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Spatio-temporal pattern and risk factors of HIV/AIDS prevalence in Zhejiang, China, from 2005 to 2022 using R-INLA

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ABSTRACT

Background: The number of reported HIV/AIDS cases in the Zhejiang province, China, has increased drastically. However, spatial disparity and temporal trends in HIV/AIDS risk at the fine level remain unclear. We analyzed HIV/AIDS prevalence in Zhejiang, China to develop targeted HIV/AIDS prevention strategies and health resources.

Methods: This study included 56,699 HIV/AIDS patients reported in the Zhejiang province from 2005 to 2022. Data were obtained from the Zhejiang province Database of the National HIV/AIDS Comprehensive Response Information Management System. Spatial autocorrelation analysis was conducted using GeoDa 1.22, and factors influencing HIV/AIDS cases were identified through a Bayesian hierarchical Poisson regression model with the fast-computing R-INLA approach.

Results: Cases decreased from coastal to inland areas, while the standardized incidence ratio (SIR) and relative risk (RR) showed an overall increase. Key factors influencing RR included average diagnosed age (ADA), healthcare technical personnel per thousand people (HTP), male proportion (MP), GDP per capita (GDP), population density (PD), per capita disposable income (DPI), teachers per thousand people (TTP). The RR increased by 1.011, 0.989, 1.010, 0.997, 0.932, 0.990, and 0.830 per unit increase in ADA, HTP, MP, GDP, PD, DPI, and TTP, respectively. TTP was negatively associated with RR in high-prevalence regions but positively associated in low-prevalence regions. DPI showed a negative association in most regions but was not significant in upper-middle-prevalence areas.

Conclusion: HIV/AIDS risk varies significantly across the Zhejiang province, China. High-prevalence regions require targeted health education and rapid testing, while low-prevalence areas need improved healthcare infrastructure.

1. Introduction

According to the Joint United Nations Programme on HIV/AIDS (UNAIDS), the global estimate of the number of people living with HIV/AIDS (PLWHA) by the end of 2022 was 39.0 million, with 1.3 million new HIV/AIDS infections and 63,000 HIV-related deaths in the same year [1]. By the end of 2022, China had 1.223 million reported PLWHA cases, with approximately 129,000 newly reported HIV/AIDS cases in 2021 and 107,800 in 2022, according to the latest statistics from the National Health Commission [2,3]. Therefore, surveillance of HIV/AIDS is vital in China, as the HIV/AIDS epidemic is yet to be fully controlled [4–6]. Significant attention and efforts have been dedicated to combating the HIV/AIDS epidemic on a global scale and in China. International organizations such as the World Health Organization, Global

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Fund, and UNAIDS have developed strategies in accordance with the Sustainable Development Goal of ending the HIV/AIDS epidemic by 2030 [1]. The 2017 China Health Assembly emphasized this recognition and stated that HIV/AIDS was an important aspect of public health consolidation [7]. These collaborative global initiatives emphasize the enduring dedication to confront the challenges presented by HIV/AIDS and endeavor to contain and ultimately eradicate its impact. Despite these efforts, HIV/AIDS remains a significant global public health concern [8,9]. The identification, diagnosis, prevention, and treatment of HIV/AIDS risk factors should not be underestimated and require continued attention and resources [10].

The distribution of HIV/AIDS exhibits substantial regional variations driven by various factors such as social determinants, healthcare access, and risk behaviors. Spatio-temporal analysis plays a crucial role in understanding epidemics by allowing the identification of geographical hotspots with a high burden of HIV/AIDS [11]. By analyzing the spatial distribution of HIV/AIDS cases, clusters of infections can be identified in areas with targeted intervention and resource allocation [12,13]. Studying the spatio-temporal patterns of HIV/AIDS transmission provides insights into the dynamics of the epidemic and helps identify key routes of transmission, such as sexual networks, needle sharing among people who inject drugs, and mother-to-child transmission. This knowledge can guide the development of prevention strategies tailored to specific populations and locations [14]. Additionally, the spatio-temporal analysis provides evidence-based guidance for the development and implementation of effective prevention and control measures. By identifying regions and populations at higher risk, interventions can focus on those most in need, thereby optimizing resource allocation and maximizing the impact of limited resources in combating the epidemic [15–17].

Bayesian spatio-temporal models are powerful tools for effectively addressing the inherent spatial and temporal dependencies commonly observed in HIV/AIDS transmission. The disease exhibited noticeable clustering and diffusion patterns in space and time. Simultaneously modelling these dependencies allows for a comprehensive analysis of the spatio-temporal dynamics of HIV/AIDS transmission, resulting in more accurate findings [18–21]. Another advantage of the Bayesian spatio-temporal model is its ability to incorporate experiences and prior knowledge [22,23]. In HIV/AIDS analyzes, expert knowledge may include risk factors for viral transmission, population mobility patterns, and disease control policies. Through a Bayesian framework, this prior knowledge can be effectively incorporated into the model as prior distributions, thereby improving its accuracy and interpretation. This contributes to an improved understanding and predictive capability of the spatio-temporal distribution of HIV/AIDS [24]. The Integrated Nested Laplace Approximation (INLA) algorithm has been applied to efficiently deal with complex models because it provides a fast, computationally efficient approximation of the complexity of Bayesian spatio-temporal modelling [25].

As one of the representative provinces of eastern China, the Zhejiang province has problems with large floating populations and an unbalanced epidemic distribution. However, the characteristics of the spatial-temporal distribution of HIV/AIDS cases in the Zhejiang province and the relationship between the relative risk (RR) and socioeconomic and medical level indicators remain unknown. Understanding the spatio-temporal patterns of HIV/AIDS is crucial for the development of targeted public health interventions.

This study aimed to analyze HIV/AIDS prevalence in Zhejiang, China, using advanced Bayesian spatio-temporal modelling, highlighting the importance of integrated health strategies under the One Health framework. Given the interconnectedness of human, animal, and environmental health, HIV/AIDS prevention required a comprehensive approach that extends beyond traditional public health measures [26,27]. By integrating socioeconomic disparities, healthcare accessibility, and entertainment venues that contribute to disease transmission and burden, this study provided a comprehensive understanding of the spatio-temporal dynamics of HIV/AIDS. Understanding these patterns could help inform integrated health strategies that address human, animal, and environmental health interconnectedness, optimize resource allocation, and enhance long-term strategies for managing and preventing HIV/AIDS [28].

2. Methods

2.1. Study area

The Zhejiang province is located in the southeastern coastal region of China, with geographic coordinates ranging from approximately 27°12′ to 31°31′ north latitude and 118°01′ to 123°30′ east longitude, including a land area of 101,800 km^2. The Zhejiang province has 11 cities with 89 districts or counties (Fig. 1).

2.2. Data source

The dataset used in this study consisted of the annual number of newly reported HIV/AIDS cases in 89 counties of the Zhejiang province, China, from 2005 to 2022. It was aggregated from 56,699 individual information available from the Zhejiang Province Database of the National HIV/AIDS Comprehensive Response Information Management System (CRIMS) [29]. Participants were selected based on their current address code being listed as “Zhejiang Province” in the CRIMS, and patients with HIV/AIDS were diagnosed according to the HIV/AIDS diagnostic principles and China’s National HIV/AIDS Testing Technical Specifications and Standards in this database [30–32]. Relevant region-specific variables were also extracted, including the average diagnosed age (ADA) and the mean difference between the dates of confirmed HIV antibody positivity and the date of birth.

Meanwhile, social-economic and medical indicators at the district or county level were collected from the Statistical Yearbooks of the eleven prefecture-level cities in Zhejiang [18,19], including (1) total population (TP), the number of individuals who have lived for more than 6 months; (2) healthcare technical personnel per thousand people (HTP), the number of healthcare technical personnel divided by the total population multiplied by 1000; (3) male proportion (MP) in percentage, the male population divided by the total population in percentage; (4) GDP per capita (GDP), the GDP (adjusted with the Consumer Price Index in 2022) divided by the total population; (5) population density (PD), the number of total population divided by the total area of the district or county; (6) per capita disposable income (DPI), the total disposable income (adjusted with the Consumer Price Index in 2022) divided by the total population; (7) teachers per thousand people (TTP), the number of teachers divided by the total population multiplied by 1000. The covariates’ basic characteristics, descriptive statistics, and spatial resolutions were provided in Appendix A.1 and in Tables A.1, A.2.

Clearly, the prevalence of HIV/AIDS varied in counties owing to population size; thus, we considered how the standardized incidence ratio (SIR) of HIV/AIDS, the ratio of the observed count [33,34], was associated with the aforementioned covariates. The expected count, representing the number of cases that would be expected if the population of a county behaved similarly to the whole population, was obtained as the county-specified population multiplied by the incidence rate of the entire population (Zhejiang province).

2.3. Spatial autocorrelation analysis

Global spatial autocorrelation determines overall spatial clustering and is demonstrated by global Moran’s I, which ranges from −1 to 1 [35]. Based on the global Moran’s I, we analyzed the spatial correlation of the prevalence of newly HIV/AIDS reported cases in 89 districts and counties in the Zhejiang province from 2005 to 2022.

A value of $I > 0$ indicated a positive spatial correlation, and the closer the value is to 1, the stronger the spatial correlation in the HIV/AIDS

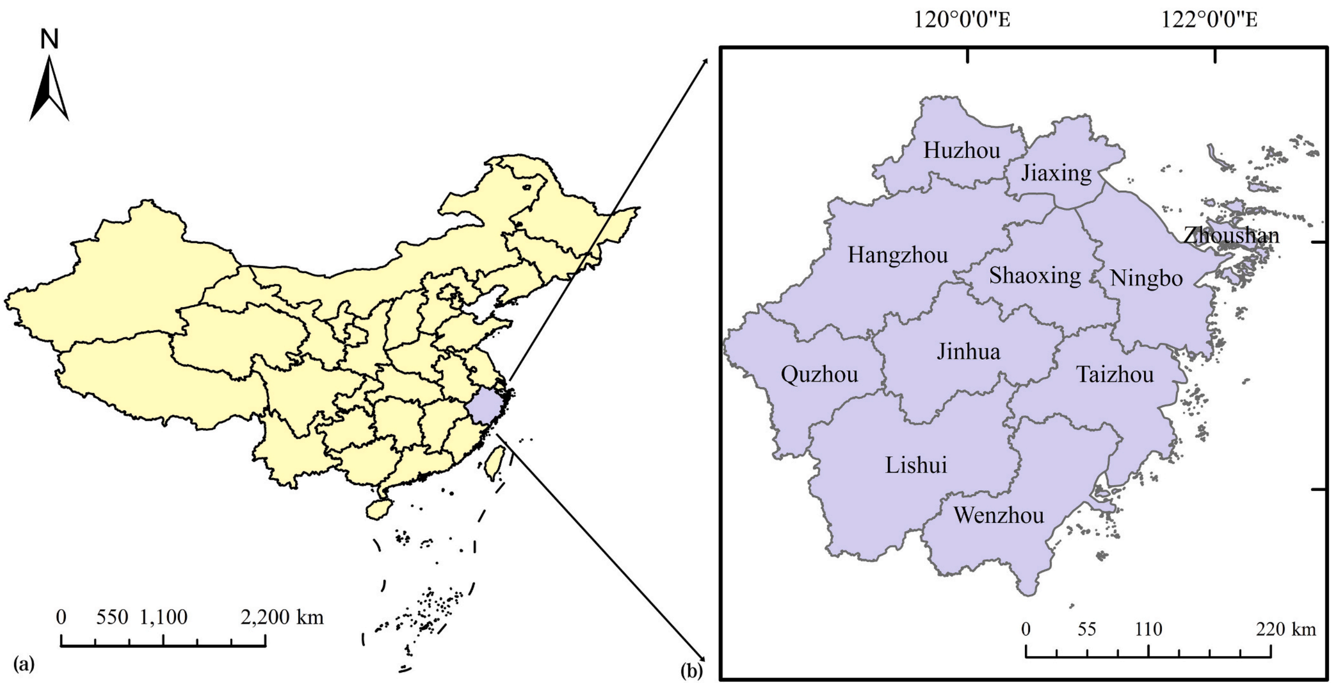

Fig. 1. Administrative map of Zhejiang province. The fundamental geographic data of municipal boundary from the National Geomatics of China.

SIR. Conversely, when $I < 0$, a negative spatial association existed, and the closer the value is to -1, the greater the variability in HIV/AIDS SIR between regions. When $I = 0$, there was no spatial association, and the HIV/AIDS SIR was randomly distributed.

Moreover, once a significant global spatial autocorrelation was identified in the study area, local spatial autocorrelation analysis was performed using local spatial association (LISA) indicators to identify and explore hot and cold spots of the disease SIR in the region [36]. LISA was classified into five categories: High-High, Low-Low, High-Low, Low-High, and None (spatial outliers not significant). The spatial autocorrelation analysis was conducted using GeoDa 1.22 software.

2.4. Bayesian spatio-temporal model

A Bayesian spatio-temporal model was built to analyze the spatio-temporal patterns of the RR of HIV/AIDS from 2005 to 2022. Let Y_{it}, i=1, 2, …, 89, t = 1, 2, …, 18 be the newly reported HIV/AIDS cases for the i-th county in year t since 2005. Suppose that Y_{it} follows Poisson distribution with mean $E_{it}\theta_{it}$ with E_{it} the expected number of cases, and θ_{it} for the RR. We will show how the RR(θ_{it}) varies across counties and in time after adjusting for the influence of a set of covariates. An RR value greater (less) than 1 indicates that the area has a higher (lower) than average HIV/AIDS risk.

Consider the following Poisson regression model

$$log\theta_{it} = \beta_0 + \sum_{k=1}^{7} x_{ik}\beta_k + \frac{1}{\sqrt{\tau_b}}\left(\sqrt{1-\phi}\,v_{*i} + \sqrt{\phi}\,u_{*i}\right) + \beta t + \delta_i t,$$

where β_0 is the intercept representing the overall log-risk, and $(\beta_1, \dots, \beta_7)$ correspond to the fixed effects associated with the covariate vector $\mathrm{x} = (x_{i1}, \dots, x_{i7})$ consisting of average diagnosed age (ADA), healthcare technical personnel per thousand people (HTP), male proportion (MP), GDP per capita (GDP), population density (PD), per capita disposable income (DPI), teachers per thousand people (TTP). The time term βt is a linear trend. The spatio-temporal interaction term $\delta_i t$ stands for the so-called differential trend δ_i's for each county, which is modelled as a random slope and accounts for departures from the main linear time trend, which is supposed to follow an intrinsic auto-regressive (IAR) model, the simplest prior in the conditional auto-regressive (CAR) class [37]. Finally, a novel composite random effect demonstrated by a Besag-York-Mollié2 (BYM2) model was considered here to account for the residual spatial autocorrelation that geographically close areas have similar incidence rates, namely $b = \frac{1}{\sqrt{\tau_b}}(\sqrt{1-\phi}\,v_* + \sqrt{\phi}\,u_*)$ [38,39]. Detailed explanations of IAR and BYM2 are provided in Appendix A.2. The prior distributions of the hyperparameters follow the INLA default prior distributions.

The current study utilized the INLA algorithm, which performs direct numerical calculations on marginal posterior distributions, avoiding the time-consuming simulations involved in the Markov Chain Monte Carlo (MCMC) method [24]. Additional information regarding this approach and the R-INLA software package can be found on the website (http://www.r-inla.org/).

Several sensitivity tests were conducted to examine the robustness of the primary findings. First, we assessed the prior distributions for the covariates using two priors, a Penalized Complexity (PC) prior and a Normal (0,1) prior, to ensure that they reflected plausible uncertainty. Second, we investigated the impact of random spatial effects and spatio-temporal interactions by comparing different models using Bayesian model selection criteria. Third, we compared the BYM2 and IAR models to evaluate the impact of random spatial effects. Fourth, we addressed low-prevalence areas by applying a zero-inflation model to account for the potential influence of zero counts. Finally, we conducted separate analyzes of cases with disease onset during 2005–2019 and 2020–2022 to assess the potential impact of the pandemic on our findings.

3. Results

3.1. Spatio-temporal analysis of HIV/AIDS newly reported cases

Between 2005 and 2022, 56,699 new cases of HIV/AIDS were reported in Zhejiang province, with an upward trend in cases that fluctuated after 2016 (Fig. 2 (a)). Furthermore, the overall number of cases varied significantly across counties (Fig. 2 (b)), with cases in the eastern coastal areas being higher than those in the western inland areas.

Fig. 3 showed the spatial heterogeneity and increasing trend of the SIR throughout Zhejiang over 18 years, with a larger SIR indicating that

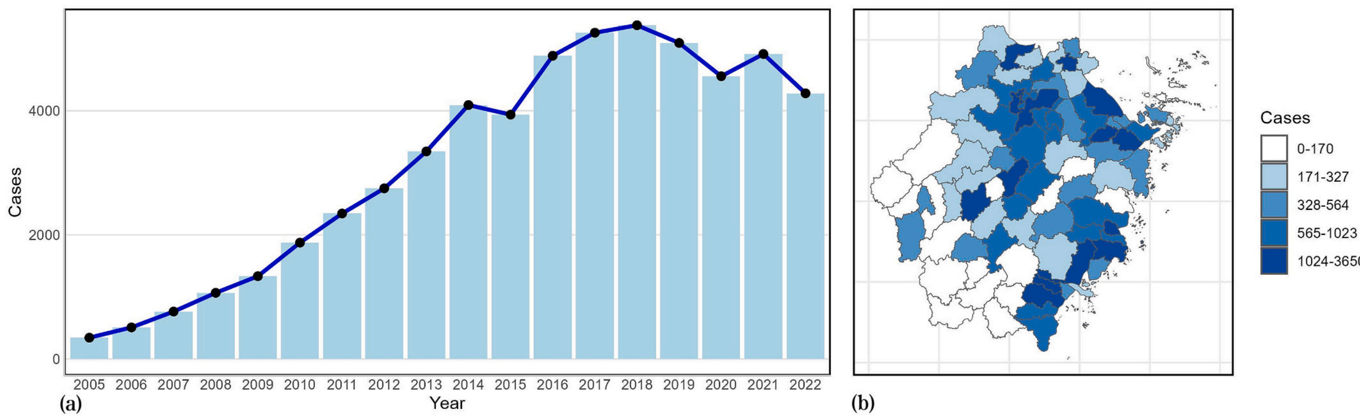

Fig. 2. Temporal trend and spatial distribution of overall reported cases of HIV/AIDS across 89 counties during 2005–2022 in Zhejiang province.

Fig. 3. Spatial distribution of HIV/AIDS SIRs per year in Zhejiang province from 2005 to 2022.

these counties had higher HIV/AIDS risks. The SIRs in eastern Ningbo, Wenzhou, central Hangzhou, and Jinhua, were generally high after 2014. Specifically, of the 89 districts and counties in the 18 years, the top 3 were Shangcheng and Hangzhou, with an SIR of 16.83 in 2015, 13.41 in 2017, and 13.26 in 2018.

3.2. *Spatial autocorrelation analysis of HIV/AIDS newly reported cases*

A spatial autocorrelation analysis was conducted on the HIV/AIDS SIR in the Zhejiang province from 2005 to 2022. The global Moran's I statistics ranged from 0.080 to 0.382, indicating a significant positive spatial autocorrelation in the HIV/AIDS SIR at the county level (Table 1). Apart from 2005, this spatial autocorrelation was statistically

Table 1
Results of global spatial autocorrelation for HIV/AIDS SIRs in Zhejiang province during 2005–2022.

Year	Moran's I	Z	*P*-value	Year	Moran's I	Z	P-value
2005	0.080	1.332	0.106	2014	0.375	6.266	<0.001
2006	0.244	3.862	0.004	2015	0.108	2.176	0.040
2007	0.184	3.059	0.008	2016	0.382	6.405	<0.001
2008	0.229	4.001	0.003	2017	0.356	5.979	<0.001
2009	0.240	4.666	<0.001	2018	0.315	5.411	<0.001
2010	0.255	4.259	0.004	2019	0.327	5.403	<0.001
2011	0.249	4.309	0.002	2020	0.291	5.060	<0.001
2012	0.294	5.127	<0.001	2021	0.127	2.388	0.016
2013	0.261	4.603	0.003	2022	0.130	2.538	0.011

significant in all the other years.

The primary areas of high-high clusters from 2005 to 2022 were the urban areas of Hangzhou city (Fig. 4). As the capital of the Zhejiang province, Hangzhou's higher economic development, greater population mobility, more medical resources, and higher social have activity likely contributed to the spatial clustering of HIV/AIDS cases. Meanwhile, the low-low clusters were mainly located in the western and southern inland areas. Note that elevated risks (as measured by the SIRs) were likely to occur by chance if the expected count was small, the disease was rare, and/or the population at risk is small. To overcome this problem, a Bayesian regression model was adopted to analyze the RR of HIV/AIDS using covariate information and a set of random effects. The random effects borrowed strength from values in neighboring areas, reducing the likelihood of risk excesses occurring by chance.

3.3. Bayesian analysis of HIV/AIDS newly reported cases

Before establishing the Bayesian spatio-temporal model, we tested for multicollinearity using the Variance Inflation Factor (VIF). All the VIF values were below 2 (<10), suggesting the absence of multicollinearity [40].

Summary statistics for the fixed effects, including the posterior mean, RR, and their 95 % credible intervals, as shown in Table 2. The RR of HIV/AIDS was positively associated with the average diagnosed age (ADA), and male proportion (MP). Specifically, the RR increased by 1.1 % for every one-unit increment in ADA. In contrast, GDP per capita (GDP), healthcare technical personnel per thousand people (HTP), population density (PD), per capita disposable income (DPI), and teachers per thousand people (TTP) were negatively associated with the RR of HIV/AIDS. Furthermore, the posterior mean of the spatial effect, represented by ϕ, was estimated as 0.138, which means the spatial dependence accounts for 13.8 % variation. Additionally, the variance of spatio-temporal interaction (δ_i) was 196.863, indicating a high degree of heterogeneity in how different regions responded to the temporal trends in the RR of HIV/AIDS. This highlighted significant regional variations in their response to temporal changes.

To further understand the similarities and differences in risk factors among the four regions of HIV/AIDS prevalence, we applied the same Poisson regression analyzes to the subsamples of high-prevalence (75–100 %), upper-middle-prevalence (50–75 %), lower-middle-prevalence (25–50 %), and low-prevalence (0–25 %), with regions classified based on SIR quartiles. Table 3 showed that in high-prevalence regions, the number of teachers per thousand people (TTP) was negatively associated with the RR of HIV/AIDS, whereas TTP showed a positive association in low-prevalence regions. Per capita disposable income (DPI) is not significantly associated with the RR of HIV/AIDS in the upper-middle-prevalence region but exhibits a negative association in all other regions. Furthermore, in high-prevalence regions, the male proportion (MP), GDP per capita (GDP), and population density (PD) were negatively associated with the RR of HIV/AIDS, whereas the average diagnosed age (ADA) was positively associated.

Table 2
Posterior mean of the fixed effect β_k's associated with each covariate, and its 95 % credible intervals and the RR with RR $= exp(\beta_k)$.

Covariate	Mean (95 % CI)	RR (95 % CI)
ADA	0.011 (0.008 to 0.014)	1.011 (1.008 to 1.014)
HTP	− 0.011 (− 0.016 to − 0.006)	0.989 (0.984 to 0.994)
MP	0.010 (0.002 to 0.018)	1.010 (1.002 to 1.018)
GDP	− 0.003 (−0.004 to −0.002)	0.997 (0.996 to 0.998)
PD	−0.070 (−0.081 to −0.058)	0.932 (0.922 to 0.944)
DPI	−0.010 (−0.011 to −0.009)	0.990 (0.989 to 0.991)
TTP	−0.186 (−0.218 to −0.154)	0.830 (0.805 to 0.857)

We conducted a statistical power analysis of nonsignificant variables, and the results were provided in Appendix A.3 and in Table A.3. Healthcare technical personnel per thousand people (HTP) demonstrated relatively high power in the upper-middle-prevalence (99.24 %) and lower-middle-prevalence (92.92 %) subsamples: teachers per thousand people (TTP) showed strong power in the upper-middle-prevalence subsample (76.39 %), and gross domestic product per capita (GDP) exhibited relatively high power in the lower-middle-prevalence subsample (71.65 %), while other variables have relatively low power. Specifically, our analysis suggests that MP had an impact on the RR of HIV/AIDS, as confirmed in the full sample, and the subgroup analysis lacked sufficient statistical power to confirm the absence of a significant effect.

The RR of HIV/AIDS showed an upward trend from 2005 to 2022 (Fig. 5). There were regional differences in RR, with the eastern and

Fig. 4. Local indicators of spatial association cluster map of the HIV/AIDS SIRs in Zhejiang province during 2005–2022.

Table 3
Posterior mean of the fixed effect β_k's associated with each covariate and its 95 % credible intervals for low-prevalence (0–25 %), lower-middle-prevalence (25–50 %), upper-middle-prevalence (50–75 %), and high-prevalence (75–100 %) regions, classified by SIR quantiles.

Covariate	Mean (95 % CI)			
	Low-prevalence	Upper-middle-prevalence	Lower-middle-prevalence	High-prevalence
ADA	0.005 (−0.003 to 0.012)	0.001 (−0.005 to 0.006)	−0.001 (−0.006 to 0.004)	0.008 (0.001 to 0.015)
HTP	0.003 (−0.018 to 0.024)	0.010 (−0.005 to 0.024)	0.015 (−0.006 to 0.024)	0.003 (−0.003 to 0.008)
MP	0.023 (−0.007 to 0.051)	−0.046 (−0.072 to −0.020)	−0.004 (0.020 to 0.011)	−0.011 (−0.020 to −0.002)
GDP	0.029 (−0.007 to 0.052)	0.001 (−0.003 to 0.004)	0.000 (−0.001 to 0.001)	−0.002 (−0.003 to −0.001)
PD	−0.008 (−0.018 to 0.001)	0.001 (−0.005 to 0.006)	0.001 (−0.002 to 0.004)	−0.014 (−0.028 to −0.003)
DPI	−0.005 (−0.007 to −0.003)	0.000 (−0.001 to 0.001)	−0.001 (−0.001 to −0.001)	−0.007 (−0.008 to −0.006)
TTP	0.085 (0.007 to 0.169)	0.003 (−0.035 to 0.042)	−0.010 (−0.047 to 0.027)	−0.047 (−0.090 to −0.004)

central regions being significantly higher than the western regions. During the 18-year study period, the average was 1.042, and 12 counties had values greater than 6. The top 3 RR-ranked areas are Shangcheng of Hangzhou, of the 89 districts and counties in the 18-year period, with RR of 16.87 in 2020, 14.77 in 2019, and 13.87 in 2018.

3.4. Sensitivity analysis

The sensitivity analysis confirmed the consistent findings of our main results (see Appendix A.4). First, we assessed the impact of prior distributions by comparing a Penalized Complexity (PC) prior and a Normal (0,1) prior, revealing that only the 95 % confidence interval of the DPI differed by 0.001, whereas the other covariates remained unchanged (Tables A.4 and A.5). Second, we evaluated spatial random effects and spatio-temporal interactions using Bayesian model selection criteria, showing that incorporating spatial effects significantly improved the model fit, as reflected by a substantial reduction in DIC and WAIC (Table A.6). Third, a comparison of the BYM2 and IAR models revealed slight differences in the coefficients of HTP, MP, and PD, but the estimates for the other variables remained consistent (Table A.7). Fourth, applying a zero-inflated Poisson model to the low-prevalence areas yielded results consistent with those of the Poisson analysis (Table A.8). Fifth, separate analyzes of disease onset during 2005–2019 and 2020–2022, as shown in Table A.9, revealed changes in the effects of specific covariates, suggesting that the pandemic may have influenced the underlying dynamics of the RR of HIV/AIDS. Finally, Table A.10 showed that the addition of entertainment venues using Gaode's Points of Interest (POI) data revealed a positive RR for entertainment venues, indicating that a higher density of such venues was associated with increased HIV/AIDS risk. POI data for entertainment venues were obtained through the Gaode Map (Amap) API, which provides only current data because historical POI data are unavailable.

4. Discussion

We conducted a comprehensive analysis of the spatio-temporal pattern of HIV/AIDS spread in the Zhejiang province at the county level from 2005 to 2022, contributing to an improved understanding of geographical disparities in disease prevalence. The total number of cases and SIRs decreased from the eastern coastal regions to the inland areas [41]. The strong economic development of coastal cities, large population size, and high population mobility were the main reasons for the increase in the SIR of HIV/AIDS in these areas [42]. Additionally, owing to the prevailing household registration system in China at the time, floating populations faced difficulties in obtaining permanent residence status in destination cities, which affected their access to HIV/AIDS education, public health services, and medical insurance. The challenges were particularly pronounced in economically developed coastal areas [43,44]. Consequently, there were significant regional differences in the proportion of the floating populations receiving HIV/AIDS health

Fig. 5. Spatial distribution of the RR of HIV/AIDS in Zhejiang province from 2005 to 2022.

education, thereby exerting an influence on the distribution of total HIV/AIDS cases.

Our research revealed significant associations between the key factors and the RR of HIV/AIDS. Specifically, when the average age of individuals diagnosed with an HIV-positive status increased by 1 year, it was expected to increase by 1.1 %. As individuals aged, their average education level decreased, which reduced their knowledge of HIV/AIDS transmission routes, prevention strategies, and treatment programs, thereby increasing their risk of infection [45]. For every additional health technician per 1000 people, the RR decreased by 1.1 %. Regions with greater healthcare resources were more effective in controlling HIV/AIDS incidence as they provided better access to routine examinations and drug resistance testing, enabling timely adjustments to antiretroviral treatment [46]. Furthermore, the "designated hospital" system enhanced medical support for people living with HIV/AIDS, further strengthening the overall healthcare response [47]. Similarly, for every 1 % increase in the male proportion, the RR increased by 1.0 %. The epidemic among men who have sex with men continued to expand worldwide, possibly because of the high risk of HIV transmission through anal sex [48]. However, the RRs decreased by 0.3 %, 6.8 %, and 1.0 % for each 1000 yuan increase in per capita GDP, 100-person increase per square kilometer, and 1000 yuan increase in per capita disposable income, respectively. This indicated that people living in economically developed regions with higher GDP per capita, population density, and capita disposable income may have more knowledge about HIV/AIDS and were more likely to use condoms during sexual intercourse, leading to a low RR for HIV/AIDS, which was consistent with previous findings [49]. Meanwhile, teachers per thousand people had a positive association in low-prevalence regions but showed a negative association in high-prevalence regions. This notable finding regarding low-prevalence regions may be linked to the rising number of HIV/AIDS cases among college students [50], as these regions were often coastal areas with abundant university resources. A national survey in China found that only 58.9 % of young people had adequate HIV/AIDS knowledge [51], underscoring the need for universities to enhance targeted, youth-focused prevention strategies.

The spatial distribution of newly reported HIV/AIDS cases was associated with economic, population, and medical facility ratios, exhibiting characteristics of spatial clustering in transmission [18]. The results showed that the posterior mean estimate of the spatial effect in the BYM2 model was 0.138, indicating spatial fluctuations in the risk of HIV/AIDS. Consequently, a significant spatial correlation was evident in the number of new HIV/AIDS cases in the Zhejiang province, illustrating the interdependency in the risk patterns of adjacent areas. Notably, Moran's I declined during the COVID-19 outbreaks in 2021 and 2022, indicating lower spatial aggregation of HIV/AIDS SIRs. The strict lockdown and isolation measures imposed during the new coronary pneumonia had a significant impact on the ability to detect and spread HIV/AIDS [52,53], particularly in large, densely populated cities, resulting in a reduction in the spatial clustering of SIR. The spatial autocorrelation of the HIV/AIDS SIR in the Zhejiang province showed that high-high clustering was concentrated in economically developed areas with large population flows, such as Hangzhou, which was consistent with the RR results predicted by the Bayesian spatio-temporal model.

The main linear trend in the Bayesian spatio-temporal model was estimated to be 0.097 after adjusting for the influence of risk factors and other random effects, indicating that the overall RR in the Zhejiang province had an increasing trend, whereas the RR spatial distribution map shows that only a small number of counties and districts had a decreasing trend in RR. Zhenhai Ningbo, Hangzhou, and Yiwu experienced significant increases in SIR after 2010. Yiwu is a major trading center for small commodities in China, attracting traders and laborers from across the country and internationally [54]. This diverse population movement and business activities increased the risk of infectious disease transmission, including HIV/AIDS, thereby increasing RR. Hangzhou's urban area and Zhenhai in Ningbo served as economic, cultural, medical, and educational hubs with a relatively complete infrastructure [55]. This enabled more people to access health screening and medical care, increasing the likelihood of potentially infected individuals being diagnosed and reported, and ultimately leading to a higher RR.

This study has some limitations. First, during the COVID-19 pandemic, a lag in reported cases, along with a decreased willingness to test, reporting delays, and insufficient reporting, may have decreased the accuracy and timeliness of the data, thereby introducing biases into the analysis of influencing factors and epidemic trends. Our sensitivity analysis further supported this observation, highlighting the need for future studies to consider stratified modelling approaches that can disentangle the effects of such pandemics from underlying disease dynamics [56]. Second, this study focused on Zhejiang province, and the results may be applicable to areas with developed economies and rich medical services, such as Jiangsu and Shandong. However, the generalizability of these results may be limited to inland provinces, where demographic and healthcare conditions differ significantly. Finally, using reported cases as proxies for actual prevalence may introduce bias, including potential underreporting and inconsistencies in reporting mechanisms [57], such as cases where the infection did not occur in Zhejiang but could not be included in the data.

In conclusion, this study contributes to a comprehensive understanding of the spatio-temporal dynamics of the RR of HIV/AIDS in the Zhejiang province. Integrating spatial autocorrelation analysis and Bayesian spatio-temporal model assessment provides a holistic perspective on disease transmission patterns. These findings have significant implications for evidence-based strategies aimed at mitigating the impact of HIV/AIDS and have the potential to inform policy decisions and resource allocation. Targeted health education and rapid testing services have been implemented in areas of high-prevalence, focusing on mobile populations and high-risk groups [58]. In economically disadvantaged regions, healthcare resource allocation should be optimized, training for primary healthcare workers should be strengthened, and medical service coverage should be improved [59]. Comprehensive strategies can be developed to combat HIV/AIDS by adopting an interdisciplinary approach that integrates public health, epidemiology, and environmental health [60]. This aligns with the One Health perspective, which seeks to address health challenges by integrating multiple fields and considering human, animal, and environmental health.

CRediT authorship contribution statement

Yifan Tang: Writing – original draft, Visualization, Software, Methodology, Formal analysis. **Yifan Chen:** Writing – original draft, Visualization, Software, Methodology, Formal analysis. **Jinglei Zheng:** Data curation. **Wei Cheng:** Data curation. **Yurong Jing:** Data curation. **Yushu Zhang:** Data curation. **Chengliang Chai:** Writing – review & editing, Project administration, Conceptualization. **Chengxiu Ling:** Writing – review & editing, Project administration, Conceptualization, Methodology. **Ying Wang:** Writing – review & editing, Project administration, Conceptualization.

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Declaration of competing interest

The authors declare that they have no competing interests.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.onehlt.2025.101038.

Data availability

The data used in this study are not publicly available. Access to the data requires approval from the Zhejiang Provincial Center for Disease Control and Prevention in eastern China. For inquiries, please contact the corresponding author, Chengliang Chai.

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