural barriers to healthcare access in western China.

3.5.1 Terrain and Accessibility Constraints

High elevations and rugged terrain are fundamental determinants of spatial inequality in healthcare accessibility. Studies have shown that the Qinghai–Tibet Plateau's steep relief, fragmented valleys, and permafrost conditions significantly restrict both road network development and travel efficiency (Yang et al., 2019). The anisotropic walking model used in this research confirmed that increased slope and elevation impose exponential travel-time penalties, a pattern consistent with transport accessibility models that demonstrate a marked decrease in accessibility above 4,000 m (Gao et al., 2019).

Moreover, the combined influence of terrain and environmental conditions, such as permafrost and seasonal snow cover, further limits the sustainability and reliability of healthcare infrastructure. Remote sensing studies indicate that permafrost degradation and cryogenic landforms are widespread across the plateau, complicating the maintenance of both transportation and healthcare facilities (Shi et al., 2018) . Such factors exacerbate travel resistance and reduce the effective service areas of medical institutions, even where nominal facility density appears adequate.

3.5.2 Settlement Patterns and Healthcare Distribution

The low 15-minute accessibility rates observed are closely tied to the spatial distribution of settlements in Tibet. Residential clustering along river valleys and transport corridors, typically between 3,000 and 5,000 m, has been documented in spatial analyses of Tibetan population distribution (Niu et al., 2022). However, these settlement zones do not consistently align with medical facility locations, especially in sparsely populated counties such as Zuogong and Bomê. The resulting spatial mismatch between healthcare supply and population centers intensifies inequality in service access.

Furthermore, climatic and environmental risks—such as permafrost thaw and glacial valley flooding—periodically disrupt accessibility, isolating high-altitude communities from nearby medical centers (Wang et al., 2021). These geographic vulnerabilities reinforce the need for adaptive, terrain-sensitive healthcare planning, integrating both spatial and environmental datasets to support resilient service delivery.

3.5.3 Socioeconomic and Policy Implications

Accessibility disparities on the Qinghai–Tibet Plateau are not solely environmental but also reflect socio-economic and infrastructural inequities. Despite significant national investments through the Western Development Strategy and transportation expansion, spatial fairness in accessibility remains limited (Gao et al., 2019). Counties with better-connected road networks—such as Mainling City—demonstrated notably higher accessibility, highlighting the synergistic role of transportation and healthcare infrastructure.

In addition, ecological conservation policies and terrain protection zones

impose restrictions on facility expansion in fragile ecosystems, especially near permafrost or glacial regions (Wang et al., 2022). Balancing ecological preservation with public health service provision remains a critical policy challenge for sustainable development on the plateau.

3.5.4 Future Directions

To enhance healthcare accessibility under high-altitude conditions, future research should integrate real-time terrain data, permafrost monitoring, and climate projections into healthcare network modeling. The development of telemedicine and mobile health units may serve as effective adaptive strategies, reducing reliance on fixed facilities constrained by terrain. Additionally, cross-sectoral coordination between transportation, environmental, and health planning agencies is essential to build resilient healthcare systems in mountainous regions.

3.6 Summary

This section shows that Tibet's nine representative counties sit at jointly high elevation (mean >4,000 m) and relief (RDLS ≈2.23), forming contiguous belts of rugged terrain that fragment valleys and constrain movement. Fifteen-minute pedestrian coverage of primary care is uniformly low (mean 6.3%; median 5.2%), with Mainling the only relative outlier (12.5%) and Zuogong the worst (1.1%). Per-capita supply helps in a few places, but terrain-induced, anisotropic walking costs and dispersed settlements sharply compress effective catchments. The analysis links poor access to steep relief, high altitude, permafrost/snow dynamics, and a spatial mismatch between facilities and valley-clustered residences, compounded by variable road connectivity and ecological protection zones. Policy implications include context-sensitive benchmarks (e.g., near-range 15–30 min targets), decentralized siting and micro-infrastructure to expand walkable catchments, and integration of terrain/climate data into routine planning. Future efforts should pair terrain-sensitive models with telemedicine, mobile clinics, and cross-sector coordination to build resilient healthcare access under extreme topography.

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Chapter 4

MULTI FACTOR ASSESSMENT OF SPATIAL ACCESSIBILITY

Chapter 4

Multi Factor Assessment of Spatial Accessibility

Timely access to essential primary healthcare services is critical for achieving health equity, particularly in geographically constrained mountainous regions where terrain imposes significant barriers to mobility. However, existing national planning standards in China rely on uniform service radii or walking-time thresholds, often failing to reflect the true accessibility conditions in complex highland environments. To address this gap, this study develops a Multi-Factor Integrated Mountain Walkability Model (MIMWM) that incorporates high-resolution Digital Elevation Models (DEM), slope-adjusted walking speeds, land-use resistance coefficients, and physiological walking capacity decline at altitude. Embedded within the Two-Step Floating Catchment Area (2SFCA) framework, the model is applied to Diqing Tibetan Autonomous Prefecture in Yunnan Province, a high-altitude region characterized by rugged terrain and sparse healthcare infrastructure. Results demonstrate that traditional Euclidean and network-based methods substantially overestimate accessibility, particularly within the 15–60-minute walking thresholds. The MIMWM reveals a critical threshold effect at approximately 30 minutes, beyond which accessibility improvements diminish. Moreover, most residents in the study area fall below the baseline criteria for access set by national healthcare standards, highlighting the inadequacy of uniform service thresholds in mountainous settings. This study underscores the dominant influence of terrain and walking capacity constraints and advocates for location-specific accessibility metrics and near-distance infrastructure investment to improve rural health equity. The model provides a replicable approach for integrating terrain sensitivity into healthcare accessibility planning in other topographically complex regions.

4.1 Introduction

Timely access to essential primary healthcare services is a fundamental component of achieving health equity, especially in underdeveloped and geographically constrained regions. In the mountainous areas of western China, residents are confronted with a range of formidable challenges that hinder their ability to reach healthcare facilities within clinically critical timeframes. These barriers are not merely infrastructural but are deeply rooted in the region's complex physical geography. Steep and uneven slopes, highly fragmented road networks, and diverse land surface conditions substantially increase travel resistance, particularly for pedestrian movement, which remains a common mode of transportation in many rural settlements. Such physical constraints are compounded by systemic healthcare disparities. Western China continues to exhibit significantly lower healthcare facility coverage compared to eastern regions, with many counties lacking sufficient numbers of clinics or township-level health centers. At the same time, the region is home to large and dispersed populations, many of whom reside in remote villages scattered across rugged terrains. This imbalance between sparse medical infrastructure and high potential demand results in pronounced spatial inequities in healthcare accessibility. In this context, conventional accessibility evaluation methods may fail to capture the true extent of spatial disadvantage, underscoring the need for refined, terrain-sensitive models that reflect real-world conditions in mountainous environments.

Traditional spatial accessibility models—most notably the two-step floating catchment area (2SFCA) method—commonly employ circular buffers or simple network radii, which often fail to capture the true travel constraints of complex terrain(Luo & Wang, 2003a). The traditional 2SFCA method assumes that all locations within the service area have the same accessibility, ignoring the distance attenuation effect caused by factors such as terrain obstacles, which is particularly evident in mountainous areas (B & C, 2009; Song et al., 2010). The use of a fixed service area is not applicable in areas with different terrains and population densities (McGrail, 2012). Furthermore, it assumes that all modes of transport have the same travel time or distance, ignoring the differences between multimodal modes of transport (Tao et al., 2018). These limitations are particularly problematic in rural Southwest China, where medical resource allocation directly impacts the well-being of vulnerable populations

(Guagliardo, 2004).

Over the past two decades, the 2SFCA method has become a mainstream tool for evaluating healthcare accessibility and guiding health resource planning(W. & Y., 2009). Numerous enhancements have addressed limitations related to distance-decay, variable catchment sizes, and multimodal travel modes (Delamater, 2013; Langford et al., 2012). Beyond impedance-focused refinements, non-spatial adjustments to supply and demand have also been proposed, such as the Supply–Demand Adjusted 2SFCA (SDA-2SFCA), which reweights provider capacity and local need to better align effective access with service pressure(Shao & Luo, 2022).However, adaptations tailored for rugged mountainous environments are still sparse. Although 2SFCA has been widely used in urban environments, scholars have pointed out that ignoring terrain and surface resistance systematically overestimates accessibility estimates in rugged terrain, prompting the development of terrain-sensitive methods(Apparicio et al., 2008; K et al., 2015). Most studies remain at the level of adjusting buffer radii or incorporating simple road-network-based cost distances, without integrating the full spectrum of terrain and land-use constraints. Additionally, online map data is subject to network limitations and typically assumes a default, slope-independent walking speed, which provides limited representation of the non-networked footpaths common in mountainous villages and lacks transparent, repeatable resistance parameters. In contrast, MIMWM constructs a continuous anisotropic cost surface that combines slope-dependent walking ability, land use resistance, and vertical/horizontal factors, enabling the generation of isochrones across both mapped and unmapped terrain with auditable and reproducible parameters.

Recent attempts in Southwest China, including in Guizhou and Yunnan provinces, have improved the 2SFCA framework by considering road types or approximate travel speeds(Hu et al., 2023). Yet, these models often neglect the cumulative effects of elevation gain, slope-induced fatigue, surface types, and walking network density, leading to potential misestimation of true walkable catchments (Guo et al., 2021). The traditional 2SFCA's simple handling of the distance attenuation function also easily leads to errors (Weiwei Dai, 2022). Fine-grained integration of these factors remains a critical research gap.

Meanwhile, advances in walkability research—spanning urban studies,

transport geography, and public health—demonstrate that high-resolution digital elevation models (DEMs), open-access pedestrian networks (such as OpenStreetMap), and remote-sensing-derived land-cover data can be fused to estimate spatial variations in walking speed (Spearpoint, 2012). Various studies have also improved methods to enhance the model's responsiveness to distance attenuation effects (Chen et al., 2024). Nevertheless, the incorporation of such multi-factor walkability surfaces into health service accessibility models, especially in rural mountain regions, is limited.

To address the limitations, this study proposes a Multi-Factor Integrated Mountain Walkability Model (MIMWM), designed to more accurately capture the complexity of pedestrian accessibility in mountainous terrain. The model incorporates four key components. A walkability surface derived from high-resolution Digital Elevation Model (DEM) data, accounting for non-obstructed areas and feasible walking zones; An elevation gain adjustment module that reflects the physiological burden of cumulative uphill movement on human walking capacity; A land-cover-based surface resistance coefficient layer, constructed from recent land-use data to differentiate walking impedance across surfaces such as bare land, forest, cropland, and built-up areas; A slope-informed walking speed correction, integrating empirical relationships between terrain gradient and pedestrian travel velocity. In mountainous residential areas, residents often utilize informal paths such as field ridges, field edges, dry riverbeds, staircase shortcuts, and seasonal trails for mobility. Since these paths are often informal, private, or weather-dependent, obtaining complete and up-to-date path information is challenging, making it difficult for web-based isochrone methods to accurately reflect the actual feasible path set. To address this issue, the MIMWM models' movement on a continuous anisotropic cost surface (considering slope, land cover, and vertical/horizontal factors) and 'burns' reliable paths into low-resistance units, prioritizing them when available. This method retains the advantages of road/sidewalk data while avoiding assumptions about network completeness. Compared to traditional road network-based isochrone methods, MIMWM generates isochrones on continuous terrain constraint surfaces, allowing movement in non-road areas (such as slopes, fields, and trails) and adjusting costs based on terrain and land cover types. This method can generate mixed isochrones to reflect the realistic accessibility of mountainous residential areas and combine with the two-step floating catchment area (2SFCA) framework to generate

terrain-sensitive accessibility scores.

The empirical analysis was conducted in Diqing Tibetan Autonomous Prefecture, located in northwestern Yunnan Province, China—an area characterized by highly rugged topography, with elevations ranging from approximately 1,500 to over 5,500 meters, steep slopes often exceeding 15°, and a fragmented terrain structure. These extreme geographical constraints impose significant barriers to pedestrian mobility and make Diqing a representative case for testing terrain-sensitive healthcare accessibility models. Under such conditions, conventional Euclidean or network-based travel estimation methods tend to underestimate the true cost of access.

This study aims to answer four research questions:

(1) How effectively can the proposed Multi-Factor Integrated Mountain Walkability Model (MIMWM) delineate realistic pedestrian catchment areas for primary healthcare services in mountainous terrain?

(2) How do accessibility scores generated by the MIMWM-based 2SFCA compare to those produced by traditional Euclidean buffer and network-based approaches in terms of spatial coverage and equity sensitivity?

(3) How do different walking-time thresholds influence the measurement of spatial accessibility and health equity, and are existing national planning benchmarks suitable for application in high-altitude regions?

(4) How do individual factors—including slope-induced walking impedance, altitude-related physiological constraints, and land-use resistance—independently influence pedestrian mobility and healthcare access?

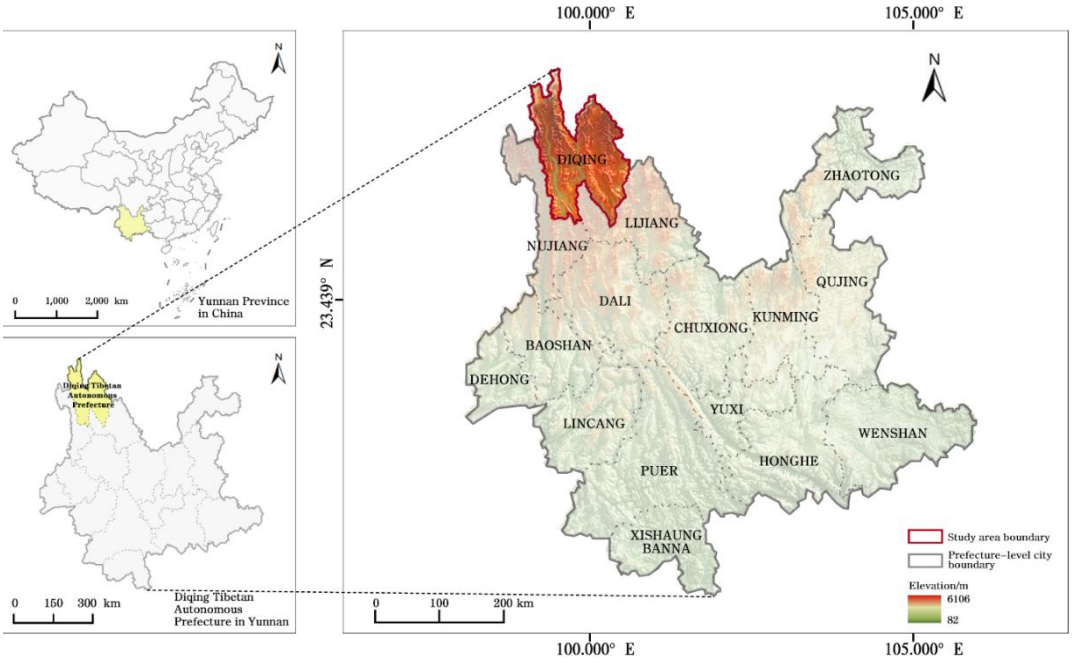
Methodologically, this study bridges walkability modeling and healthcare geography by embedding a multi-factor, physics-informed pedestrian cost surface into the classical Two-Step Floating Catchment Area (2SFCA) framework. Empirically, it produces the first fine-scale, terrain-adjusted accessibility maps for Diqing, providing a robust evidence base for assessing spatial inequality in health service delivery. Policy-wise, the findings support refining uniform service thresholds, advocating for location-specific accessibility standards, and guiding the strategic planning of "last-mile"

healthcare infrastructure in topographically constrained regions.

The remainder of the paper is organized as follows: Section 2 describes data sources and methods; Section 3 presents the results; Section 4 discusses implications for healthcare planning in mountainous regions; Section 5 concludes and highlights avenues for future research.

4.2 Materials

4.1.1 Study Area

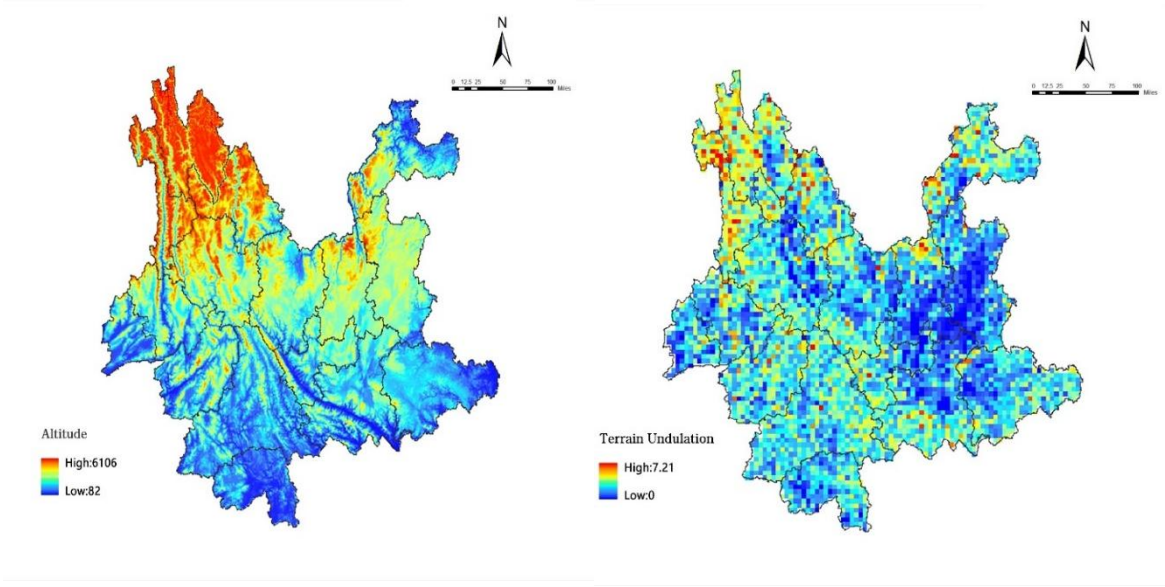


* Maps were generated by the authors using ArcGIS Pro 3.2 (Esri, Redlands, CA, USA; https://pro.arcgis.com).

Figure 4-1. Research object location.

This study focuses on Diqing Tibetan Autonomous Prefecture, a representative high-altitude mountainous region located at the junction of Yunnan, Tibet, and Sichuan provinces in northwestern Yunnan, China (Figure 4-1). According to the Seventh National Population Census (2021), Diqing Tibetan Autonomous Prefecture has a permanent population of approximately 395,000, with an urbanization rate of 33.92%. The region is predominantly rural and ethnically diverse, with Tibetan communities constituting the majority of

the population(China, 2021b). The prefecture spans approximately 23,870 km² and is characterized by steep terrain, deep river valleys, and widely scattered settlements. The average elevation exceeds 2,000 meters, and the terrain undulation index is greater than 2, indicating considerable vertical relief and complex topography. According to China's topographic and geomorphological classification system, elevation and surface undulation are essential indicators for delineating mountainous regions (Feng et al., 2007; Li et al., 2008). Based on this classification, areas with elevation above 2,000 meters (Figure 4-2(a)) and undulation index greater than 2 (Figure 4-2(b)) are defined as high-altitude mountainous zones. Diqing meets both criteria, making it an ideal case for assessing healthcare accessibility in remote mountainous settings.



(**a**) (**b**)

* Maps were generated by the authors using ArcGIS Pro 3.2 (Esri, Redlands, CA, USA; https://pro.arcgis.com).

Figure 4-2. Analysis of Yunnan Province's Topography: (a) Yunnan Province Altitude; (b) Yunnan Province Terrain.

4.1.2 Data

The data sources include residential points, roads, rivers, and land use data from the National Basic Geographic Information Center (2021) (National Basic Geographic Information Center , 2021). DEM data is obtained from ASTER

GDEM (90m, 2022) and SRTM (30m and 90m, 2022) through the Geospatial Data Cloud (Cloud, 2022). Population data is sourced from the seventh national census of China (2021) (National Census of China, 2021a). The location information of medical facilities is sourced from the Baidu API (Baidu Maps API), while information on the number of medical beds, medical technicians is obtained from the Yunnan Provincial Health Statistical Yearbook (2021) (Yunnan Provincial Health Statistical Yearbook, 2021).

4.3 Measuring Accessibility

4.3.1 2SFCA Measuring Accessibility

The Two-Step Floating Catchment Area (2SFCA) method, first developed by Radke and Mu (Radke & Mu, 2000) and refined by Luo and Wang (Luo & Wang, 2003a, 2003b), is a gravity-based model widely used to measure healthcare accessibility. It includes two steps(Wang & Luo, 2005; Yang et al., 2006).

Step 1: Create a catchment area of a certain radius d_0 around each service facility. Calculate the service supply of each facility within its catchment area using the formula:

$$S_i = \sum j \in D(i, d_0) P_j / \mathrm{d}_{ij} \quad (1)$$

where: S_i is the service supply of facility i. P_j is the population of demand point j. d_{ij} is the distance or travel time between facility i and demand point j. D (i , d_0) is the set of all demand points within the catchment area radius d_0 of facility i. Step 2: From the perspective of the demand points, create a catchment area of the same radius d_0 around each demand point. Calculate the overall accessibility of each demand point to all service facilities within its catchment area using the formula:

$$A_j = \sum i \in F(j, d_0) S_i / d_{ij} \quad (2)$$

where: A_j is the overall accessibility of demand point j. S_i is the service supply of facility i (calculated in Step 1). d_{ij} is the distance or travel time

between facility i and demand point j. F (j, d_0) is the set of all service facilities within the catchment area radius d_0 of demand point j.

This method overcomes limitations of simple proximity or ratio-based measures but assumes uniform access within catchments. To address this, the Enhanced 2SFCA (E2SFCA) introduces distance decay weights(W. & Y., 2009). Furthermore, in mountainous regions, traditional buffer or network-based methods may misrepresent actual access. This study proposes a new distance accumulation approach to enhance catchment delineation under rugged terrain.

4.3.2 Euclidean Buffer

The Euclidean buffer is a basic spatial analysis technique in Geographic Information Systems (GIS), used to delineate service areas by generating circular zones around points or parallel buffers along lines and polygons based on straight-line (Euclidean) distance (Figure 4-3). For healthcare facilities, this approach approximates service coverage within a predefined radius, but it assumes uniform travel conditions and neglects terrain, infrastructure, and individual movement constraints. Consequently, it may overestimate service accessibility, especially in complex environments such as mountainous or urbanized regions.

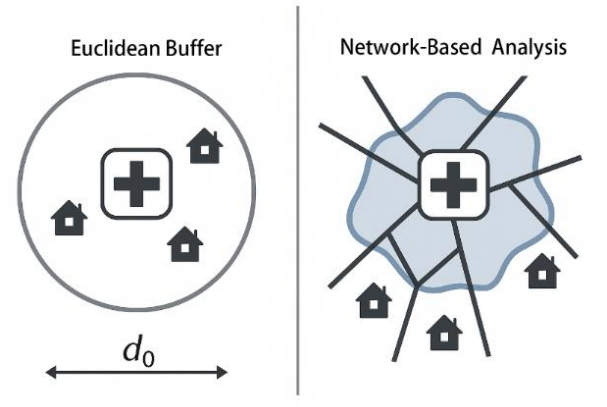


Figure 4-3. Euclidean Buffer and Network-Based Analysis for Service.

4.3.3 Network-Based Analysis

Unlike the Euclidean method, network-based analysis integrates the structure and constraints of transportation infrastructure into spatial

accessibility assessment (Figure 3). When coupled with the 2SFCA method, it models real-world travel by computing shortest travel times or distances between demand and supply points using algorithms such as Dijkstra or A*. The approach typically employs an Origin-Destination (OD) cost matrix to evaluate accessibility based on actual travel paths. Advanced versions incorporate multiple travel modes (e.g., walking, driving, transit) to better reflect urban mobility behaviors (Ni et al., 2019), thereby improving the accuracy and policy relevance of healthcare accessibility models.

4.3.4 Multi-Factor Distance Accumulation Analysis

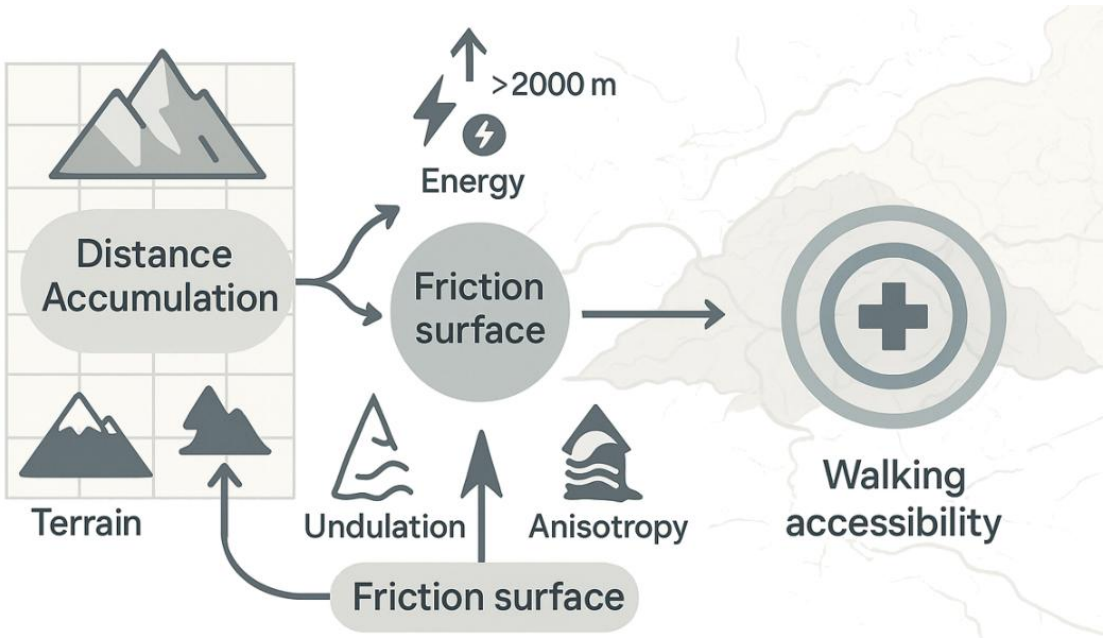


Figure 4-4. Multi-Factor Distance Accumulation Analysis.

Distance accumulation calculates the minimum accumulated cost from each raster cell to source points by integrating straight-line, cost, and true surface distances, with vertical and horizontal cost adjustments (Documentation, 2023). Considering increased energy expenditure and physiological strain during walking at altitudes above 2000 m (Makogonov et al., 2019), this study incorporates multiple factors—mountainous terrain, elevation-induced penalties, terrain undulation, directional anisotropy, and impassable barriers—into a composite friction surface (Figure 4-4). Using this friction surface, accurate walking accessibility zones for medical facilities in high-altitude mountainous areas are derived, improving service radius estimation compared to traditional Euclidean and network-based methods.

4.4 Accessibility Analysis in High-Altitude Mountainous Regions

This study applies the Two-Step Floating Catchment Area (2SFCA) method to evaluate healthcare accessibility in high-altitude mountainous regions (Figure 4-5). To more accurately reflect pedestrian mobility in such complex terrains, we developed a Multi-Factor Integrated Mountain Walkability Model. This model accounts for key constraints unique to mountainous environments, including topography, surface conditions, human physiological limitations, slope-specific walking characteristics, and route selection preferences. Building upon this model, we systematically compare the effects of individual factors on healthcare accessibility and assess how varying walking-time thresholds influence accessibility outcomes. Furthermore, the study evaluates and contrasts the performance of three different catchment delineation approaches in computing accessibility, highlighting their respective strengths and limitations in the context of mountainous settings.

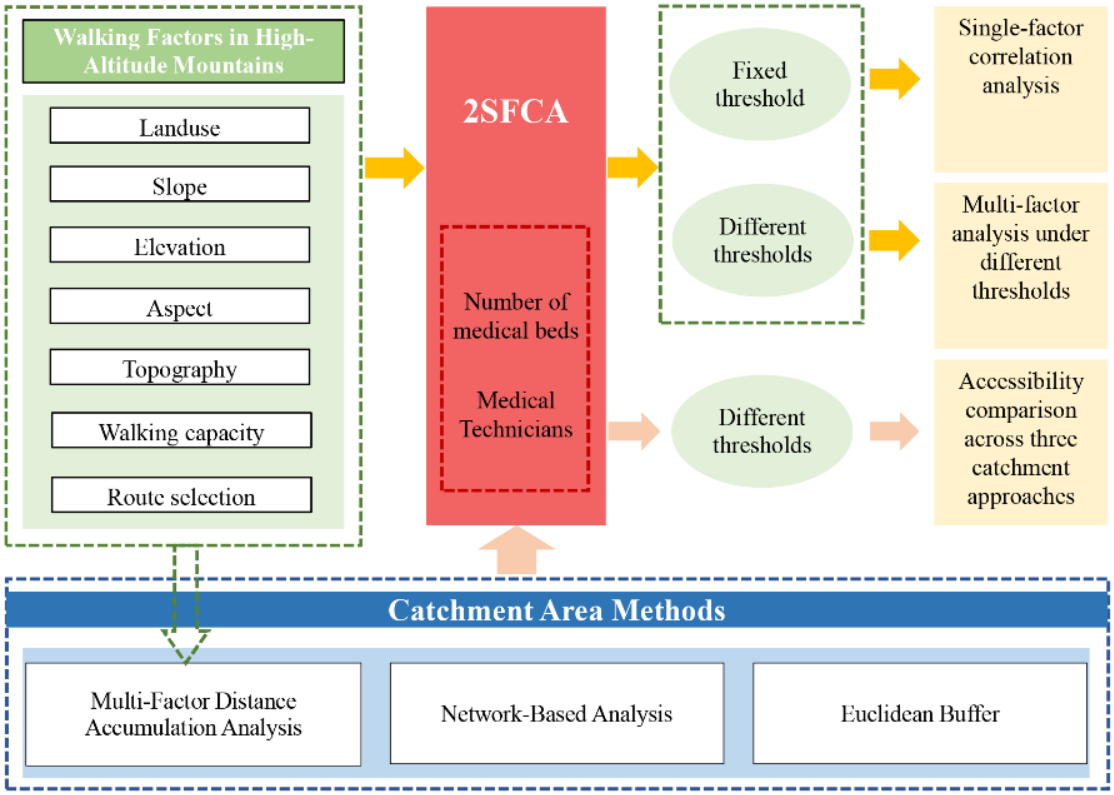


Figure 4-5. Workflow Diagram of the Study.

4.4.1 Multi-Factor Integrated Mountain Walkability Model

To account for the influence of terrain, slope, and altitude on pedestrian movement in mountainous regions, a modified cost function was constructed to estimate the walking impedance c_{ij} between a demand location i and a supply location j. The cumulative accessibility score C_j for each medical facility j is defined as:

$$C_j = \sum_i c_{ij} \quad (3)$$

where the cost c_{ij} is calculated by:

$$c_{ij} = \frac{d_{ij} \cdot l_{ij}}{v_0 \cdot \exp\left(-3.5 \cdot \left|s_{ij} \pm 0.05\right|\right) \cdot \exp\left(-\alpha \cdot \frac{H_j}{1000}\right)} \quad (4)$$

Here: d_{ij} denotes the horizontal distance between points i and j; l_{ij} represents the land use resistance coefficient (Table 1); v_0 is the base walking speed at sea level, set to 5km/h ; s_{ij} indicates the slope between points i and j; H_j is the elevation of the destination medical facility j; α is an empirically derived coefficient reflecting the decline in walking capacity with elevation. This formulation extends the classical Tobler's hiking function (Tobler, 1993) by incorporating land surface resistance (Zhou et al., 2019) and high-altitude physiological constraints (Chen et al., 2021; West, 2004), making it suitable for accessibility modeling in complex mountainous terrain.

Table 4-1. Land use types, average walking speeds, and derived resistance coefficients.

Land Use Type	Average Walking Speed (km/h)	Resistance Coefficient	Data Sources
High-grade Road	5.00	1.00	(Tobler, 1993)
General Road	3.50	1.43	(Chen et al., 2023)
Farmland	3.24	1.54	(Banick & Kawasoe, 2019)
Forest	3.24	1.54	(Banick & Kawasoe, 2019)
Shrubland	3.60	1.39	(Banick & Kawasoe, 2019)

Grassland	4.86	1.03	(Banick & Kawasoe, 2019)
Water Body	0.06	99.00	(Banick & Kawasoe, 2019)
Snow and Ice	1.62	3.09	(Banick & Kawasoe, 2019)
Barren Land	3.00	1.67	(Banick & Kawasoe, 2019)
Impervious Surface	4.70	1.06	(Kang et al., 2017)
Wetland	2.41	2.07	(Gruchy et al., 2017)

* Note: Resistance coefficients were normalized using the formula $R = v_{ref}/v_{landuse}$, where v_{ref}= 5 km/h.

The land use resistance coefficient l_{ij} was derived based on walking speeds associated with different surface types. Specifically, resistance values were inversely calculated from empirically or literature-supported average walking speeds under various land cover conditions, such as paved roads, bare soil, grassland, forest, and water bodies. A slower walking speed indicates a higher resistance value. These values were normalized to ensure comparability across land use categories. The final resistance coefficients are presented in Table 4-1.

To quantify the impact of high-altitude environments on pedestrian mobility, this study adopts an exponential decay function to model the reduction in walking capacity with increasing elevation:

$$f(H) = \exp\left(-\alpha \cdot \frac{H_j}{1000}\right) \quad (5)$$

where: $f(H)$ represents the relative walking capacity at elevation H, normalized to 1 at sea level; H_j is the elevation (in meters); α is the decay coefficient representing the rate of physiological decline per 1000 meters. Based on previous studies on maximal oxygen uptake (VO2 max) decline at high altitudes, which typically report a 6–10% reduction per 1000 m gain in elevation (Fulco et al., 1998; Kayser et al., 1991; West et al., 2013), the coefficient α is set to 0.10 in this study to represent an average 10% reduction in walking capacity per 1000 m of elevation gain.

To integrate the combined influences of terrain, directional preference, and

physical barriers into accessibility modeling, the Distance Accumulation tool in ArcGIS Pro (Esri, Redlands, CA, USA) was employed. Specifically, we utilized digital elevation models (DEM) to derive slope and elevation factors, integrated directionality via horizontal factor surfaces and applied barrier raster to represent impassable geographic features such as water bodies or steep cliffs. The modified cost function (Equation 4) was input as the fundamental impedance surface, and the cumulative least-cost travel-time raster from each medical facility was generated. Subsequently, the accumulated cost C_j values were extracted for use in the subsequent two-step floating catchment area (2SFCA) accessibility analysis.

4.4.2 Defining Distance Thresholds by Transport Model

This study focuses on walking as the primary mode of transportation, given that environmental conditions—such as terrain, slope, and surface characteristics—have a substantial influence on pedestrian accessibility, particularly in mountainous regions. According to the Residential Area Planning and Design Standards of China (GB 50180-2018) (China., 2018), the recommended walking time to access primary healthcare facilities should not exceed 15 minutes. To examine the sensitivity of accessibility outcomes to walking range assumptions, a series of travel-time thresholds were defined, starting at 15 minutes and increasing in 15-minute increments up to 120 minutes. The upper bound reflects the generally accepted maximum walking time for healthcare-seeking behavior in rural and mountainous contexts.

4.4.3 Comparing Accessibility Measures

This study applies the Two-Step Floating Catchment Area (2SFCA) model to evaluate the accessibility of medical facilities in mountainous regions, using two core indicators: the number of hospital beds per capita and the number of medical technicians per capita. Multiple scenarios were designed to examine accessibility under varying assumptions and methods.

First, we compared accessibility outcomes across three different catchment delineation approaches: Euclidean Buffer, Network-Based Analysis, and Multi-Factor Distance Accumulation Analysis, such as Figure 4-6. Second, using the Multi-Factor Distance Accumulation Analysis method, we evaluated

accessibility across multiple walking-time thresholds (ranging from 15 to 120 minutes in 15-minute intervals) to assess how accessibility changes with increased walking capacity in high-altitude mountainous environments. Pairwise t-tests were conducted to identify the threshold beyond which accessibility values become statistically stable (i.e., differences are no longer significant). Finally, under a fixed threshold, we isolated the influence of individual factors within the Multi-Factor Distance Accumulation framework by recalculating accessibility with only one variable included at a time. The examined factors included mountain terrain, walking capacity, and geomorphological conditions, and correlation analyses were used to assess their respective impacts on accessibility patterns (Figure 4-7).

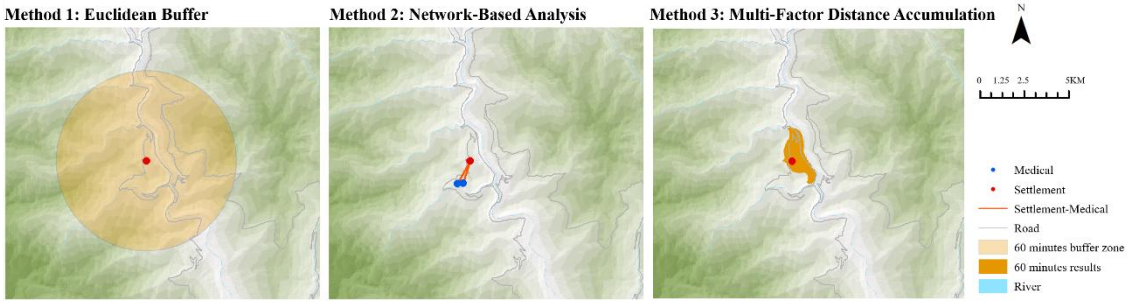


Figure 4-6. Service Radius for Three Methods.

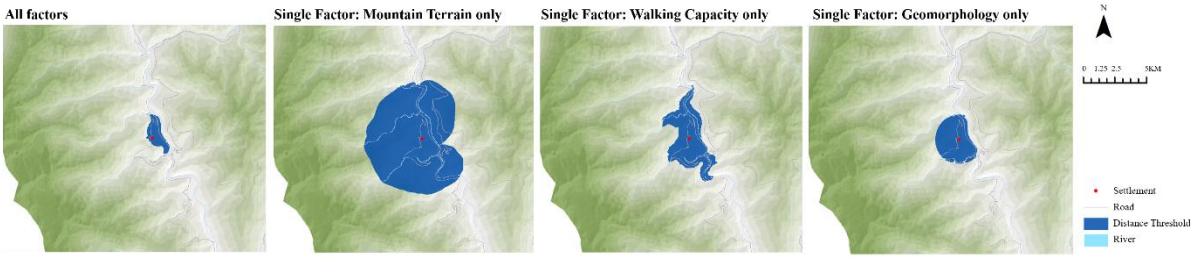


Figure 4-7. Service radius of Multi-Factor Distance Accumulation Analysis for Single Factors.

4.5 Results

4.5.1 Model Performance and Threshold Effects in High-Altitude Accessibility Evaluation

As shown in Table 4-2, disparities between the novel approach (Group A: Multi-Factor Distance Accumulation) and conventional methods (Group B: Euclidean Buffer; Group C: Network-Based Analysis) exhibit significant spatiotemporal variations. In terms of time, the most pronounced differences occur at the 45 minutes threshold, AVS C: Significant differences for both Number of medical beds (p=0.023) and Medical Technicians (p=0.021)；AVS B: Extremely significant differences for both metrics (p=0.000). In terms of accessibility standards, Medical Technicians shows greater sensitivity to methodological differences at 60 minutes (AVS C: $p = 0.047$), while accessibility for Number of medical beds is non-significant ($p = 0.067$). In addition, differences diminish beyond $\geqslant$90 minutes (e.g., 120 minutes: $p > 0.05$), as extended time buffers dilute terrain impacts, validating the walking capacity threshold effect described in the Methods.

Table 4-2. Accessibility Analysis of Three Methods Under Different Time Thresholds.

Time Category	Group Comparison	Accessibility Standards	Correlation Coefficient	p value
15 Minutes	A* VS B*	Number of medical beds	-	**0.012**
		Medical Technicians	-	**0.013**
	A VS C*	Number of medical beds	-	**0.012**
		Medical Technicians	-	**0.014**
30 Minutes	A VS B	Number of medical beds	0.171	**0.001**
		Medical Technicians	0.213	**0.001**
	A VS C	Number of medical beds	0.324	**0.007**
		Medical Technicians	0.415	**0.002**
45 Minutes	A VS B	Number of medical beds	0.478	**0.000**
		Medical Technicians	0.482	**0.000**
	A VS C	Number of medical beds	0.232	**0.023**
		Medical Technicians	0.238	**0.021**
60 Minutes	A VS B	Number of medical beds	0.515	**0.012**
		Medical Technicians	0.499	**0.007**
	A VS C	Number of medical beds	0.317	0.067
		Medical Technicians	0.332	**0.047**
75 Minutes	A VS B	Number of medical beds	0.593	**0.001**
		Medical Technicians	0.580	**0.001**
	A VS C	Number of medical beds	0.501	**0.014**
		Medical Technicians	0.503	**0.012**
90 Minutes	A VS B	Number of medical beds	0.586	**0.000**
		Medical Technicians	0.563	**0.001**
	A VS C	Number of medical beds	0.641	**0.002**
		Medical Technicians	0.626	**0.004**
105 Minutes	A VS B	Number of medical beds	0.635	**0.006**
		Medical Technicians	0.622	**0.008**
	A VS C	Number of medical beds	0.609	**0.003**
		Medical Technicians	0.597	**0.006**
120 Minutes	A VS B	Number of medical beds	0.609	0.194
		Medical Technicians	0.606	0.165
	A VS C	Number of medical beds	0.694	0.366
		Medical Technicians	0.694	0.363

* Group A: Multi-Factor Distance Accumulation; Group B: Euclidean Buffer; Group C: Network-Based Analysis.

According to China's national standards for healthcare resource allocation (China, 2022), this study defines the qualified accessibility thresholds as: Number of medical beds accessibility: ⩾6.46 beds per 1,000 population; Medical Technicians accessibility: ⩾2.9 persons per 1,000 population.

Table 4-3. Percentage of accessibility criteria met.

Time Category	Accessibility Standards	Method 1: Euclidean Buffer	Method 2: Network-Based Analysis	Method 3: Multi-Factor Distance Accumulation
15Minutes	Number of medical beds	8.79%	7.69%	0.00%
	Medical Technicians	18.13%	14.29%	0.00%
30 Minutes	Number of medical beds	12.09%	11.54%	2.75%
	Medical Technicians	23.08%	21.98%	2.20%
45Minutes	Number of medical beds	16.48%	14.84%	3.85%
	Medical Technicians	28.57%	25.27%	6.59%
60Minutes	Number of medical beds	17.58%	16.48%	4.95%
	Medical Technicians	32.42%	29.67%	8.24%
75Minutes	Number of medical beds	25.27%	18.68%	5.49%
	Medical Technicians	39.01%	29.67%	9.89%
90Minutes	Number of medical beds	24.73%	20.33%	6.04%
	Medical Technicians	42.31%	31.87%	12.09%
105Minutes	Number of medical beds	20.88%	22.53%	7.69%
	Medical Technicians	37.36%	34.07%	13.74%
120Minutes	Number of medical beds	25.27%	26.37%	9.34%
	Medical Technicians	47.80%	35.16%	17.58%

* The number of medical beds and medical technicians is calculated per 1,000 residents.

As shown in Table 4-3, the three methods yield markedly different accessibility results across varying time thresholds. Within 15 minutes, the estimated accessibility to medical technicians reaches 18.13% using the Euclidean method and 14.29% using the network-based method, while the multi-factor distance accumulation model reports 0%, reflecting its sensitivity to terrain constraints. With increasing time thresholds, accessibility improves under all methods, yet the multi-factor model consistently reports lower values. At the 60-minute threshold, accessibility to medical technicians is estimated at 32.42% (Euclidean), 29.67% (network-based), and only 8.24% (multi-factor). Even at 120 minutes, the multi-factor model yields 17.58%, significantly lower than the Euclidean (47.80%) and network-based (35.16%) approaches. Overall, the multi-factor model—by integrating terrain, land-use resistance, and walking capacity—produces more conservative estimates, offering a more realistic reflection of access limitations in mountainous regions. In contrast, traditional methods may overestimate service coverage. All three approaches confirm the generally low accessibility of healthcare facilities in the high-altitude mountainous study area.

4.5.2 Identifying the Walking-Time Threshold for Effective Healthcare Access

Figure 4-8 shows a series of visualizations generated by the MIMWM that was built. The system shows how the spatial accessibility of medical beds and medical personnel for residents in the Diqing area changes at different walking time thresholds. To assess the significance of accessibility improvements across time thresholds, a series of paired t-tests were conducted for both accessibility standards—number of medical beds and number of medical technicians. As shown in Table 4-4, the comparison between 15 and 30 minutes revealed a statistically significant increase in accessibility to medical beds ($t = -2.053$, $p = 0.041$), while the improvement in access to medical technicians approached significance ($p = 0.088$). For other consecutive time intervals, no statistically significant differences were observed ($p > 0.05$), although the mean accessibility values continued to increase （Figure 4-9）. This suggests that the most notable change in accessibility occurred within the first 30 minutes, after which improvements became more gradual and statistically nonsignificant. These findings highlight a potential threshold effect in mountainous healthcare accessibility, where additional walking time beyond 30 minutes yields

diminishing returns in terms of population coverage.

Table 4-4. Accessibility Analysis Based on Multi-Factor Distance Accumulation Under Different Time Thresholds.

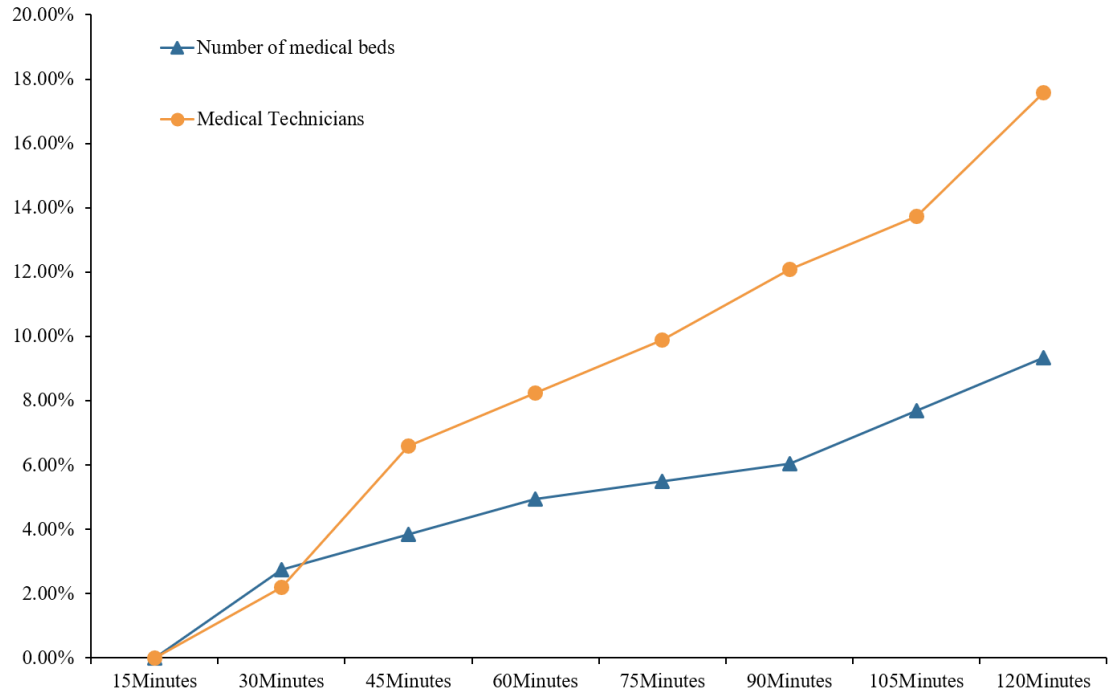
Pairing Group	Accessibility Standards	Mean	Standard Deviation	t value	p value
15Minutes VS 30Minutes	Number of medical beds	-0.618	4.063	-2.053	**0.041**
	Medical Technicians	-0.544	4.278	-1.717	0.088
30Minutes VS 45Minutes	Number of medical beds	-0.868	8.935	-1.310	0.192
	Medical Technicians	-1.438	12.108	-1.602	0.111
45Minutes VS 60Minutes	Number of medical beds	-1.106	12.559	-1.188	0.236
	Medical Technicians	-1.379	16.565	-1.123	0.263
60Minutes VS 75Minutes	Number of medical beds	-0.314	3.132	-1.354	0.177
	Medical Technicians	-0.475	4.722	-1.358	0.176
75Minutes VS 90Minutes	Number of medical beds	-0.235	6.897	-0.459	0.647
	Medical Technicians	-0.554	9.555	-0.782	0.435
90Minutes VS 105Minutes	Number of medical beds	-0.291	4.951	-0.793	0.429
	Medical Technicians	-0.209	6.071	-0.464	0.643
105Minutes VS 120Minutes	Number of medical beds	-1.694	14.246	-1.604	0.110
	Medical Technicians	-2.774	23.048	-1.624	0.106

* p is significant below the 0.05 level. The number of medical beds and medical technicians is calculated per 1,000 residents.



* The figure shows the accessibility spatial distribution map calculated using the MIMWM method at a specific time threshold. The redder the color, the higher the accessibility; the greener the color, the lower the accessibility. Maps were generated by the authors using ArcGIS Pro 3.2 (Esri, Redlands, CA, USA; https://pro.arcgis.com).

Figure 4-8. Temporal Trends of Healthcare Accessibility Under Two Evaluation Standards Using Multi-Factor Distance Accumulation.



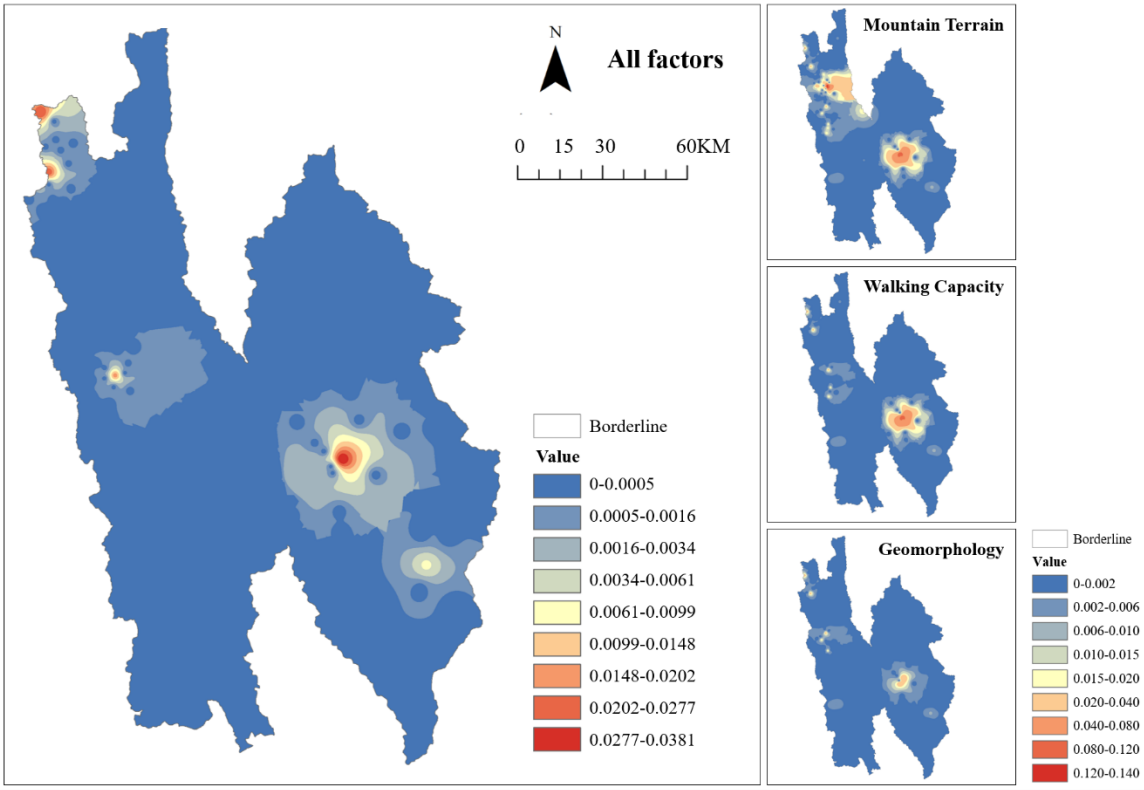
* The number of medical beds and medical technicians is calculated per 1,000 residents.

Figure 4-9. Qualified Accessibility Rates by Time Threshold Using Multi-Factor Distance Accumulation.

4.5.3 Single-Factor Sensitivity and Integrated Effects in the MIMWM

To evaluate the relative influence of individual walking constraints, we compared the accessibility outcomes of the full-factor MIMWM against three single-factor models: Mountain Terrain only, Walking Capacity only, and Geomorphology only, as visually illustrated in Figure 4-10. The paired t-test results are summarized in Table 4-5, using both the number of medical beds and the number of medical technicians as evaluation standards. The comparison with the Mountain Terrain only model revealed significant differences for both evaluation standards, with $p = 0.006$ for medical beds and $p = 0.003$ for medical technicians, indicating that the inclusion of other factors (e.g., walking capacity, surface resistance) significantly alters accessibility outcomes. For the Walking Capacity only model, the difference was statistically significant for medical technicians ($p = 0.026$), while the result for medical beds was marginally non-significant ($p = 0.064$), suggesting walking capacity plays a more

substantial role in access to human resources than physical infrastructure. The comparison with the Geomorphology only model showed a significant difference only for medical technicians (p = 0.008), while the difference in medical bed accessibility was not significant (p = 0.161). This suggests geomorphological variation has a more limited impact on facility-based accessibility compared to human resource availability. Overall, the results demonstrate that no single factor can adequately substitute for the integrated effects captured in the full-factor model. Among the three, mountain terrain exerts the most consistent and significant influence across both accessibility standards.



* The Value in the figure represents the accessibility score calculated using MIMWM, which indicates the level of medical resources available at each location. Warmer colors (such as red) indicate higher accessibility, while cooler colors (such as blue) indicate lower accessibility. Maps were generated by the authors using ArcGIS Pro 3.2 (Esri, Redlands, CA, USA; https://pro.arcgis.com).

Figure 4-10. Comparison of Accessibility Outcomes Between Full-Factor and Single-Factor Models.

Table 5. Paired t-Test Results Comparing Full-Factor and Single-Factor Accessibility Models.

Pairing Group	Accessibility Standards	Mean	Standard Deviation	t value	p value
All factors VS	Number of medical beds	-0.004	0.018	-2.806	0.006
Mountain Terrain only	Medical Technicians	-0.006	0.027	-2.964	0.003
All factors VS	Number of medical beds	-0.002	0.012	-1.860	0.064
Walking Capacity only	Medical Technicians	-0.002	0.015	-2.244	0.026
All factors VS	Number of medical beds	-0.001	0.005	-1.407	0.161
Geomorphology only	Medical Technicians	-0.001	0.006	-2.693	0.008

* p is significant below the 0.05 level. The number of medical beds and medical technicians is calculated per 1,000 residents.

4.6 Discussion

Our findings carry important methodological and policy implications for evaluating healthcare accessibility in mountainous regions.

First, about delineating realistic service areas (Q1), the Multi-Factor Integrated Mountain Walkability Model (MIMWM) has advantages over traditional Euclidean distance methods and network-based methods in capturing the physical barriers posed by rugged terrain. These advantages are especially evident at shorter walking thresholds (15–30 minutes), where the MIMWM model revealed substantial service gaps that were overlooked by conventional approaches (Apparicio et al., 2008; D. J. Weiss et al., 2018; K et al., 2015).This corroborates prior research indicating that neglecting terrain and surface-resistance factors can lead to substantial overestimation of healthcare accessibility, particularly in mountainous and remote settings

Second, in comparing different modeling strategies (Q2), MIMWM -based 2SFCA scores were consistently lower and more spatially differentiated than those derived from Euclidean or network-based models. This finding highlights the limitations of uniform buffer zones and underscores the need for spatial models that reflect pedestrian experience in complex terrains. Relying on simplistic proximity measures risks masking critical inequalities in access to care, particularly in under-resourced areas with sparse infrastructure (Hu et al., 2013; Ouma et al., 2018; W. & Y., 2009).

Third, concerning the impact of walking-time thresholds (Q3), our results

identified a threshold effect at approximately 30 minutes, beyond which further increases in travel time yield diminishing returns in accessibility improvements. This has direct implications for national planning benchmarks, which often employ fixed thresholds without consideration of geographic context. Our findings suggest that standardized thresholds may misrepresent access in high-altitude settings and contribute to misallocation of health resources(Ray & Ebener, 2008; Stock, 1983; Tanser et al., 2006).

Fourth, in assessing individual spatial constraints (Q4), the comparison between the full-factor and single-factor models confirmed the dominant role of terrain in shaping healthcare accessibility, followed by walking capacity and land-use resistance. Specifically, walking capacity had a stronger influence on access to medical technicians, likely due to their dispersed distribution compared to centralized infrastructure. In contrast, geomorphological variation exerted a more limited impact, particularly on access to hospital beds, reinforcing the importance of selecting appropriate accessibility indicators depending on the service type (Delamater et al., 2012; Guagliardo, 2004).

Notably, walking capacity exerted a significant impact on access to medical technicians, likely due to the dispersed locations of human resources compared to centralized healthcare infrastructure. In contrast, geomorphology alone demonstrated a more limited influence, particularly concerning medical beds, highlighting the differential impacts of various physical constraints on different healthcare accessibility standards.

Together, these findings advocate for the integration of multifactorial environmental and physiological constraints into spatial accessibility models, particularly in topographically complex regions. Doing so not only improves the technical validity of accessibility assessments but also enhances their relevance for equity-oriented policymaking (McGrail & Humphreys, 2014; PETERS et al., 2008). Policymakers aiming to promote inclusive healthcare coverage in mountainous regions must explicitly account for the physical realities of walking-based mobility, especially where formal transport networks are sparse.

Based on these findings, we offer several policy recommendations. First, national and regional health planners should adopt differentiated service

coverage benchmarks for mountainous regions. A flexible 30-minute walking-time threshold could be integrated as a context-sensitive standard to guide rural facility allocation. Second, decentralized, near-distance infrastructure investments should be prioritized in high-altitude and topographically fragmented areas to reduce access barriers. Third, terrain-sensitive accessibility models such as the MIMWM should be incorporated into routine health planning, budget allocation, and service evaluation frameworks to ensure that spatial equity is operationalized in practice. Finally, indicators used to measure healthcare accessibility should be tailored to environmental context, distinguishing between infrastructure-based and workforce-based access constraints.

Building on these recommendations, our findings offer several actionable directions for planners:

(i) Facility siting and upgrading: Cells and villages that remain below the national benchmarks within the 0–30 min walking isochrone should be prioritized for new village clinics, outreach stations, or capacity upgrades (Qian et al., 2009). The 30-minute threshold, where gains start to diminish, can be used as a terrain-sensitive service benchmark when screening candidate sites.

(ii) Pedestrian micro-infrastructure: In deficit clusters identified by the MIMWM maps, small-scale works—trail hardening, stairways/switchbacks on steep segments, footbridges, slope stabilization, and wayfinding—can materially expand effective catchments at low cost(Gannon et al., 2001).

(iii) Low-volume motorized support: For dispersed hamlets beyond 30 minutes on foot, demand-responsive shuttles or scheduled market-day minibuses linking hamlets to the nearest clinic can convert otherwise unreachable populations into the service area (Lakatos et al., 2020), especially for maternal/child and chronic care.

(iv) Land-use coordination: new housing, public service points, and village regeneration should prefer locations that co-locate with the 15–30 min isochrones, avoiding further dispersion into high-resistance terrain.

(v) Mobile and outreach services: Periodic mobile clinics and medicine drop-points targeted at the most persistent low-access cells can hedge against

seasonal isolation (Rennert et al., 2024; S et al., 2015).

Together, these strategies translate MIMWM outputs into a practical portfolio that improves equity under rugged topography.

Future studies should continue refining the MIMWM by incorporating dynamic components such as time-varying service availability, emergency mobility behavior, seasonal accessibility constraints, and population-specific walking capacities. These enhancements will be critical to designing resilient, evidence-based, and equitable health resource allocation strategies that meet the needs of geographically marginalized populations.

4.7 Summary

This study demonstrates the critical importance of integrating terrain-sensitive factors into healthcare accessibility models for mountainous regions. The proposed Multi-Factor Integrated Mountain Walkability Model (MIMWM) can more accurately and realistically reflect service coverage compared to traditional Euclidean and network-based approaches. By incorporating slope-induced walking impedance, high-altitude physiological decline, and land-use resistance, the model captures the real-world mobility constraints faced by residents in rugged terrains.

Our findings reveal a 30-minute walking-time threshold beyond which accessibility improvements plateau and show that conventional national standards may systematically overestimate service access in high-altitude contexts. The comparison with single-factor models further highlights the dominant influence of terrain and walking capacity on access inequality, underscoring the inadequacy of one-size-fits-all planning benchmarks.

Policy implications include the need to revise healthcare service coverage standards for mountainous regions, prioritize decentralized infrastructure development, and adopt terrain-sensitive models in routine planning and resource allocation. The MIMWM framework provides a replicable and adaptable tool for improving spatial equity in healthcare access across diverse topographies.

While this study focused on walking to foreground terrain effects, the framework is readily extensible. First, a road-network layer with class-specific speeds, gradient penalties, and weather/seasonal adjustments can generate door-to-door driving times for 2SFCA. Second, scheduled public transport can be integrated using stop access/egress walking, timetable-based travel times (GTFS), transfer/waiting penalties, and service frequency to compute time-dependent transit accessibility. Third, informal transport (e.g., village vans or motorcycle taxis) can be represented via headway-based waiting time and empirical speeds along minor tracks. These mode-specific impedance surfaces can be combined either as separate accessibility layers for targeted policy (e.g., maternal care transit planning) or as a composite generalized-cost surface (e.g., log sum or minimum-time fusion) to assess realistic multimodal catchments. Embedding these extensions within E2SFCA variants would help inform national planning where walking, driving, and transit jointly shape access in mountainous regions.

Future research should extend this framework by incorporating dynamic travel patterns, seasonal accessibility fluctuations, and demographic-specific walking constraints. For example, seasonal changes (such as snow, rain, and vegetation changes) may significantly affect walking behavior and accessibility. To model these factors, time series analysis or seasonal adjustment models can be introduced to capture the impact of environmental conditions on walking behavior. Additionally, combining geographic information system data and climate data can more accurately simulate walking conditions and accessibility changes across different seasons. Such enhancements will support the development of resilient and equitable health systems that better serve geographically marginalized populations.

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Chapter 5

CONCLUSIONS AND PROSPECTS

Chapter 5

Conclusion and Prospects

5.1 Key Cross-Chapter Findings

5.1.1 Population Dynamics — SPMI

The study first identifies the principal drivers of population change across high-altitude counties in Sichuan and proposes the Sustainable Population Migration Index (SPMI). SPMI demonstrates both explanatory and predictive power for retention/out-migration, foregrounding healthcare accessibility and public service provision as core determinants—thereby specifying the "demand-side" pressure that subsequent facility and accessibility analyses must address.

5.1.2 Facility Efficiency and Near Distance Coverage

In representative "large-relief high-mountain" counties in Tibet (mean elevation high; RDLS 2–5), even when per-capita supply appears adequate, near-distance access (15-minute circle) remains systematically low. This exposes a structural gap between nominal supply and effective, walkable coverage due to rugged terrain, dispersed settlements, and anisotropic walking resistance. The evidence supports decentralized sitting, micro walking-infrastructure, and mobile/remote services as priority strategies.

5.1.3 Terrain-Sensitive Accessibility — MIMWM

In Diqing, the Multi-Factor Integrated Mountain Walkability Model (MIMWM) is developed and embedded in 2SFCA to integrate slope-induced impedance, altitude-related physiological decline, land-surface friction, directionality, and barriers. The model shows that Euclidean and network methods systematically overestimate accessibility in mountains; sequential isochrones reveal a diminishing-returns threshold at ≈30 minutes; single-factor

tests indicate terrain exerts the most stable and strongest influence. The implication is clear: equitable mountain healthcare requires near-distance targets and terrain-sensitive parameterization.

5.2 Multi-Level Coupling Framework and Methodological Integration

The dissertation's conceptual spine links population dynamics (SPMI, macro) to facility efficiency and configuration (meso), then to terrain-sensitive accessibility (MIMWM+2SFCA, micro), and finally to digital-twin scenario evaluation for policy–budget–equity optimization—closing the loop from who needs care (demand) to where to provide (supply), whether people can actually reach it (mobility), and how to optimize under constraints (decision). This is operationalized through a validation loop: demand is established via SPMI's spatiotemporal evolution and econometric testing (Ch.2); supply is assessed through facility/workforce tiering and 15-minute near-distance diagnostics (Ch.3); mobility is captured by terrain-sensitive isochrones, threshold detection, and factor sensitivity (Ch.4); and decision is enabled by integrating these outputs into a Digital Twin for multi-scenario comparison and selection.

5.3 Policy Implications and Implementation Pathways

5.3.1 Healthcare-first and Near-distance Orientation

Building on the Chapter 4 MIMWM results, the largest accessibility improvements occur within 15–30 minutes, while marginal gains diminish beyond roughly 30 minutes. This pattern supports a "near-distance first" allocation strategy that delivers higher coverage efficiency.

Considering the primary-care shortfalls documented in the Chapter 3 Yunnan–Tibet high-mountain cases, prioritize capacity additions at village clinics and outreach sites of central township health centers, with an initial focus on deficit grids inside the 0–30-minute isochrones. Evaluate progress under both metrics: beds per 1,000 people and medical technicians per 1,000 people.

For "low-coverage–high-resistance" grid clusters, implement rolling micro-updates that—each round—concentrate on the 0–30-minute fringe to unlock the largest increases in effectively covered population with minimal investment. Consistent with Chapter 2's population–migration evidence, treat near-distance medical access as a core lever for stabilizing resident and rural populations, and assign it greater weight in project appraisal and funding decisions.

5.3.2 Differentiated Thresholds and Tiered Standards

15-minute target (towns/central townships): Use a 15-minute threshold as the basic guarantee for routine care and health management. This aligns cleanly with existing national and municipal indicators, making it easy to audit, budget, and monitor performance across jurisdictions.

30-minute mountain-sensitive threshold (dispersed villages/high-resistance zones): Apply a 30-minute target where terrain and dispersion make short trips unrealistic. Evidence shows that expanding isochrones beyond 30 minutes yields diminishing, often statistically insignificant gains; after this point, investment shifts from enlarging service areas to adding service points and micro-facilities (e.g., small outreach sites, micro-infrastructure).

Extreme-terrain note (>4,000 m, e.g., Tibet): Current 15-minute coverage between towns and residential points is markedly low (often <10%). These areas require tiered thresholds and a distributed, multi-point network—combining near-distance sites, micro-infrastructure, and scheduled outreach—to raise coverage efficiently under severe topographic constraints.

5.3.3 Micro Walking Infrastructure

Prioritize a low-cost, high-return package of works targeted at the "resistance cliffs" and "bottleneck breakpoints" identified by the MIMWM: trail hardening and slope works (steps, switchbacks, anti-slip surfacing), small pedestrian bridges over gullies and watercourses, slope-stabilization with drainage improvements, and high-visibility wayfinding and safety signage. These items directly reduce local walking resistance and restore short-range connectivity where the friction surface is steepest, thereby yielding outsized gains in near-distance accessibility for everyday healthcare trips.

Project selection should be governed by a cost-effectiveness rule that ranks candidates by the "incremental effectively covered population per unit investment." Using the gridded accessibility-gap map as the common basemap, first implement "micro-linkage" and "micro-resistance reduction" along the 0–30-minute fringe (where marginal returns are highest) and then roll outward to the 30–45-minute ring in subsequent waves. This staged approach concentrates limited funds on segments that convert the largest number of residents from non-compliant to compliant within clinically meaningful time thresholds.

For technical implementation, "burn in" completed trails and footbridges to the anisotropic friction surface of the MIMWM by lowering cell-level costs along improved segments, increasing their traversal priority, and snapping them to existing path/road vectors where appropriate. Recompute isochrones to visualize benefits immediately after each intervention and retain a before–after archive to verify that observed coverage gains match design expectations.

5.3.4 Secondary Accessibility via Motorized Services

For dispersed settlements beyond the 30-minute walking catchment, convert non-walkable populations into serviceable ones through a motorized-plus-outreach model that (i) runs scheduled shuttles linking remote villages to the nearest medical point on a weekly or biweekly basis, (ii) deploys mobile clinics and medicine drop-off points on regular circuits that prioritize grid clusters with high seasonal isolation risk, and (iii) overlays telemedicine for chronic-disease follow-ups and return visits to dampen peaks in long-distance care demand.

5.3.5 Digital Twins and Equity Evaluation

Build a three-layer Digital Twin (DT) platform integrating SPMI–facilities–accessibility to enable rapid sandbox simulations and pressure assessments across multiple scheme combinations, with an integrated dashboard to balance equity gains (e.g., the share of population meeting 15/30-minute targets), fiscal constraints (cost per newly compliant person), and service pressure (bed and medical-technician loads). Core KPIs include: K1—the proportion of population meeting 15/30-minute targets (by both beds and medical-technician capacity); K2—improvements in target-achievement rates among vulnerable groups (elderly, maternal, and chronic-disease populations); K3—newly compliant

population per unit investment (persons per 10,000 CNY); and K4—the conversion rate of "secondary accessibility" for populations beyond 30 minutes (coverage via motorized/outreach services). For process evaluation, conduct paired tests for staged threshold advances (15→30→45 minutes) to detect any "no longer statistically significant" plateau, and accordingly recalibrate investment priorities in real time.

5.3.6 Planning and Land Use

Co-location priority: New resettlement sites and education/public-service nodes should be preferentially sited within deficit grids located inside the 15–30-minute isochrones to avoid "building farther away" and resultant spatial fragmentation.

Small-radius, high-frequency: Promote a near-distance, multi-point micro-network pattern ("near-distance multi-points—small radius and high frequency"), replacing the outward expansion of single large facilities with distributed sites and high-frequency services.

Integrated coordination of elements: Bundle land consolidation, village regeneration, and "micro walking infrastructure" for joint implementation, and encode them as binding control lines and project-list items in statutory and sectoral plans.

5.4 Scholarly Contributions (Theory – Methods – Evidence)

5.4.1 Theoretical Contributions

This study proposes a transferable Population–Health–Space coupling paradigm as an overarching theoretical framework for examining health equity in high-altitude mountainous regions. Starting from the two-way feedback among population attraction/retention, the efficiency of healthcare facility provision, and walkable accessibility, the framework explains how population change and public service provision are spatially linked to one another.

The research identifies a closed feedback loop in which healthcare accessibility shapes healthcare utilization and health status, which in turn influence residents' willingness to migrate or stay, ultimately reshaping spatial patterns and facility allocation. Drawing on the three empirical studies, it conceptualizes population, facilities, transportation, and terrain as a dynamically coupled system and demonstrates the mutually constraining relationship between population attraction and stability on the one hand, and the provision of basic healthcare services on the other.

This work extends the discussion of health equity from conventional urban or plain areas to high-altitude, strongly undulating mountain regions, highlighting the fundamental role of terrain and walking capacity in securing health rights. It further argues for a shift from "equalized provision" to "terrain-sensitive equity", suggesting that differentiated service standards and threshold settings are necessary under extreme topographic conditions.

5.4.2 Methodological Contributions

This study develops an evaluation index system for population migration potential in high-altitude counties, integrating healthcare accessibility, infrastructure conditions, ecological constraints, and related factors into a unified framework. Using panel regression and scenario simulations, it verifies the explanatory power and predictive capability of SPMI for observed population changes.

The research proposes a multi-factor mountain walking resistance model that jointly considers slope, altitude-induced decline in walking capacity, land-cover–specific friction, movement direction, and impassable barriers. Supported by DEM data, it constructs an anisotropic cost surface that enables fine-grained simulation of walking accessibility in off-road areas such as field paths, footpaths, and sloping terrain.

MIMWM is embedded into the 2SFCA framework, forming a transparent, auditable, and reproducible workflow that links mountain walking processes with healthcare service supply and demand in an integrated manner. The study systematically compares Euclidean buffers, conventional network analysis, and multi-factor distance accumulation, and quantitatively demonstrates the

systematic overestimation of accessibility by traditional methods.

Through multi-threshold experiments covering 15 to 120 minutes of walking time, the study identifies an approximate 30-minute critical threshold for walking accessibility and reveals that marginal gains in population coverage are highest within the short-distance range. By constructing a sensitivity spectrum that contrasts the full-factor model with single-factor models, it compares the relative influence of mountain terrain, walking capacity, and geomorphological conditions on accessibility outcomes.

The results of SPMI and terrain-sensitive accessibility are integrated into a Digital Twin-based Simulation and Decision-support Platform (DTSDP), enabling joint simulation of population responses and service accessibility under different policy scenarios. This provides ready-to-use models and parameter sets for subsequent automated facility location, route optimization, and multi-objective balancing among population coverage, investment costs, and terrain constraints.

5.4.3 Evidential Contributions

Using 42 high-altitude counties in Sichuan Province as case areas, the study quantifies the main drivers of changes in resident, urban, and rural populations, and identifies healthcare accessibility as a core factor shaping population retention in high-altitude regions. Through the temporal evolution of SPMI, it reveals a general deterioration in migration attractiveness in these high-altitude counties between 2010 and 2020 and uses the digital twin platform to simulate how different policy combinations could mitigate this trend.

Focusing on nine counties with large terrain relief in Tibet, the study integrates medical facility points of interest, population distribution, road networks, and terrain amplitude to map the spatial pattern of township- and village-level primary healthcare facilities. Using benchmark evaluation and 15-minute catchment analyses, it shows that in areas above 4,000 m elevation, primary healthcare service radii are severely insufficient, and coverage is low. The findings indicate that a traditional pattern dominated by county-level public hospitals cannot meet the everyday health needs of high-mountain townships and villages, providing empirical support for strategies that shift

services downward to townships and embed facilities within villages.

In Diqing Tibetan Autonomous Prefecture in Yunnan Province, the study builds an MIMWM+2SFCA model to generate high-resolution walking-time isochrones and accessibility raster. It demonstrates that conventional Euclidean and network-based methods significantly overestimate accessibility within the 15–60 minute time range, while the multi-factor model produces estimates that are more consistent with residents' real walking experiences. The analysis identifies a pronounced inflection point at the 30-minute threshold, showing that additional gains in population coverage decline rapidly beyond this point and thus providing quantitative evidence for an investment strategy that prioritizes short-distance accessibility.

By linking the population–migration diagnosis in Sichuan, the facility equity assessment in Tibet, and the terrain-sensitive walking accessibility modeling in Yunnan, the research constructs a macro–meso–micro chain of empirical evidence. It establishes a complete technical pipeline that progresses from identifying population-related problems, to locating spatial gaps in facility provision, to characterizing walking routes and critical thresholds, and finally to proposing near-distance optimization and facility location strategies. Through cross-regional and cross-scale comparison of results, the study demonstrates the transferability and broader application potential of the Population–Health–Space coupling paradigm.

5.5 Limitations

5.5.1 Static Analysis Framework and Lack of Temporal Dynamics

In the Tibet and Yunnan chapters, the cost rasters are built for a single time slice (a "typical year" or "average conditions"). They do not explicitly incorporate seasonal changes. Road passability, river water levels, and whether farmland can be crossed are all treated as fixed conditions. Disturbances such as rainy seasons, frozen ground, road construction, and landslides are not considered.

In high-altitude areas, winter snow cover, freeze–thaw cycles, and ice can greatly reduce accessibility. However, the current models only reflect these

effects indirectly through slope and land-cover types. Summer heavy rainfall, debris flows, landslides, and river flooding during the monsoon season are also not included in a time-dependent accessibility simulation.

The Sichuan SPMI time-series analysis shows that migration attractiveness worsened between 2010 and 2020. However, this has not been directly matched with a time series of accessibility changes over the same period. The Tibet and Yunnan case studies are mainly based on single-year or short-term cross-sectional analyses. They do not yet form a complete temporal chain linking year-to-year change, policy or institutional adjustment, and subsequent population response.

Directions for future improvement include building monthly or seasonal multi-scenario cost surfaces (such as rainy versus dry season and snow versus no-snow conditions) to analyze seasonal accessibility windows, integrating meteorological disaster warnings and real-time road conditions into the digital twin platform so that accessibility can be evaluated as time-dependent rather than static, and linking multi-period accessibility results with the Sichuan SPMI time series to explore the dynamic relationship between accessibility improvement and population retention or return.

5.5.2 Limited consideration of differences in walking capacity

In the Yunnan MIMWM model, a single decay coefficient α is used to describe the average decline in walking capacity with altitude (for example, a 10% reduction in capacity for every 1000 m gain in elevation). This essentially assumes an "average person" and does not distinguish between different types of residents. In the Tibet 15-minute catchment analysis and the Sichuan SPMI framework, a uniform walking speed or commuting cost is also assumed. Vulnerable groups are not distinguished, which may underestimate the accessibility barriers faced by them.

Older adults, children, pregnant women, and patients with chronic diseases (such as hypertension or cardio-respiratory conditions) have significantly lower walking capacity on slopes and under load, especially in hypoxic high-altitude environments. Their actual walking speed and endurance are likely to be much lower than that of healthy working-age adults. In contrast,

herders, farmers, and manual laborers may have better physiological adaptation to high altitude and stronger physical fitness. Their effective service radius – that is, the distance or time they can reasonably walk to reach medical care – may be considerably larger than that of less-adapted groups.

All three studies mainly rely on theoretical formulas and parameters derived from the literature. They lack empirical measurements of walking speed and route choice based on GPS tracks, wearable devices, or detailed travel diaries collected in high-altitude communities. Behavioral thresholds and psychological expectations for seeking care – for example, under what circumstances people are willing to walk 30, 60, or 90 minutes to see a doctor – have not yet been quantified through systematic questionnaires or in-depth interviews. As a result, the current models may not fully reflect actual health-seeking behavior.

Directions for future improvement. In selected representative counties (high-altitude counties in Sichuan, large-relief alpine counties in Tibet, and Diqing Prefecture in Yunnan), walking experiments should be conducted for different population groups. These experiments can be used to calibrate multiple speed–slope–load functions that reflect the physical capacity of specific groups. By combining mobile phone trajectory data, large-scale questionnaires, and health records, it is possible to build a behavioral model linking group characteristics, travel behavior, and healthcare utilization. This would help to understand who uses which facilities, under what travel costs, and for what types of services. In the MIMWM and 2SFCA calculations, a "population stratification" mode should be introduced. This would allow the use of stricter time thresholds and accessibility standards for older adults, pregnant women, and patients with chronic diseases, ensuring that accessibility evaluation more accurately reflects the needs of vulnerable populations.

5.5.3 Limitations of the 2SFCA-based Accessibility Assessment

In addition, the accessibility calculations in this study mainly rely on the standard two-step floating catchment area (2SFCA) method, which can only provide a relatively simplified representation of the balance between service supply and population demand within fixed catchment areas. We do not yet incorporate more advanced extensions, such as enhanced 2SFCA, multi-modal

2SFCA, or gravity-based approaches, which can more realistically capture distance decay, competition between facilities, and the effects of overlapping catchments.

At the same time, the current models generally use a single service-time threshold and a single travel mode, and they treat service capacity within each catchment as static. They do not explicitly represent crowding and congestion during peak visiting hours, temporal differences between outpatient and inpatient services, or variations in travel behavior and travel modes across different population groups. In high-altitude mountainous environments, where walking conditions are highly constrained and clearly anisotropic, this simplified "equal access inside the threshold and zero access outside the threshold" assumption can create strong edge effects, especially in communities near the boundary of service areas. The results are also very sensitive to the choice of time thresholds and resistance parameters, but this study has not yet carried out a systematic sensitivity analysis.

Therefore, the 2SFCA-based accessibility estimates in this work should still be interpreted as a first-order approximation rather than a fully realistic measure. Future research should build on this framework by introducing time-dependent accessibility calculations, integrating multiple travel modes and networks, and applying more behavior-sensitive weighting functions. These improvements would allow for more refined assessments that better reflect actual travel patterns and healthcare access conditions in high-altitude mountainous regions.

5.6 Future Research Directions

5.6.1 Toward Dynamic and Seasonal Accessibility Modeling

Building on the three case studies in Sichuan, Tibet, and Diqing, future research should move from largely static, single-mode accessibility evaluation toward a more dynamic, behavior-sensitive, and transferable "mountain health" modeling framework. The macro-scale SPMI analysis in high-altitude Sichuan, the meso-scale efficiency and equity evaluation of primary facilities in Tibet, and the micro-scale MIMWM application in Diqing together provide a solid

foundation, but they also reveal clear methodological and empirical gaps that future work can address.

First, there is substantial scope to advance dynamic and seasonal modeling of accessibility. The current analyses in all three chapters largely assume time-invariant road conditions and walking parameters, yet the field evidence from Sichuan, Tibet, and Diqing indicates that snow cover, heavy rainfall, landslides, and seasonal road closures can sharply reduce effective accessibility in certain months. Future studies should therefore construct monthly or seasonal accessibility surfaces that explicitly incorporate road passability, hazard alerts, and satellite-derived surface states (e.g., snow/ice cover, soil moisture, vegetation). Within this framework, time-weighted 2SFCA models could be developed in which the supply–demand ratios are aggregated over a full year, but weighted by the number of months in which facilities are realistically reachable within clinically meaningful time thresholds. Such dynamic modeling would also allow the SPMI to be extended from a purely structural index to a time-sensitive one that reflects seasonal accessibility bottlenecks and their influence on migration decisions.

5.6.2 Multimodal and Multi-Network Integration

Second, future research should generalize from single-mode walking to multimodal and multi-network accessibility. The Diqing case deliberately foregrounds walking to isolate terrain effects, while the Tibet and Sichuan chapters implicitly assume that walking and simple road travel dominate. In practice, residents combine walking with motorcycles, village vans, informal taxis, and, in some corridors, scheduled buses. A logical next step is to construct a unified generalized-cost surface that fuses (i) anisotropic walking impedance derived from MIMWM, (ii) motorized travel times on road networks with class-specific speeds, gradient penalties, and seasonal capacity losses, and (iii) public transport modeled via GTFS-like timetables, including access/egress walks and waiting times. On this basis, service-type-specific accessibility layers could be generated—for example, near-distance walking access for routine outpatient care, multimodal access for maternal and child health, and rapid motorized access for emergency services. Embedding these layers into enhanced 2SFCA variants would make it possible to evaluate trade-offs between different transport investments and service delivery models in a more

realistic way.

5.6.3 Comparative Validation

Third, the transferability and comparative robustness of the proposed methods require systematic testing beyond the three study areas. The terrain classification framework, the RDLS-based definition of large undulating alpine areas, and the MIMWM parameterization were calibrated on high-altitude counties in Sichuan, large-relief counties in Tibet, and Diqing Prefecture. Future work should re-parameterize and re-validate key thresholds (e.g., 15–30-minute "near-distance" targets, altitude-dependent walking coefficients, resistance values for land-cover types) across other Qinghai–Tibet corridors, as well as in international mountain belts such as the central Himalaya or the Andes. Such cross-regional and cross-national applications would help distinguish which components of the framework are context-specific (e.g., institutional standards, facility taxonomies) and which are genuinely generalizable to high-relief environments worldwide. This, in turn, is essential for building a portable planning toolkit rather than a set of isolated case studies.

5.6.4 Behavioral and Population-Side Deepening

A fourth, critical direction is to deepen the population-side representation of behavior. In the current thesis, population is mainly represented by census grids or county-level indicators, and walking behavior is approximated via altitude-adjusted functions and literature-based resistance coefficients. Future research should integrate travel diaries, GPS traces, mobile-phone data, and wearable devices (e.g., step counters, heart-rate monitors) for different demographic and occupational groups—such as elderly residents, herders, farmers, pregnant women, or schoolchildren—to derive empirically grounded speed–slope–fatigue curves. These data would allow separate parameter sets for vulnerable groups, for example, reduced walking capacity for the elderly or steeper fatigue curves for individuals with chronic illness. Linking such micro-behavioral models to SPMI and MIMWM would sharpen the analysis of equity by highlighting who is structurally excluded even when average accessibility appears acceptable.

5.6.5 AI, Open Data, and Benchmarking for Mountain Health

Fifth, there is an opportunity to leverage AI and open data for large-scale mountain-health analytics. The Tibet and Diqing chapters have already demonstrated the importance of accurate settlement and path data, as well as fine-resolution DEM and land-cover products. Future work could deploy deep-learning models to: (i) automatically extract settlement footprints and dispersed hamlets from high-resolution optical or SAR imagery; (ii) detect informal paths, terraces, and micro-infrastructure that are typically missing from standard map products; and (iii) predict near-future population dynamics or service demand using spatiotemporal models informed by SPMI and observed migration patterns. To ensure reproducibility and encourage collaboration, these efforts should culminate in the release of versioned, openly documented datasets—DEM-derived terrain metrics, facility locations, road and path layers, accessibility surfaces, and parameter tables—together with code repositories. Such resources would form the core of an open "mountain-health benchmark" against which new models and interventions can be tested.

5.6.6 Emergency Response

Finally, future research should more explicitly address emergency response and resilience in high-altitude mountain health systems. The present work mainly evaluates routine access to primary care, yet the same terrain and network constraints are even more critical for emergency transport, vaccine outreach, and post-disaster medical siting. Building on the dynamic and multimodal extensions outlined above, time-dependent, weather-aware toolkits could be developed to simulate ambulance routing options under different hazard scenarios; prioritize locations for pre-positioning mobile clinics or emergency stockpiles; and optimize temporary facility deployment after earthquakes, landslides, or road washouts. These emergency-oriented models should be integrated into the digital-twin platforms already piloted in the Sichuan chapter, enabling planners to interactively explore "what-if" scenarios that combine population change, infrastructure upgrading, and extreme events.

In summary, future research should move toward a multi-scale, multi-modal, and behavior-sensitive framework for mountain healthcare accessibility and population sustainability. By combining dynamic seasonal modeling, multimodal generalized-cost surfaces, cross-regional transfer tests, behaviorally calibrated walking models, AI-driven data extraction, and

resilience-oriented emergency toolkits, subsequent studies can transform the thesis framework into a robust, open, and actionable "mountain health" platform. This will not only refine scientific understanding of population–health–space coupling in high-altitude regions but also provide decision-makers with operational tools to design more just and resilient health systems under extreme terrain constraints.

5.7 Concluding Remarks

This dissertation has examined healthcare accessibility and population sustainability in high-altitude mountainous regions through an integrated Population–Health–Space perspective. Across three core case studies—SPMI-based population dynamics in high-altitude Sichuan, facility efficiency and near-distance coverage in large-relief Tibetan counties, and terrain-sensitive accessibility modeling via MIMWM+2SFCA in Diqing—it demonstrates that healthcare accessibility is not merely a technical indicator but a structural determinant of migration, settlement stability, and social equity. By linking demand (population attraction/retention), supply (facility and workforce configuration), mobility (terrain-constrained walkability), and decision support (digital-twin simulation), the dissertation builds a closed-loop analytical spine that renders "who needs care, where, and at what cost" visible and quantifiable under extreme topographic constraints.

Empirically, the findings converge on several robust conclusions. First, in high-altitude, large-relief areas, nominal per-capita provision masks severe deficits in near-distance access: within 15–30 minutes, coverage is systematically low, especially above 4,000 m, and traditional Euclidean or road-network methods consistently overestimate accessibility. Second, the identification of an approximate 30-minute walking threshold, beyond which marginal gains in covered population rapidly diminish, provides a terrain-sensitive benchmark for planning. Third, across Sichuan, Tibet, and Diqing, healthcare accessibility repeatedly emerges as a core lever shaping population retention, underscoring a "healthcare-first and near-distance-oriented" strategy as central to both rural revitalization and high-altitude sustainability. Together, these results challenge uniform national standards and argue for differentiated thresholds, tiered service systems, and

micro-scale walking infrastructure tailored to rugged environments.

At the same time, the dissertation is explicit about its limitations and uses them to chart a forward-looking research agenda. The reliance on static, single-mode, and average-capacity assumptions, as well as standard 2SFCA formulations, means that the current results should be viewed as first-order approximations rather than fully behavior-sensitive simulations. The proposed directions—dynamic and seasonal cost surfaces, multimodal generalized-cost integration, cross-regional re-parameterization, population-stratified walking models, AI-assisted data extraction, and emergency-oriented digital-twin toolkits—sketch a concrete pathway for transforming the current framework into an open "mountain health" platform. Ultimately, the work aspires to move debates on health equity beyond the lowland and urban focus, showing that under conditions of thin air, steep slopes, and dispersed settlements, achieving just and resilient health systems requires terrain-sensitive equity: not only equal provision, but standards, tools, and investments that are calibrated to the realities of mountain life.