

Original Article

Association of Meteorological Factors and Population Characteristics with Cutaneous Leishmaniasis Occurrence in an Urban Area of Southeastern Morocco: An Application of the PLS-SEM Model

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Abstract

Background: Cutaneous leishmaniasis (CL) remains a major public health concern in Morocco, particularly in arid and semi-arid regions where environmental and demographic conditions favor transmission. Understanding the determinants of CL occurrence is essential for improving surveillance and control. This study investigated climatic and demographic factors associated with CL in an endemic area of southeastern Morocco during 2014–2023.

Methods: This retrospective ecological time-series study used monthly data from 2014 to 2023, and Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyse structural relationships. PLS-SEM was chosen for its ability to analyze complex relationships among latent variables and its suitability for relatively small samples and non-normal data. The conceptual model incorporated climatic variables (temperature, humidity, precipitation, wind speed) and population characteristics. Additional diagnostic analyses assessed trend, seasonality, stationarity, and autocorrelation.

Results: Climatic factors were significantly associated with CL occurrence ($\beta = -0.576$, $p < 0.001$), and the model explained 33% of the variance in CL occurrence. Population characteristics were also positively associated with CL occurrence ($\beta = 0.247$, $p < 0.001$). However, the hypothesized relationship between climatic factors and population characteristics was not statistically significant ($\beta = 0.207$, $p = 0.053$).

Conclusions: Both climatic variability and population characteristics are associated with CL occurrence in southeastern Morocco, highlighting complex relationships shaping disease dynamics. Integrating these determinants into surveillance systems may improve early detection and guide targeted control strategies for vector-borne diseases in endemic regions.

Keywords: Cutaneous leishmaniasis; Disease control; PLS-SEM; Time series analysis; Climate Change

Introduction

Leishmaniasis is a neglected tropical disease caused by protozoan parasites of the genus *Leishmania* and transmitted to humans through

the bite of infected female sand flies. The disease affects millions of people every year, with approximately 350 million individuals in at least

98 countries considered to be at risk (1, 2). Among its different clinical forms, cutaneous leishmaniasis (CL), mostly characterized by skin lesions, is the most common and widely distributed form (3). In the Old World, including North Africa, infection is mainly transmitted by sand flies belonging to the genus *Phlebotomus*, which act as vectors of *Leishmania* parasites. In the Americas, vectors belong to different genera, particularly *Lutzomyia* (4).

In Morocco, leishmaniasis continues to be a public health problem, with many parts of the country having endemic foci of CL (5). Ouarzazate Province is one of the most affected areas in Morocco, with the primary causative agents being *Leishmania major* and *Leishmania tropica* (6–8). Between 2018 and 2022, a total of 2,713 CL cases were reported across the 17 communes of the province, of which 1,140 (42%) were recorded only in the urban commune of Ouarzazate (7).

Previous studies have established that climatic conditions, particularly temperature, precipitation and humidity, significantly influence CL transmission by affecting vector breeding, survival, abundance, development and seasonal activity, whereas demographic factors such as population size, density and urbanization may affect human–vector contact and consequently modify the risk of vector-borne disease transmission (9–11). Among these factors, environmental and climatic conditions play a critical role in shaping the distribution of sand fly vectors and the incidence rate of CL (12–14). In Morocco, studies have shown strong associations between climatic variables, such as temperature and humidity, and CL occurrence, highlighting the complex and interconnected relationships underlying disease transmission (7). Thus, understanding the complex associations between these factors and CL occurrence is essential for developing effective prevention and control strategies to reduce the burden of CL.

Serval statistical approaches have been employed to evaluate relationships between these

factors and CL, particularly regression models (7, 15–18). However, despite their increasing popularity, these models present several limitations, including sensitivity to non-normal data distribution, potential bias due to unobserved variables, and issues related to overdispersion and endogeneity (19, 20). Moreover, conventional regression approaches may be limited when the objective is to simultaneously examine complex and interrelated relationships among multiple variables, underscoring the need for advanced multivariate methods that allow both measurement and structural relationships to be modeled within a single analysis.

Compared to conventional methods, the partial least squares structural equation modeling (PLS-SEM) offers several advantages, such as efficiency with small sample sizes, the capacity to model complex relationships among variables, the ability to handle data that are not normally distributed, the ability to accommodate both formative and reflective constructs, and a balance between prediction and explanation (21–23). The partial least squares structural equation modeling has increasingly been applied in epidemiological and public health research to explore complex interrelationships among environmental, demographic, behavioral and health-related determinants (21, 24). In infectious and parasitic diseases, where multiple interacting factors contribute to transmission dynamics, latent-variable approaches may provide complementary insights beyond conventional univariate or regression-based analyses (24). However, PLS-SEM has certain limitations, as it is primarily explanatory rather than causal and can be sensitive to model specification. Previous studies in Morocco have largely examined climatic, demographic and socioeconomic determinants of CL independently or using conventional regression and time-series approaches. However, the simultaneous relationships among climatic conditions, population characteristics and CL occurrence remain insufficiently understood. In particular, it remains unclear whether climatic conditions are associated with CL occurrence primarily

through direct pathways or through their interactions with demographic characteristics. A structural modeling framework may therefore provide additional insight into these interconnected relationships. The novelty of the present study lies in applying PLS-SEM to simultaneously examine these relationships within an integrated framework in an endemic urban area of southeastern Morocco.

Therefore, this study aimed to examine the relationships between climatic variables, population characteristics and CL occurrence in the urban commune of Ouarzazate, a well-known endemic focus of the disease in Morocco, using a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach.

Materials and Methods

Study design and setting

This was a retrospective ecological time-series study based on secondary data on cutaneous leishmaniasis cases in the urban commune of Ouarzazate, Morocco, covering the period from 2014 to 2023. The study was conducted in the urban commune of Ouarzazate, located in the Draa-Tafilalet region of southeastern Morocco, at around 30°55'17"N latitude and 6°54'59"W longitude (Fig. 1). It has a total area of 50 km², which represents approximately 0.4% of the total province territory of 12,464 km². According to the 2024 General Population and Housing Census (RGPH), the legal population was estimated at 75,847 inhabitants (37,234 males and 38,613 females), representing 24.89% of the provincial population, with a population density of at least 1,517 persons/km². According to the Köppen–Geiger climate classification, Ouarzazate has a hot desert climate (BWh), characterized by low annual precipitation, hot and dry summers and marked seasonal temperature variations.

The urban commune of Ouarzazate was selected as the study area due to its epidemiological relevance as a persistent endemic fo-

cus of CL in southeastern Morocco (7, 8). The area concentrates a substantial proportion of reported CL cases at the provincial level and represents a climatic transition zone characterized by arid to semi-arid conditions, increasing population density, and high seasonal fluctuations in temperature and humidity, which are known to influence vector ecology and disease transmission dynamics (7, 25). These characteristics create a complex epidemiological setting in which multiple interrelated factors may contribute to CL occurrence. The partial least squares structural equation modeling was therefore considered appropriate because it enables climatic and population-related indicators to be integrated into latent constructs and their relationships with CL occurrence to be assessed simultaneously.

Data sources

Data for this study were obtained from multiple reputable sources. Monthly climatic data, including average air temperature, relative humidity, cumulative rainfall and wind speed, from 2014 to 2023, were obtained from the Provincial Meteorological Center (PMC) of Ouarzazate Province. Population characteristics, including total population size, population density, the number of female individuals, and the number of individuals under the age of 15 years, were sourced from the High Commission for Planning (HCP, <https://resultats2024.rgphapps.ma/>) of Morocco (26). Data on CL cases were obtained from the official website of the Ministry of Health and Social Protection, Morocco (MoH, <https://www.sante.gov.ma/Publications/Pages/default.aspx>).

Prior to analysis, data quality was assessed by checking for missing values, duplicate records, formatting inconsistencies, and implausible values. The dataset contained no missing values, and all monthly data from January 2014 to December 2023 were retained in the analysis.

Variables and measurement

The research model in this study consists of independent variables, dependent variables and their respective indicators. The independent variables are Climate (CLM) and Population (POP), while CL Occurrence (CLO) serves as the dependent variable in this study.

CLO is measured by the total number of cases. CLM is measured by temperature, precipitation, humidity and wind speed. POP is measured by total population, population density, female population and population under 15 years of age. Population data were available annually and were therefore matched to the corresponding monthly climatic and CL data, creating a temporal resolution mismatch. The summary of the variables used in the study is presented in Table 1.

Population-related variables were selected based on data availability at the commune level, temporal consistency across the study period, and their documented relevance to CL transmission in endemic settings. Total population and population density were included to capture human aggregation and potential host-vector contact intensity. The population under 15 years of age was considered because children are often more exposed to CL due to outdoor activities and lower acquired immunity. The female population was initially included to explore potential sex-specific demographic patterns. Other potentially relevant variables, such as housing conditions and socioeconomic status, were not included because consistent data at the commune level were unavailable during the study period.

Research model and hypotheses

As illustrated in Figure 2, the conceptual model proposed in this study comprises three latent constructs measured through a total of nine indicators. CL occurrence is considered the dependent variable, and Climate is considered an exogenous variable, while Population serves as both an endogenous and an exogenous variable in the model.

Based on this conceptual framework, the following hypotheses were formulated:

Hypothesis 1 (H1): Climate is significantly associated with CL occurrence.

Hypothesis 2 (H2): Population characteristics are significantly associated with CL Occurrence.

Hypothesis 3 (H3): Climate is significantly associated with population characteristics.

This hypothesis is based on evidence suggesting that climatic variability may influence human mobility and population distribution, particularly in arid and semi-arid regions where drought, changes in temperature, precipitation and water availability may affect environmental suitability and livelihoods (27).

Data analysis

Following the data collection procedure, the data were analyzed using the PLS-SEM approach using the open-source "SEMinR" package in R software version 4.5.0 (R Development Core Team). A significance level of $\alpha = 0.05$ was employed to test the hypotheses. The PLS algorithm was applied with a maximum of 300 iterations and a stop criterion of 10^{-7} . Bootstrapping was conducted with 5,000 subsamples to test the significance of the hypothesized path coefficients.

The partial least squares structural equation modeling is a leading statistical technique for testing and estimating complex direct and indirect relationships between several non-observable variables that focus on explaining the variance in the dependent variable (28). The partial least squares structural equation modeling was chosen due to its capability to estimate and handle complex models with relatively few data restrictions (29). More importantly, it allows the simultaneous estimation of multiple relationships within an integrated measurement and structural model. In the context of CL epidemiology, climatic factors and population characteristics are interrelated and may exert both direct and indirect effects on disease occurrence. PLS-SEM al-

lows these relationships to be modeled simultaneously, providing insight into the structural pathways linking climatic and demographic factors to seasonal variations in the occurrence of CL (30).

To examine the temporal structure of the monthly CL time series, autocorrelation was assessed using the autocorrelation function (ACF), partial autocorrelation function (PACF), and the Ljung–Box test. Stationarity was evaluated using the Augmented Dickey–Fuller (ADF) test, while STL decomposition with a 12-month seasonal period was applied to separate the time series into trend, seasonal and residual components.

In addition, climatic factors such as temperature, relative humidity and wind speed are often strongly correlated, leading to multicollinearity issues in traditional regression-based models. PLS-SEM addresses this limitation by modeling these indicators as latent constructs, thereby reducing collinearity and simultaneously estimating measurement and structural models, offering advantages over traditional multivariate approaches (31, 32).

Multicollinearity was assessed using the Variance Inflation Factor (VIF). All VIF values were found to be below the commonly accepted threshold of 5, ranging from 1.00 to 2.52, indicating no multicollinearity concerns in the model (33). Bootstrapped HTMT confidence intervals were also examined to further assess discriminant validity.

The model's robustness was assessed through several measures. Cronbach's Alpha (CA) and Composite Reliability (CR) were used to examine internal consistency reliability, with strong, reliable values set at > 0.7 (34). Construct validity was evaluated using convergent and discriminant validity tests. The evaluation of convergent validity involves the assessment of factor loadings and average variance extracted (AVE) (21). Factor loadings are the coefficients that represent the relationship between each indicator and its corresponding latent construct in a measurement model (35). Factor loadings of the indicators should be above

the common threshold of 0.70 (36). A common measure to establish convergent validity on the construct level is the AVE, with valid scores set at >0.5 . Discriminant validity between latent variables was assessed using the Hetero-Trait and Mono-Trait (HTMT) ratio of the correlations, with acceptable thresholds below 0.85 (37).

Bootstrapping with 5,000 subsamples was used to test the significance of path coefficients, with statistical significance defined as $p < 0.05$. The coefficient of determination (R^2) values were used to evaluate the model's explanatory power (38). The recommended values of R^2 are 0.25, 0.5, and 0.75, which refer to weak, moderate and high explanatory power, respectively (39). Effect size (f^2) is used to measure the effect of exogenous constructs on endogenous constructs. Strong, moderate and small effects are defined by thresholds of 0.35, 0.15, and 0.02 (36).

Results

Descriptive analysis

The descriptive statistics of the variables included in the model are presented in Table 2. The mean monthly number of CL cases in the urban commune of Ouarzazate from 2014 to 2023 was 27.34 (SD= 38.12), indicating substantial temporal variability in disease occurrence over the study period.

For climatic variables, temperature, relative humidity, and precipitation exhibit positive skewness values, reflecting right-skewed distributions. On the other hand, population variables have skewness values close to zero, indicating a relatively symmetrical distribution. In addition, most variables had negative kurtosis values, which means that their distributions had flatter peaks than the normal distribution.

The monthly distribution of CL cases showed strong seasonal variation, with most cases occurring in the colder winter season (Fig. 3). January recorded the highest cumula-

tive number of cases ($n=699$), representing the peak month for CL occurrence, followed by February ($n=535$), whereas August recorded the lowest number of cases ($n=43$).

The monthly time series showed substantial fluctuations in CL occurrence over the study period, with pronounced peaks between 2018 and 2021, followed by a marked decline from 2022 onward (Fig. 4). The 12-month moving average further illustrated changes in the temporal pattern of reported CL cases over the study period.

Temporal characteristics of CL occurrence

To further characterize the temporal structure of the monthly CL series, additional analyses were conducted to examine long-term trend, seasonality, stationarity, autocorrelation and overdispersion.

STL decomposition with a 12-month seasonal period revealed distinct trend and seasonal patterns in monthly CL occurrence, with the highest seasonal component observed in January (35.22) and the lowest in August (-18.24) (Fig. 5). The trend component increased progressively from 2014, reached its highest level around 2019–2020, and subsequently declined, with a pronounced decrease after 2021. The seasonal component showed recurrent fluctuations across the study period, with greater seasonal amplitude during the years of higher CL occurrence. The residual component showed several pronounced deviations, particularly during the periods characterized by major peaks in reported cases.

The ADF test applied to the original monthly CL series yielded a test statistic of -1.229 ($p=0.661$), indicating that the null hypothesis of a unit root could not be rejected and that the original series was non-stationary. After first differencing, the ADF statistic was -3.864 ($p=0.002$), indicating that the differenced series was stationary.

The autocorrelation function (ACF) showed substantial positive autocorrelation at the first lags, particularly at lag 1, as well as a recurrent pattern of positive correlations around the

annual lag (Fig. 6). This pattern was consistent with temporal dependence and an annual seasonal structure in the monthly CL series. The partial autocorrelation function (PACF) showed a strong positive correlation at lag 1, followed by a marked negative correlation at lag 2, with additional correlations at subsequent lags (Fig. 7).

The Ljung–Box test further indicated significant autocorrelation in the monthly CL time series at the 12-month lag ($Q=297.64$, $p<0.001$), providing further evidence of temporal dependence in monthly CL occurrence.

Measurement model assessment

The reliability and validity of the constructs were evaluated through internal consistency reliability, convergent validity and discriminant validity. Cronbach's alpha, composite reliability, indicator reliability and average variance extracted were examined to assess internal consistency and convergent validity. An initial model including all selected indicators was first evaluated based on outer loadings and measurement model criteria. Indicators with inadequate outer loadings were subsequently removed, and the model was re-estimated to obtain the final specification. Based on the results of the convergent validity test, it was found that outer loadings of some indicators do not exceed the standard threshold value of 0.708 (21), namely wind speed (0.201), precipitation (0.575) and female population (0.437). These indicators were removed from their respective constructs to improve measurement accuracy. This decision is supported by both statistical evidence and epidemiological considerations. No alternative indicators were tested due to data availability and temporal consistency requirements.

As shown in Table 3, all retained constructs had AVE values above 0.5, confirming convergent validity. Furthermore, all CA and CR values exceed the minimum acceptable threshold of 0.70, indicating that the constructs are internally consistent and reliable.

Beyond the assessment of reliability and

convergent validity, discriminant validity among the measurement model constructs was evaluated using the Heterotrait–Monotrait (HTMT) ratio of correlations, as presented in Table 4. All HTMT values were below the predefined threshold of 0.85, with the highest value being 0.523 for the relationship between Climate and CL Occurrence, supporting discriminant validity. In addition, the 95% bootstrapped confidence intervals (CIs) for all HTMT values did not include 1, further supporting discriminant validity.

Structural model assessment

After confirming the reliability and validity of the measurement model, the assessment of the structural model is conducted to analyze the hypothesized relationships between exogenous and endogenous variables. The struc-

tural model was tested using a non-parametric bootstrapping procedure with 5,000 subsamples. Table 5 and Figure 8 show the results of the structural model. The model explained 33% of the variance in CL occurrence and 4% of the population.

The results indicated a significant negative association between Climate and CL Occurrence ($H1$, $\beta = -0.576$, $t = 10.243$, $f^2 = 0.475$). Population characteristics were also significantly and positively associated with CL Occurrence ($H2$, $\beta = 0.247$, $t = 3.347$, $f^2 = 0.087$). In contrast, the positive relationship between Climate and Population characteristics is not supported by the findings ($H3$, $\beta = 0.207$, $t = 1.937$, $f^2 = 0.045$), with the 95% confidence interval including zero (-0.018 to 0.390), confirming the non-significance.

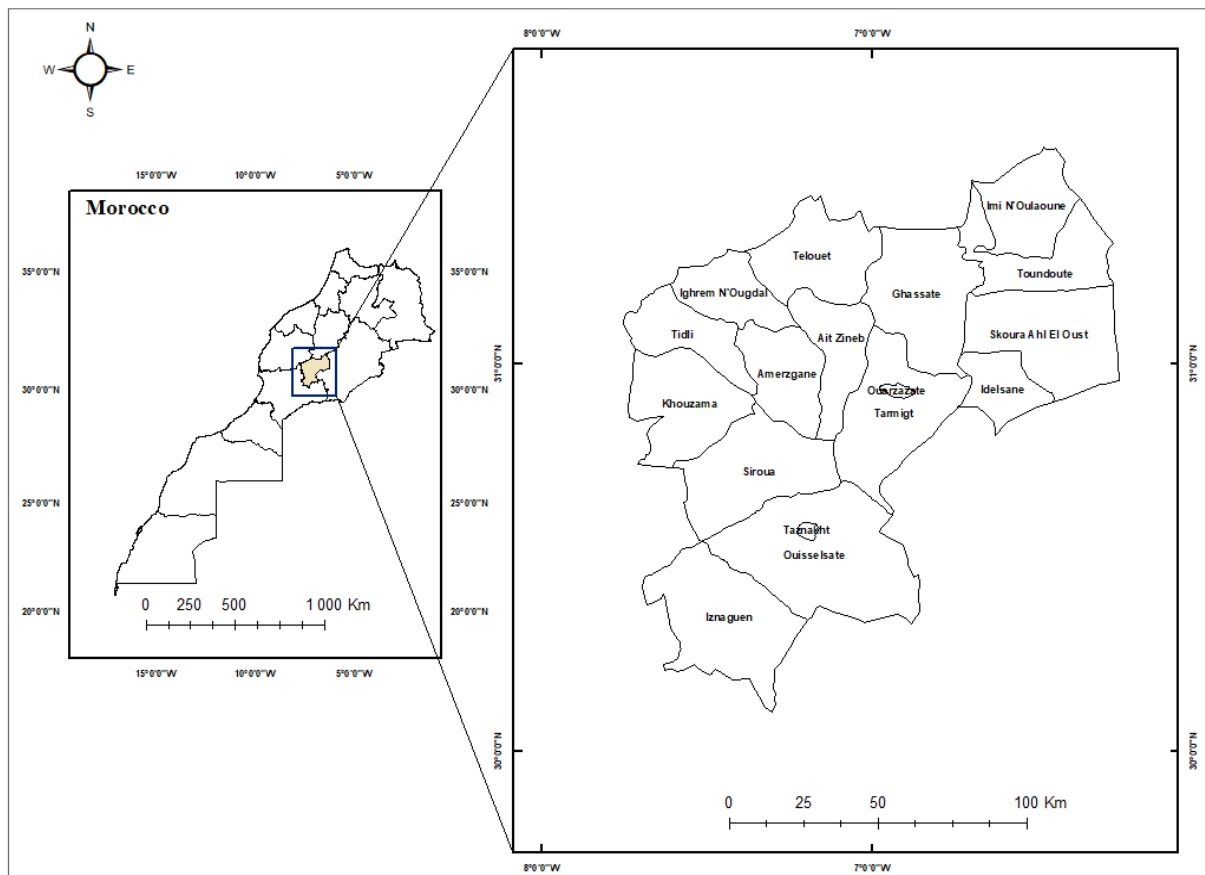
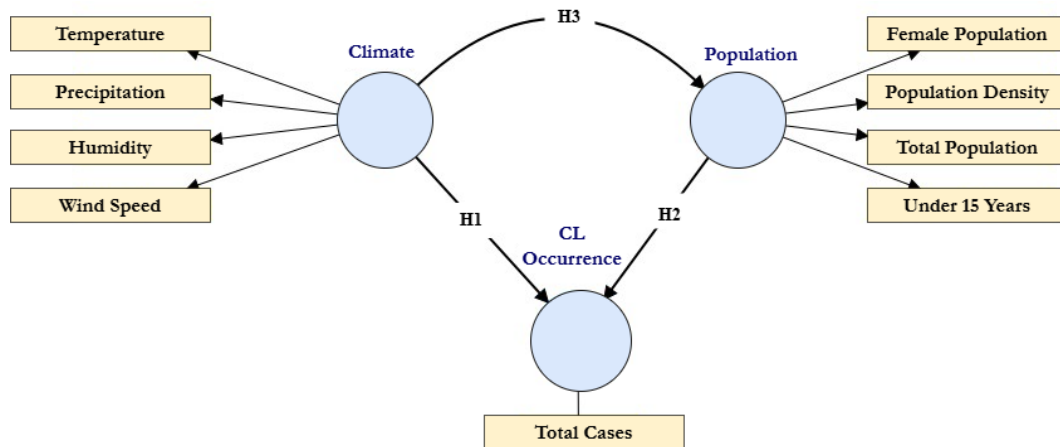
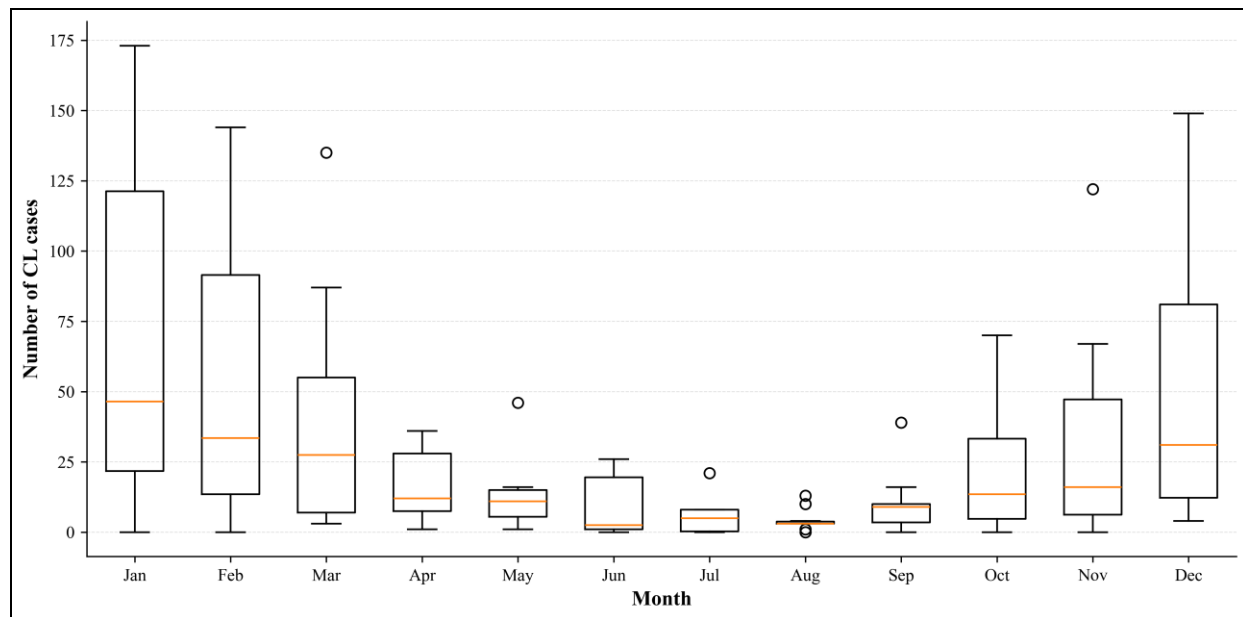


Fig. 1. Location of Ouarzazate Province and the studied municipality, southeastern Morocco, for the analysis of cutaneous leishmaniasis occurrence and associated climatic and population characteristics, 2014–2023

Table 1. Variables and indicators used to examine the relationships between climatic variables, population characteristics and cutaneous leishmaniasis occurrence in the urban commune of Ouarzazate, southeastern Morocco, 2014–2023

Latent Variables	Indicators	Description	Source
Climate (CLM)	Temperature (°C)	The average monthly temperature	PMC
	Precipitation (mm)	Total precipitation amount	PMC
	Relative humidity (%)	The mean monthly relative humidity	PMC
	Wind Speed (m/s)	Wind speed at 2m	PMC
Population (POP)	Total Population	Number of individuals	HCP
	Population density	Individuals/km ²	HCP
	Female population	Number of female individuals	HCP
	Under 15 years	Number of individuals under the age of 15 years	HCP
CL Occurrence (CLO)	Total CL cases	Number of individuals with CL recorded monthly	MoH

**Fig. 2.** Proposed conceptual model for examining the relationships between climatic variables, population characteristics and cutaneous leishmaniasis occurrence in the urban commune of Ouarzazate, southeastern Morocco, 2014–2023**Fig. 3.** Monthly distribution of cutaneous leishmaniasis cases in the urban commune of Ouarzazate, Morocco, 2014–2023

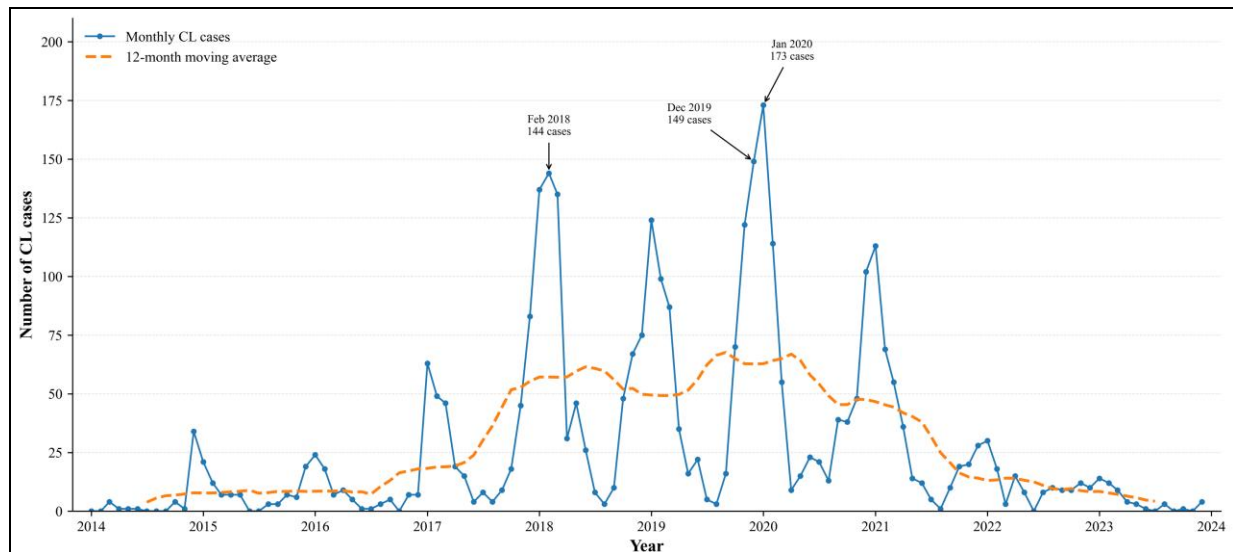


Fig. 4. Monthly time series of cutaneous leishmaniasis cases for the urban commune of Ouarzazate, Morocco, 2014–2023

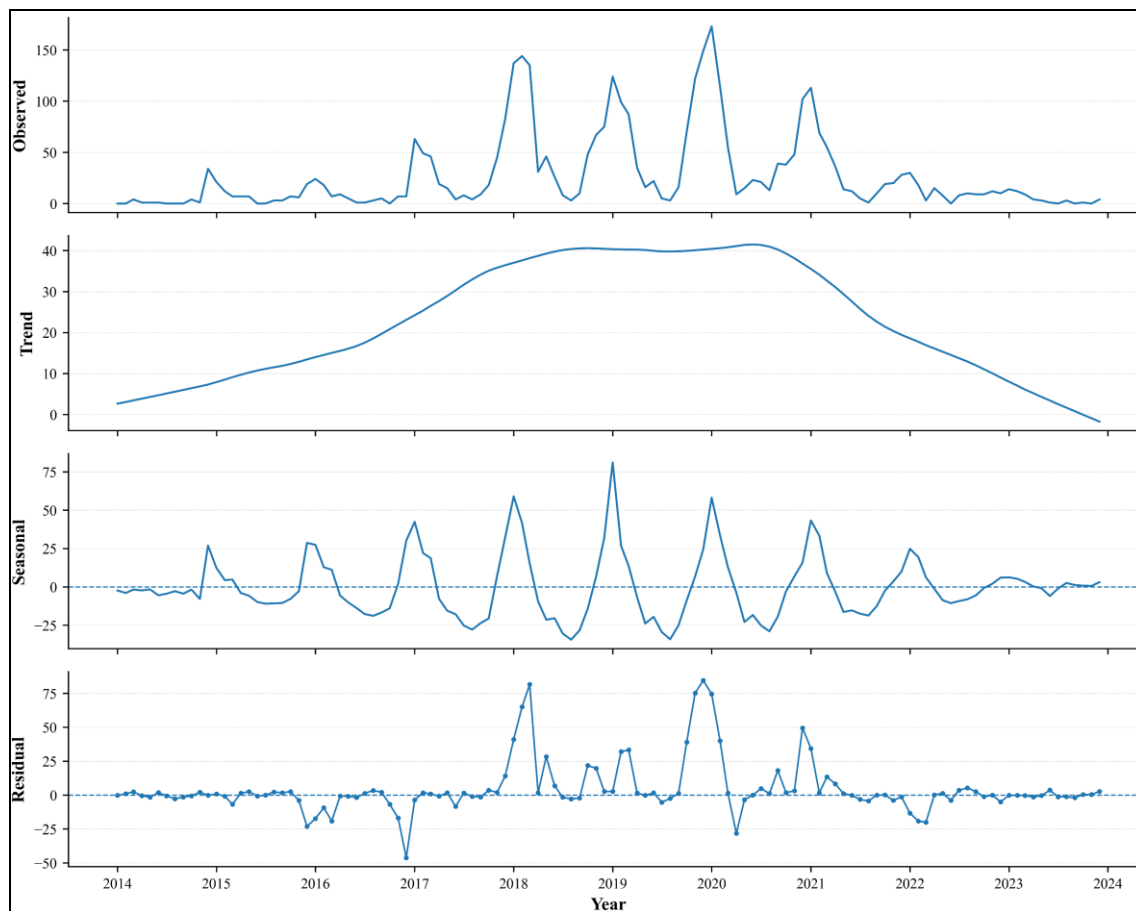


Fig. 5. Seasonal-Trend decomposition using Loess (STL) of monthly cutaneous leishmaniasis cases in the urban commune of Ouarzazate, southeastern Morocco, 2014–2023

Table 2. Characteristics of the manifest variables for each latent variable based on monthly data of Ouarzazate, Morocco, 2014–2023

Latent Variable	Manifest Variable	Mean	Median	Min	Max	Standard Deviation	Skewness	Kurtosis
Climate	Wind Speed	2.622	2.635	1.170	4.340	0.559	-0.009	0.029
	Temperature	20.371	20.925	8.350	33.400	7.135	0.011	-1.348
	Relative Humidity	38.014	37.665	10.400	67.470	12.859	0.108	-0.804
	Precipitation	8.827	3.450	0	90.500	14.400	2.981	10.811
Population	Total Population	74734.500	74734.500	71067	78402	2350.724	0	-1.224
	Female Population	37385.604	37389.81	35746.701	39012.52	1046.596	-0.009	-1.224
	Population Density	1494.690	1494.690	1421.340	1568.040	47.014	0	-1.224
	Under 15 Years	21560.308	21568.132	20893.698	22203.446	419.809	-0.045	-1.223
CL Occurrence	Total CL Cases	27.342	10	0	173	38.119	1.960	3.135

Table 3. Reliability and convergent validity results of cutaneous leishmaniasis cases for the urban commune of Ouarzazate, Morocco, 2014–2023

Latent variable	Manifest variable	Outer loading	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Population	Total Population	0.811	0.841	0.851	0.656
	Under 15 years	0.878			
	Population density	0.735			
Climate	Temperature	0.993	0.875	0.887	0.799
	Humidity (%)	0.783			
CL Occurrence	Total CL cases	1.000	1.000	1.000	1.000

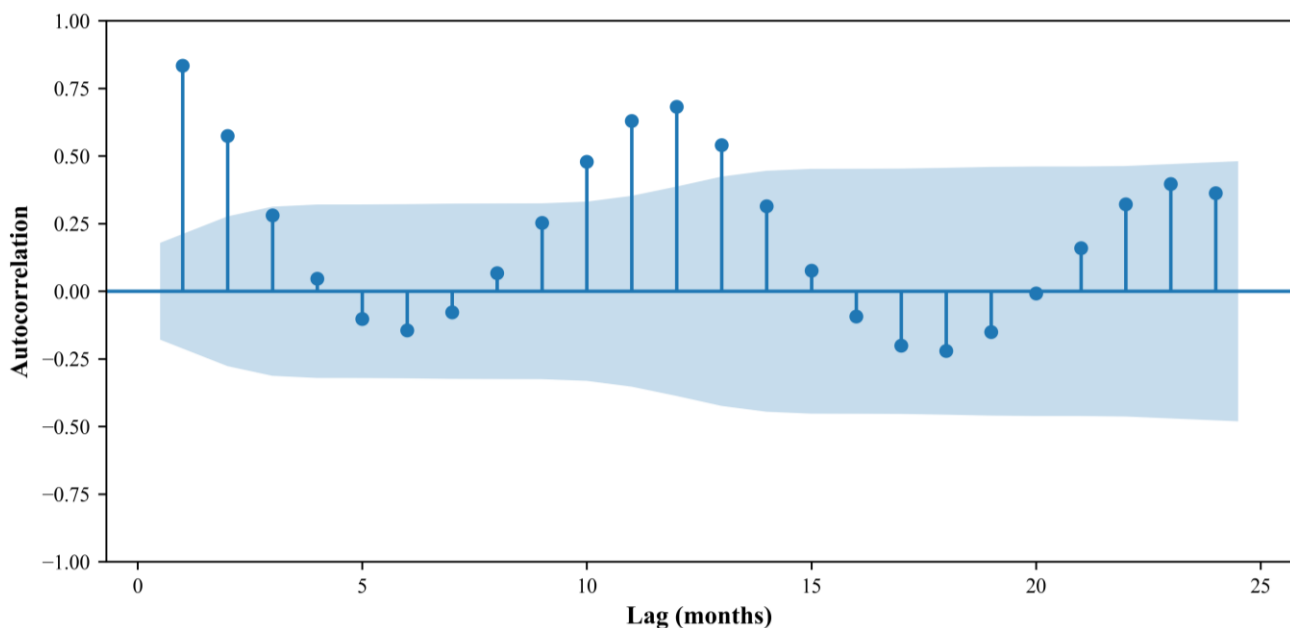
**Fig. 6.** Autocorrelation function (ACF) of monthly cutaneous leishmaniasis cases in Ouarzazate, Morocco, 2014–2023

Table 4. Discriminant validity (HTMT) of the measurement model of cutaneous leishmaniasis cases for the urban commune of Ouarzazate, Morocco, 2014–2023

Constructs	HTMT ratio	95% Bootstrap CI
Climate ↔ CL Occurrence	0.523	0.416-0.611
Population ↔ CL Occurrence	0.128	0.011-0.224
Climate ↔ Population	0.213	0.087-0.369

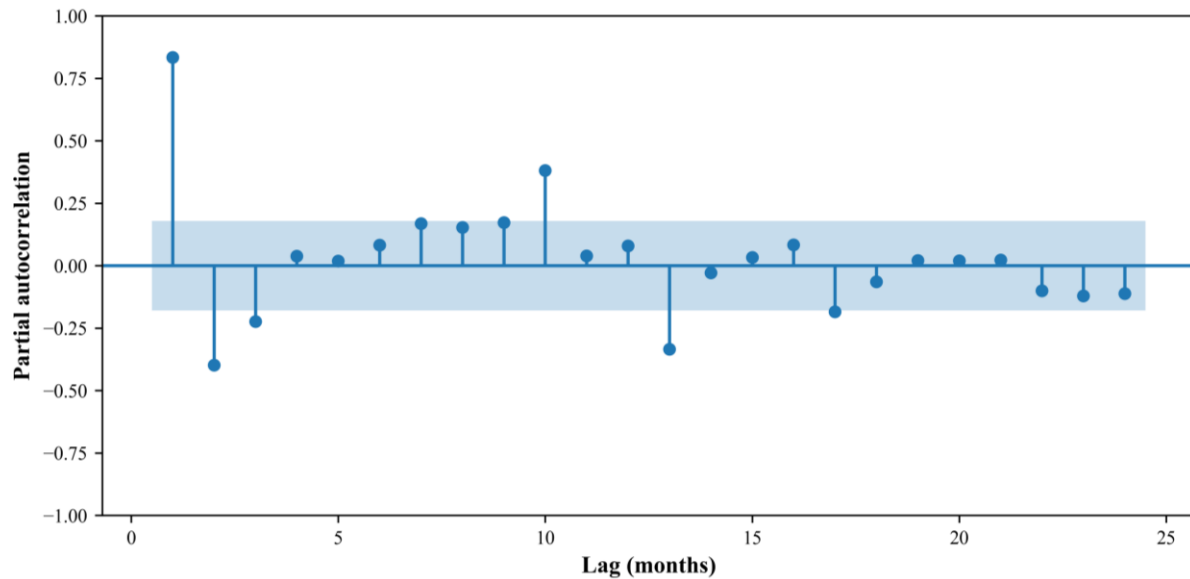
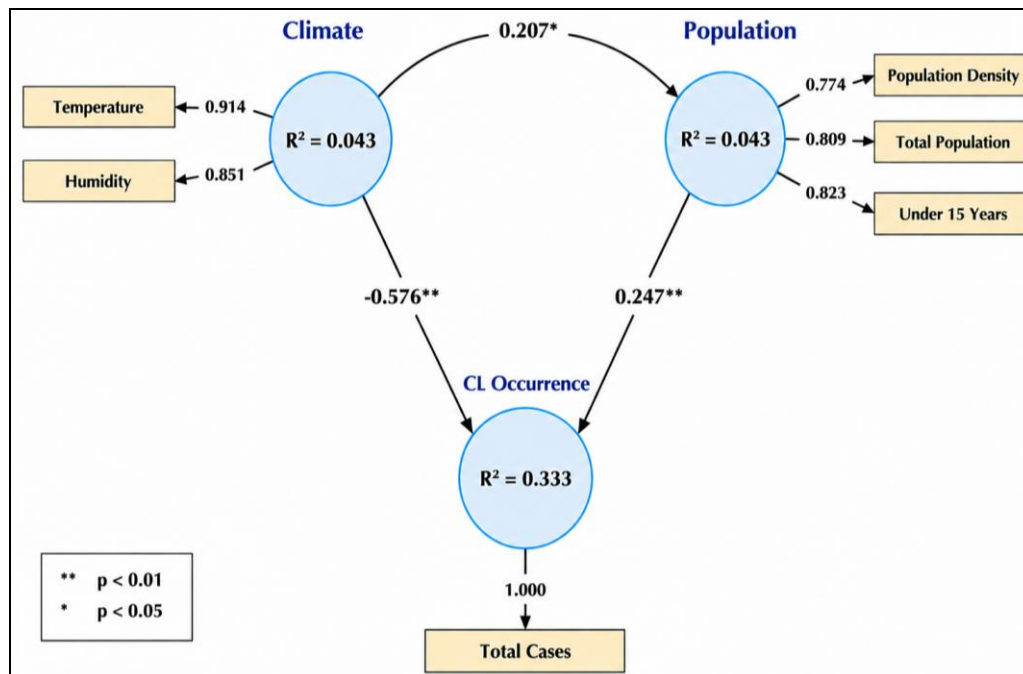
**Fig. 7.** Partial autocorrelation function (PACF) of monthly cutaneous leishmaniasis cases in Ouarzazate, Morocco, 2014–2023**Fig. 8.** Structural model results illustrating the relationships between climatic factors, population characteristics and cutaneous leishmaniasis occurrence, including path coefficients (β), coefficients of determination (R^2) and significance levels, in the urban commune of Ouarzazate, southeastern Morocco, 2014–2023

Table 5. Structural model assessment results of cutaneous leishmaniasis cases for the urban commune of Ouarzazate, Morocco, 2014–2023

Hypotheses	Path	Path coefficient	f ²	2.5% CI	97.5% CI	t-value	p-Value	Decision
H1	CLM → CLO	-0.576	0.4755	-0.693	-0.477	10.243	P< 0.0001*	Accepted
H2	POP → CLO	0.247	0.0874	0.085	0.383	3.347	P< 0.001*	Accepted
H3	CLM → POP	0.207	0.0450	-0.018	0.390	1.937	P= 0.053	Rejected

*Statistically significant

2.5% CI and 97.5% CI represent the lower and upper bounds of a confidence interval, respectively

Discussion

This study aimed to identify and examine the climatic and population factors associated with CL occurrence in the endemic urban commune of Ouarzazate, southeastern Morocco, from 2014 to 2023. Understanding these factors is important for assessing the potential risk of CL and developing effective surveillance and control strategies. The present study used PLS-SEM approach to simultaneously examine the relationships among climatic factors, population characteristics and CL occurrence. The results of the PLS-SEM analysis indicated that climatic factors, mainly temperature and relative humidity, were significantly and negatively associated with CL Occurrence (H1). However, the finding did not support our hypothesis (H3), which proposed that climate is directly associated with population characteristics in our final model. In addition, population characteristics showed a significant positive association with CL occurrence (H2). Additionally, the effect sizes provide further insight into the relative importance of these relationships. Climate showed the strongest association with CL occurrence ($\beta = -0.576$, $f^2 = 0.4755$), whereas the association of population characteristics with CL occurrence was comparatively smaller ($\beta = 0.247$, $f^2 = 0.0874$). The climate–population relationship showed a smaller effect ($\beta = 0.207$, $f^2 = 0.0450$) and did not reach statistical significance.

Previous studies have shown that the incidence of CL in different provinces of Morocco exhibits substantial spatial and temporal

variation, with higher incidence rates reported in southeastern provinces. This distribution was associated with various factors such as altitude (40), urbanization, population rate (41, 42), social vulnerability (7, 43, 44), temperature, humidity, precipitation, vegetation and human behavior (25, 45). The findings of the present study are consistent with evidence from other CL-endemic settings showing that climatic conditions, particularly temperature, humidity and rainfall, are closely associated with CL occurrence and transmission (46, 47).

It is well established that variations in climatic factors cause fluctuations in the abundance and activity of sand fly vectors. Furthermore, some studies on effective environmental factors have shown that temperature and humidity are the two most important climatic factors affecting the activity, development and survival of phlebotomine sand fly vectors of cutaneous leishmaniasis, both during their immature stage development and during their lifetime as adults (48, 49).

In North African countries, the distribution of *P. papatasi* exhibits marked seasonal fluctuations, and its abundance is strongly associated with temperature and relative humidity, with peak vector densities usually occurring during the hot season from May to September (50). Peak densities have been reported at maximum temperatures ranging from 31.2 to 37 °C and relative humidity ranging from 32.6% to 56.6% across endemic sites in Morocco, Algeria, Tunisia and Libya (50, 51).

In Morocco, adult sand flies have been reported to survive within an approximate temperature range of 10–40 °C, with reproduction being limited below 15 °C, while *P. papatasi* is particularly abundant in arid areas at ambient temperatures of approximately 32–36 °C (50, 52).

Changes in temperature patterns may therefore alter the environmental suitability for sand fly vectors (53). Because vectors require suitable temperature ranges for survival and development, extremely high temperatures may reduce vector survival and consequently alter CL transmission. In Ouarzazate, the negative association observed between the Climate construct and CL occurrence may partly reflect the effects of very high summer temperatures on vector survival and activity. This interpretation is consistent with the observed monthly distribution of CL cases and the seasonal pattern identified by STL decomposition. However, this negative path coefficient represents the combined Climate construct, primarily characterized by temperature and humidity in the final measurement model, and should not be interpreted as an isolated negative effect of temperature. This interpretation is also consistent with the observed seasonal pattern of CL cases, which peaked during the cooler months, with the highest seasonal component occurring in January and the lowest in August, supporting the observed negative association between climate and CL occurrence. Moreover, lag effects may also be involved, as temperature in previous months might affect current vector populations and subsequently influence CL occurrence (54–56).

Humidity is another climatic factor often linked with the occurrence of leishmaniasis (57). In the present study, the significant effect of humidity on the occurrence of CL was demonstrated. Humid environments provide suitable breeding and resting habitats for sand flies, which may lead to increased vector abundance and a higher frequency of human and vector contact (58, 59).

Climatic factors, especially temperature and relative humidity, emerged as a major determinant of CL occurrence in the study area, which is biologically plausible given their well-documented effects on sand fly vector ecology (58, 59). Elevated temperatures accelerate vector development, increase biting frequency and enhance *Leishmania* parasite replication within the vector, while relative humidity contributes to vector survival and seasonal persistence, particularly in arid and semi-arid environments such as Ouarzazate (48–61).

Rather than considering climatic variables independently, the PLS-SEM framework integrated temperature and humidity indicators into a latent climatic construct. This approach more accurately reflects the biological reality that CL transmission is driven by the interaction of multiple climatic factors rather than by isolated environmental parameters (46, 47).

The positive relationship between population characteristics and CL occurrence may reflect increased opportunities for human-vector contact in more densely populated settings. High population density inherently increases the contact between humans and sand flies and consequently, the risk of sand fly bites and CL transmission. This finding aligns with previous studies in Morocco, which reported a significant relationship between population rate and CL occurrence (45, 62).

Climatic and demographic factors can influence disease dynamics, but their effects are context-dependent and may vary based on biological, behavioral and environmental conditions. This suggests that, in the context of Ouarzazate, wind speed and precipitation have limited direct influence on monthly CL incidence, and the sex-based demographic structure does not substantially affect disease occurrence when accounting for other climatic and population factors.

The exclusion of wind speed, precipitation and female population from the final model should be interpreted with caution. Their ex-

clusion reflects study-specific statistical model refinement rather than an absence of potential epidemiological or biological relevance. Although not retained in the final model, these factors may still be relevant through seasonal effects, lagged relationships, nonlinearities, local behavioral and ecological dynamics, or measurement limitations.

In particular, the relationship between precipitation and CL occurrence may depend on the temporal scale considered. Monthly rainfall may produce short-term changes in soil moisture and vector breeding or resting conditions, whereas longer-term or annual precipitation patterns may reflect broader environmental suitability for sand fly populations. Wind speed may also influence sand fly movement and dispersal rather than abundance, and this effect may therefore be poorly captured by monthly aggregated data (63). Similarly, the exclusion of the female population indicator does not imply an absence of sex-related differences in CL risk. This indicator may be less relevant in the present context but could become more relevant with a different data resolution.

Based on the guidelines of (21), the measures for reliability and validity indicated that the model is robust and reliable. All Cronbach's alpha coefficients and Composite Reliability values exceeded the recommended threshold of 0.70, demonstrating adequate internal consistency and reliability. Additionally, the AVE values were greater than 0.50, confirming convergent validity. Heterotrait-Monotrait (HTMT) ratio values reflect the degree of similarity between latent constructs, with values below the recommended threshold of 0.90 indicating adequate discriminant validity (37). In the present study, all HTMT ratios were below 0.85, confirming discriminant validity.

In disease modeling, reliability and validity testing ensures that the variables included in the model consistently and accurately represent the underlying factors influencing CL risk. By retaining only reliable variables, the model provides a clearer understanding of the

key climatic and population factors driving monthly CL incidence. Consequently, the results can be interpreted in a biologically and epidemiologically meaningful way, providing interpretable insights for public health planning and vector control interventions in the study area.

For the inner model, the overall explanatory power for CL occurrence was found to be moderate, as indicated by the R^2 values. Although the model demonstrates moderate explanatory power, explaining about 33% of the variation in CL occurrence, this level is deemed acceptable for exploratory studies (21).

The proportion of variance explained in CL studies varies considerably depending on the epidemiological context, predictors included, spatial and temporal resolution, and analytical approach. Incorporating additional environmental, entomological and socioeconomic variables, such as vegetation, land use, vector density, housing conditions, access to healthcare, population mobility and vector control activities, could potentially increase the explanatory power of the model.

The principal contribution of this study lies in the simultaneous evaluation of climatic and population constructs and their relationships with CL occurrence within an integrated PLS-SEM framework. While the associations of climatic and population factors with CL occurrence are well documented, previous studies have often examined these factors separately using conventional regression or time-series approaches. Although such models, including logistic or linear regression, are effective for estimating associations between predictors and disease occurrence, they may be limited in handling multicollinearity and complex interdependencies among variables (21–23). In this context, the present study provides a complementary perspective by simultaneously modeling multiple constructs and their structural relationships, thereby allowing the relative contributions of climatic and population characteristics to CL occurrence to be assessed within a single framework.

From a public health perspective, these findings provide empirical support for the development of climate-informed surveillance systems and the design of targeted vector control strategies. By translating complex statistical associations into interpretable risk patterns, this integrative approach enhances the practical applicability of CL epidemiological modeling for disease monitoring and prevention.

Limitations of the study

Despite the insights provided by this study, several limitations should be acknowledged. Although several statistically significant associations were identified, these findings should not be interpreted as evidence of direct causality, as the PLS-SEM approach primarily captures associative rather than causal relationships. In addition, the monthly CL series exhibited seasonality, non-stationarity, autocorrelation and over-dispersion. Although these temporal characteristics were assessed through complementary diagnostic analyses, they were not explicitly modeled within the PLS-SEM framework and should therefore be considered when interpreting the structural relationships.

Furthermore, several socioeconomic indicators known to be associated with CL risk, such as housing quality and access to healthcare, were not available at the required spatial and temporal resolution for the study area. In addition, migration and population displacement were not included and may act as potential confounding factors by modifying population distribution and exposure to CL transmission. Data on vector control activities were also unavailable, although such interventions may influence vector populations and consequently CL occurrence. The omission of these factors may affect the model's external validity and the interpretation of population-related effects.

Future research should incorporate additional determinants, including vector dynamics, lifestyle factors and socioeconomic conditions, explicitly account for autocorrelation and seasonality and investigate potential lagged

relationships between climatic factors and CL occurrence using appropriate time-series approaches.

Advanced analytical techniques such as Artificial Neural Networks (ANN) or fuzzy-set Qualitative Comparative Analysis (fsQCA) could also be explored as complementary approaches to enhance model applicability and predictive capacity.

Conclusion

The findings of this study highlight the importance of adopting integrated analytical approaches to better understand the complex determinants of cutaneous leishmaniasis. By combining climatic and population variables within a structural modeling framework, this study provides new insights into the interconnected mechanisms influencing CL occurrence in south-eastern Morocco. These results may support the development of climate-informed surveillance systems and targeted public health interventions aimed at improving the prevention and control of vector-borne diseases in semi-arid and urban endemic regions in North Africa.

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Ethical consideration

This study adhered to the principles of the Declaration of Helsinki and was authorized by the Regional Directorate of Health and Social Protection Draa-Tafilalet (authorization number 8288 on 12 December 2022) in accord-

ance with Moroccan Law No. 28–13, Article 26. The authors have fully complied with ethical standards, such as plagiarism, data fabrication and double publication. This study is based on a retrospective, non-interventional analysis of secondary, aggregated and publicly available data and does not involve direct interaction with human participants or the use of identifiable individual-level information. In accordance with Moroccan Law No. 28–13 on the protection of persons participating in biomedical research (Dahir No. 1-15-110 of 4 August 2015), non-interventional research does not require approval by a Biomedical Research Ethics Committee. For this type of study, the applicable legal requirement is authorization from the head of the health establishment, which was duly obtained.

Conflict of interest statement

The authors declare that there is no conflict of interest.

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