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Hot Spot Analysis of Visceral Leishmaniasis Disease and Evaluation of its Relation with Air Temperature in GIS

Abstarct
Visceral Leishmaniasis (VL) is a zoonotic vector born disease. Several geographical risk factors affect VL incidence including air temperature, critical to the development of sand fly. Few and scattered meteorological stations tend to record air temperature with field measurements which costly and time consuming, albeit its evaluations for preventive activities are crucial for epidemiologists. Temperature can be determined by continuous surfaces extracted via Geographic Information System. Surfaces were produced by using geostatistical methods including Ordinary Kriging/Cokriging, Universal Kriging/Cokriging in Kalaybar and Khoda-afarin districts of Iran. I determined hot spot and spatial auto-correlation analysis of VL disease by Getis-Ord Gi* statistic and global Moran's I, too. Given the z-score and p-value of 2.22 and 0.026, respectively, showed less than 5 % likelihood that this VL clustered pattern could be the result of random chance. Estimating MAE=1.9897, RMSE=2.714 and PE =13.72, was indicated the Ordinary Cokriging method was the superior method in this study. VL incidence correlated closely with air temperature as Pearson's coefficient. Epidemiologists should expand their studies on other villages similar to the involved disease-stricken villages in terms of air temperature. Albeit in these villages, the probability of sand fly activities and VL incidence are higher than others, so preventative activities seem necessary.

Keywords: Visceral Leishmaniasis; Hot spot and spatial auto-correlation analysis; Air Temperature; Geostatistics; Geographical Information System (GIS).

1- Introduction
Visceral leishmaniasis (VL), also known as kala-azar, is a fatal tropical disease with an estimated annual incidence of 500,000 cases (Zakeri et al., 2004; WHO, 2010) occurring in 70 countries around the globe as a major public health problem (Scarpini et al., 2022). VL is almost lethal if left untreated with an estimated death toll of 50 thousand people annually (WHO, 2010). Every year, a significant sum of capital is spent on treating VL patients and relevant controls around the world. According to the report of World Health Organization, the Daly[1] / year rate (One DALY is equal to one year of healthy life that is lost) for Leishmaniasis is 2.4 million in the world (WHO, 2004).
VL is a vector born parasitic disease in Iran, caused by L infantum, a zoonotic disease with a life cycle that targets female sand flies (vector), dogs (reservoir) and children (host) (Maruashvili and Bardzhade, 1966; Zakeri et al., 2004; Sabzevari et al., 2020). Zoonotic Visceral Leishmaniasis occurs sporadicly all over Iran, except in Ahar and Kalaybar that

[1] disability-adjusted life year (DALY)

are endemic zones (Mazloumi Gavgani et al., 2002). The epidemic in the north-west began in the 1980s in the Kalaybar district and has since spread to Ahar. Since 1976, the number of annually reported cases has increased considerably (MOH, 2018). Four sand fly species, *P. (Larroussius) kandelakii, P. (Larroussius) near major, P. (Larroussius) perfiliewi* and *P. (Adlerius) near chinensis*, are the likely vectors in the north-western part of Iran, as determined by the relative abundance and isolation of Leishmania from related species (Feliciangeli et al., 2023).
According to the triangle of epidemiology, factors that affect infection and incidence of Leishmaniasis are host factors (for example, age, sex), infectious agents, and the environment including air temperature, etc. (Dorak, 2009). Sand flies act as vectors for leishmania parasite, and their biological metamorphosis duration, population and development are influenced by environmental temprature. Temperatures below 5°c and above 28°c will result in reductions of sand fly activitiy (Zaeem, 1997).
I have studied the influence of air temperature on incidences of Visceral Leishmaniasis in Kalaybar and Khoda-afarin districts in northwest of Iran, as an endemic foci of VL. To achieve this goal, it was necessary to know the exact temprature of each part of the area. It is worth noting that certain parts of the region included no comprehensive meteorological stations, with the only available ones only capable of indicating temprature for specific sectors.
However, continuous temperature surface can be employed to obtain estimates of temperature in any area of a given region. Continuous surface or raster is a surface that contains rows and columns of cells, each of which store a single value; discrete values for land use; continuous values, such as temperature, or a null value if no data is available are recorded in each cell as additional values. To produce such surfaces, regression method and spatial interpolation are often applied.
Regression analysis is broadly used for prediction and forecasting, as well as for determining whether the independent variables are related to the dependent variable, and to find the forms of these relationships. Interpolation methods, on the other hand, are generally categorized as either deterministic or geostatistical methods. Inverse Distance Weighting (IDW), Spline, and Trend are among methods that fall into the deterministic category, while Kriging is classified as geostatistical. Geostatistical methods are more common for interpolation in GIS. The Kriging method is implemented in several methods such like simple, ordinary and universal. Geostatistical methods often account for estimated data position, spatial structure and correlation between data, however, selecting methods without any consideration for accuracy may result in erroneous outcomes. Given the scattered distribution of meteorogical stations and high spatial variation of temperature in mountainous regions, higher levels of accuracy is certainly required for the application of these methods to estimate temperature. Herein, spatial interpolation methods are commonly used for means of prediction, with higher precision of the produced continuous surface entailing better results. Since meteorological stations in this study were distributed sparsely and unevenly in the region, air temperature mapping was

necessary by combined method. To this aim, a combination of ordinary kriging and correlation of altitude can be used as a sort of co-kriging approach. In most cases, the combined method was superior to the other methods in terms of accuracy.

Cases of spatial interpolation used for estimating air temperature include (Ischia and Kawashima, 1993; Li et al., 2005; Benavides et al., 2007; Irmak and Ranade, 2008; Mahdian et al., 2009; Wang et al., 2017; Hsu et al., 2017; Puggioni et al., 2020; Matthew et al., 2021; Zhou et al., 2021; Laciak et al., 2021; Njoku et al., 2023), which also incorporated standard prediction error and mean absolute error for method evaluation. As the results from these studies suggest, kriging methods are best for interpolation, with better generalization, greater ability to produce observed variance, and higher consistency between observed and predicted values. Carrera - Herna'ndez and Gaskin (2007) also used kriging methods to estimate daily rainfall and minimum and maximum air temperature. Their results showed that the interpolation of daily events is improved by the use of elevation as a secondary variable even though these variables show a low correlation. Jaber et al., (2013) examined relationships between cutaneous leishmaniasis and spatial patterns of climate. They found major hotspots of relatively high incidence rates by areal interpolation. Most researches evaluate the Kriging method for producing spatial pattern of climate data in the study of correlations between disease and climate data, however regions where meteorological stations are scattered require new methods to overcome the potential challenges of this approach.

The study region includes kalaybar and Khoda-afarin districts which are the endemic regions of Mediterranean VL (Mazloumi Gavgani et al., 2002) with various species of sand flies. In this study, four interpolation methods were evaluated and compared to estimate continuous surfaces of air temperature that affect VL incidence during transmission months. Using evaluation metrics, more suitable methods for generating continuous temperature surfaces were assessed. Finally, correlation of VL incidence with temperature were calculated. We determined hot spot and spatial auto-correlation analysis of VL disease by Getis-Ord Gi* statistic and global Moran's I, too. Therefore, the novelty of this study was about using hot spot and spatial auto-correlation analysis in VL disease as pointwise in villages instead of district/county. Furthermore, spatial interpolation was used for producing air temperature continues surface in correlated with VL disease instead of studying in several meteorological stations as pointwise. This air temperature surface was predicted by using elevation as a secondry variable.

2- Materials and Methods

2-1- Study area and materials

The study area is Kalaybar and Khoda-afarin districts, situated in the northeast of East Azarbaijan province, north-west Iran, between 46.35 to 47.30 E and 38.35 to 39.20 N (Fig. 1). Data on climatic factors from 1998 to 2012 was gathered from the metrological office of East Azarbaijan province and the National metrological organization of Iran. Based on previous studies in the area, sandflies are active in late May (May 22th) until early October (October 2th), from sunset to sunrise (MOH, 2018). Accordingly, air temperature data from 15 to 03 in GMT time format was used, equivalent to 6:30 pm until

6:30 am. In collaboration with the Infectious and Tropical Diseases Research Center of the Ministry of Health (MOH), VL notification data was collected at the scale of villages, either from central registers or from district centers, between 1998 and 2012.

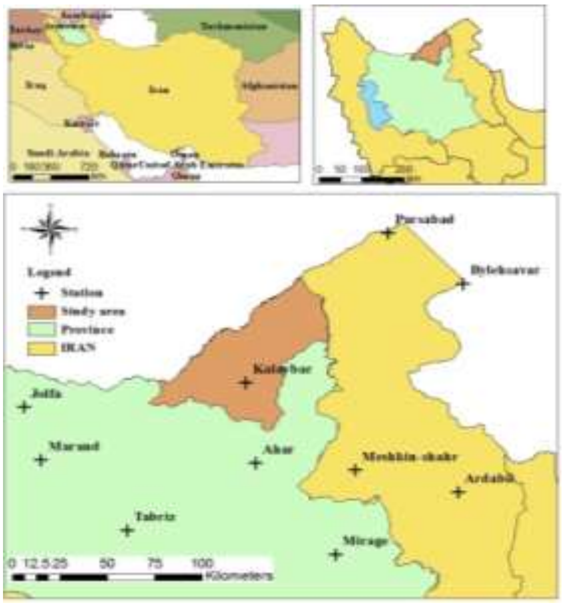

Fig. (1): Study area and position of stations in Iran
شکل (۱): منطقه مورد مطالعه و موقعیت ایستگاههای هواشناسی در ایران

2-2- Methods

2-2-1- Hot spot and auto correlation analysis

In this study, I identified statistically significant hot spots and cold spots of VL disease using the Getis-Ord Gi* statistic (equation 1). The z-scores and p-values are measures of statistical significance which tell us whether or not to reject the null hypothesis, feature by feature. In effect, they indicate whether the observed spatial clustering of high or low values is more pronounced than one would expect in a random distribution of those same values. The Gi_Bin identifies statistically significant hot and cold spots. Features in the +/-3 bins reflect statistical significance with a 99 percent confidence level; features in the +/-2 bins reflect a 95 percent confidence level; features in the +/-1 bins reflect a 90 percent confidence level; and the clustering for features in bin 0 is not statistically significant (Ord and Getis, 1995).

$$\text{Getis-Ord } G_i^* = \frac{\sum_{j=1}^{n} w_{ij}\, x_j - \bar{X} \sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{\left[n \sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2\right]}{n-1}}} \quad (1)$$

, where x_j is the attribute value for feature j, w_{ij} is the spatial weight between feature i and j, n is equal to the total number of features, $\bar{X}_i$ and S are the average and standard deviation, respectively (Dai et al., 2023). The Gi* statistic returned for each feature in the dataset is a z-score. For statistically significant positive z-scores, the larger the z-score is, the more intense the clustering of high values (hot spot). For statistically significant negative z-scores, the smaller the z-score is, the more intense the clustering of low values (cold spot). We can measure spatial auto-correlation (Global Moran's I, equation 2) based on feature locations and attribute values using the Global Moran's I statistic. It evaluates whether the pattern expressed is clustered, dispersed, or random and both a z-score and p-value are used to evaluate the significance of that Index (Mitchell, 2005).

$$\text{Moran'S Index}= \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{S_0 \sum_{i=1}^{n} {z_i}^2} \qquad (2)$$

, where z_i is the deviation of an attribute for feature I from its mean (x_i - $\bar{X}$). W_{ij} is the spatial weight between feature i and j, n is equal to the total number of features, and S_o is the aggregate of all the spatial weights (Habib et al., 2023).

2-2-2- Producing continuous surface of air temperature

- **Data preparation**

The average air temperature was calculated for each year from 1998 to 2012 and totally at the days and hours which VL transmission could occur. In order to model air temperature, continuous surface has been produced via appropriate geostatistical analysis methods such as Ordinary Kriging, Universal Kriging, Ordinary CoKriging and Universal CoKriging. For this purpose, the correlation between temperature and height was obtained to determine the extent to which CoKriging method can be applied, as in certain cases where a variable sampling is not enough for careful estimation. In such cases, one can modify estimation by considering the spatial relationship between these variables and other variables which have good sampling like elevation samples from stations (Madani, 1994).

- **spatial interpolation**

In this study, Kriging and Cokriging were used to simulate air temperature effects on VL. The general equation for different interpolation methods used in this study are found in equation 3. The difference between these methods is in the process of estimating the weighting factor.

$$z^*(x_i) = \sum_{i=1}^{n} \lambda_i . z(x_i) \qquad (3)$$

Where: $z^*(x_i)$= The estimated value of variable x; $z(x_i)$= Observed value of variable x; λ_i= Weighting value of observed data; n= No. of data; I= Observation point

Another approach for incorporating secondary information is CoKriging; that is a multivariate extension of kriging (Goovaerts, 1997). The co-located elevation y(u) tends to screen the influence of elevation data for remote regions. The CoKriging estimate can then be calculated:

$$z^*_{ck}(u) = \sum_{i=1}^{n} \lambda_i^{ck}(u) z(u_i) + \lambda_{ck}(u)[y(u) - m_Y + m_Z] \quad (4)$$

Where m_Z and m_Y are the global means of the temperature and elevation data. The crucial part of geostatistical analysis involves the calculation of semi variance (Bohling, 2005), which can be calculated as follows:

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(xi) - z(xi + h)]^2 \quad (5)$$

Where: γ (h)= Semi variance; n (h)= No. of pairs that have h distance; z (xi)= Observation value of the variable x; z(xi+h)= Observation value of x that has h distance from x.

The experimental semi-variograms of elevation and period of temperature, and their cross semi-variogram is computed as (Goovaerts, 1999):

$$\widehat{\gamma_{ZY}}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(u_i) - z(u_i + h)] * [y(u_i) - y(u_i + h)] \quad (6)$$

For purposes of investigating interpolation methods, initially, the histogram of air temperature and the normal curve was drawn (Fig. 2). Thereupon, the normality hypothesis is checked using Geostatistical analysis in GIS. Interpolation methods used to generate a surface give the best results if the data is normally distributed (a bell-shaped curve). Among common transformation functions such as None, Log and Box-Cox, the function which normalizes data more than others, is the recommended choice (ESRI, 2023). Statistical parameters studied in stations are shown in table 1.

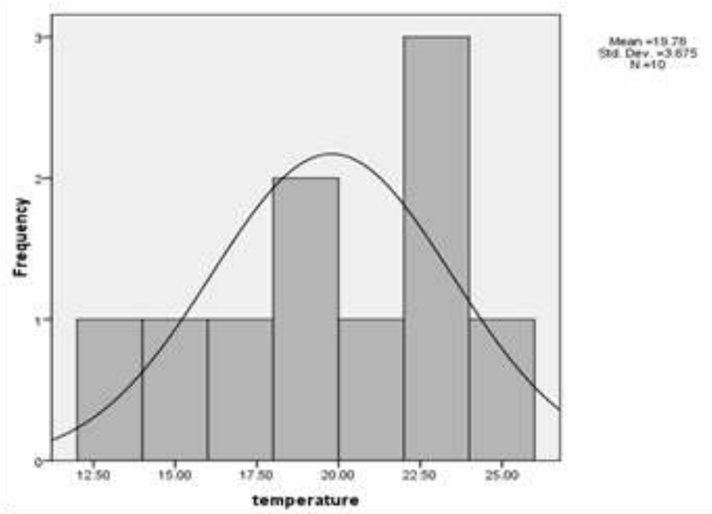

Fig. (2): Histogram of air temperature and the normal curve
شکل (۲): هیستوگرام دمای هوا و منحنی نرمال

Table (1): Statistical parameters in stations
جدول شماره (۱): اطلاعات آماری در ایستگاهها

Statistical parameters	value
station No.	10
Minimum	13.9
maximum	25
Mean	19.785
median	20.145
Std-Deviation	3.6746
Skewness	-0.30457
Kurtosis	1.9084

By a mathematical formula, we can identify the existence of a trend in the data as a deterministic component of a given surface. If the surface trend does not adequately portray the surface for our particular need, it may be removed and analysis continued accordingly, as in the case of the present study (ESRI, 2023).

- **Semi-variogram/Covariance modeling**

Semi-variograms representing the squared-difference of values between each pair of points at different distances were examined. The goal of semi-variance/covariance modeling is to determine the best fit for a model that will pass through the points in the semi-variogram. The semi-variogram is a function that relates semi-variance (or dissimilarity) of data points to the distance that separates them. Its graphic representation can be used to provide a picture of the spatial correlation of data points with their neighbors. The semi-variogram can be modelled by determining a suitable lag size for grouping semi-variogram values and fitting a spherical semi-variogram model.

Accordingly, several lag sizes and number of lags were tested for a better interpolation. The final spherical model was improved by evaluating different models of semi-variance.

- **Evaluation metrices**

A sample size of 10 may be too small to develop a reasonably stable empirical variogram, and ideally 50–100 sample points are needed (Burrough and McDonnell, 1998). But in reality, one is constrained by limited data which hinders the process of extracting the spatial correlation structure from the empirical data. In this case, there were only 10 stations in the region and the data could be obtained. After variogram analysis, Ordinary Kriging, Universal Kriging, Ordinary CoKriging and Universal CoKriging were evaluated using evaluation metrices. In addition to visualizing scattered points around this 1:1 line, a number of statistical measures could be used to assess the model's performance. For a model that provides accurate predictions, the mean error should be close to 0, the root-mean-square error and average standard error should be as small as possible (this is useful when comparing models), and the root-mean-square standardized error should be close to 1 (ESRI, 2023). In this research, by considering various models of semi-variance, lag size, nugget and number of lags, mentioned error rates were tested and the appropriate method was examined. All methods were assessed and created in ArcMap environment.

2-2-3- Evaluating optimal method

In addition to mentioned researches and the selection of more appropriate models for semi-variance, lag size, nugget and number of lags for each method, in this study, MAE, RMSE and PE (%) were used as evaluation metric techniques in addition to methods mentioned in the previous section. Mean Absolute Error (MAE) was calculated using the following equation:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|z^{*}(x_i) - z(x_i)| \quad (7)$$

Where: z* = The estimated value; z= The observed value; n = No. of data. MAE indicates the precision of estimation. The closeness of the values shows the accuracy of the estimated value to the observed value, should MAE reach zero (Mahdian et al., 2009). The percent error or PE (%), is defined as:

$$PE(\%) = \frac{RMSE}{(\frac{1}{N})\sum_{i=1}^{N} P_i^{*}} * 100(\%) \quad (8)$$

Where, RMSE= $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - P_i^{*})^2}$ (9)

, where RMSE (root mean square error) is the mean of the squared difference between the observed value (P_i*) and the predicted value (P_i), and N is the number of observations (Lu et al., 2008; Akbari, 2024).

2-2-4- Relation between temperature and VL disease

In this study, correlation of VL incidence with temperature of 123 study villages in Kalaybar and Khoda-afarin districts was determined by Pearson correlation coefficient.

$$r_{x,y} = \frac{E[(X-\mu x)(Y-\mu y)]}{\sigma x\ \sigma y} = \frac{\sum xy}{N\ \sigma_x\ \sigma_y} \quad (10)$$

, where $r_{x,y}$, $\sigma x, \sigma y$, $\mu x, \mu y$, E, and N are Pearson correlation coefficient between x and y variables, standard deviation of x and y, mean of x and y, the expectation, and number of samples, respectively (Akbari et al., 2015).

3- Results

This study determined hot spot and spatial auto-correlation analysis of VL disease by Getis-Ord Gi* statistic and global Moran's I. I found cluster of VL disease around Abeshahmad and Khomarlo cities by hot spot with 99% confidence and around Kalaybar city by hot spot with 95% confidence (Fig. 3). It returned by the Gi* statistic in the dataset and evaluated by z-score. For statistically significant positive z-scores, the larger the z-score is, the more intense the clustering of high values (hot spot). The z-score, p-value and Moran's index indicated there is a less than 5% likelihood that the VL clustered pattern could be the result of random chance. The pattern of VL disease in this county is clustered significantly by 2.221723, 0.026302, and 0.062107 as the z-score, p-value, and Moran's index, respectively (Fig. 4).

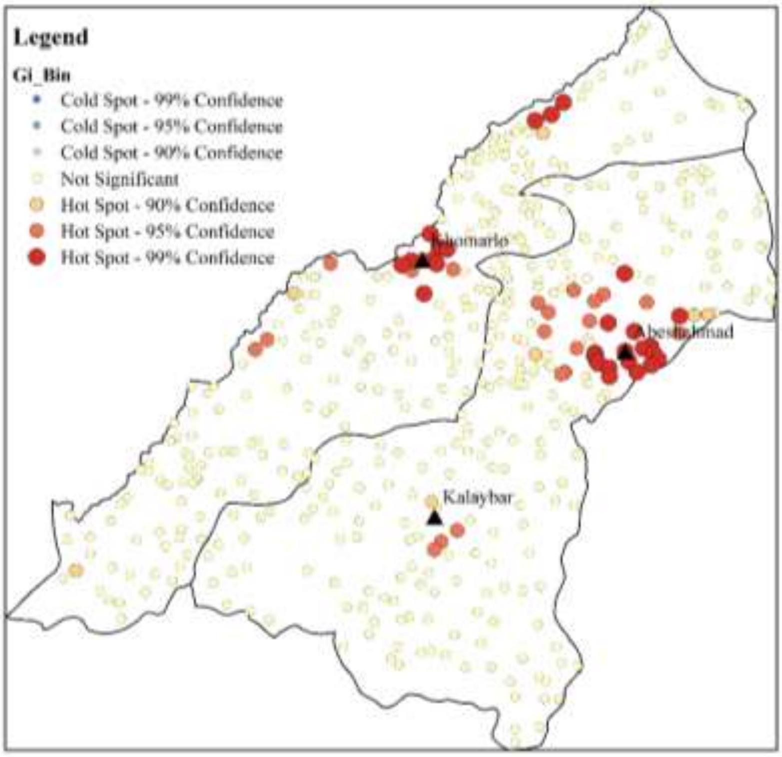

Fig. (3): Hot spot analysis of VL disease

شکل (۳): آنالیز نقاط تمرکز بیماری VL

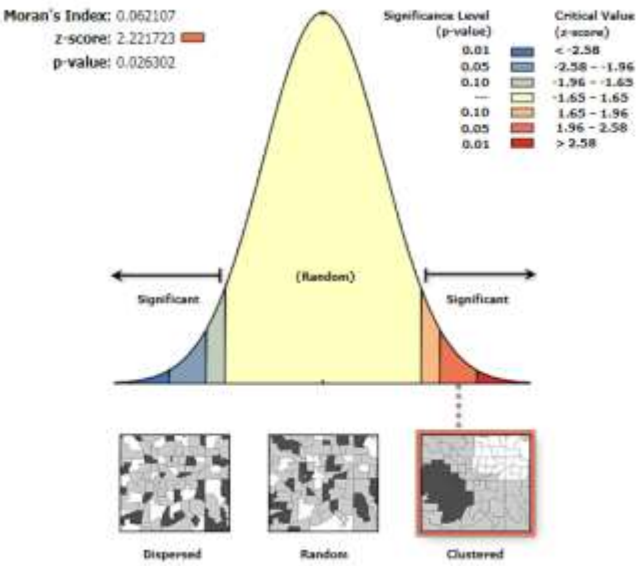

Fig. (4): Spatial auto-correlation of VL disease

شکل (۴): خود همبستگی مکانی بیماری VL

Table 2 shows the error of interpolation methods. Based on the value of MAE, RMSE and PE (%), Ordinary Cokriging is more accurate and the preferred interpolation method for generating temperature surfaces compared to other methods (Fig. 5), with no significant difference between Ordinary Cokriging and Ordinary Kriging methods. The prediction standard error surface for determining the uncertainty for each location was mapped to examine the quality of predictions in GIS (Fig. 6). A simple rule of thumb is that 95 percent of the time, the true value of the surface will be within the interval formed by the predicted value ± 2 times the prediction standard deviation of error, provided that the data is distributed normally. Also, in the prediction standard error surface, locations near sample points generally have lower errors (ESRI, 2023).

Table (2): Errors of interpolation methods

جدول شماره (۲): خطاها در روشهای درون‌یابی

Method / Error	Ordinary Kriging	Universal Kriging	Ordinary Cokriging	Universal Cokriging
MAE	1.9958	2.6869	1.9897	2.6959
RMSE	2.737	3.385	2.714	3.384
(%) PE	13.83	17.11	13.72	17.10

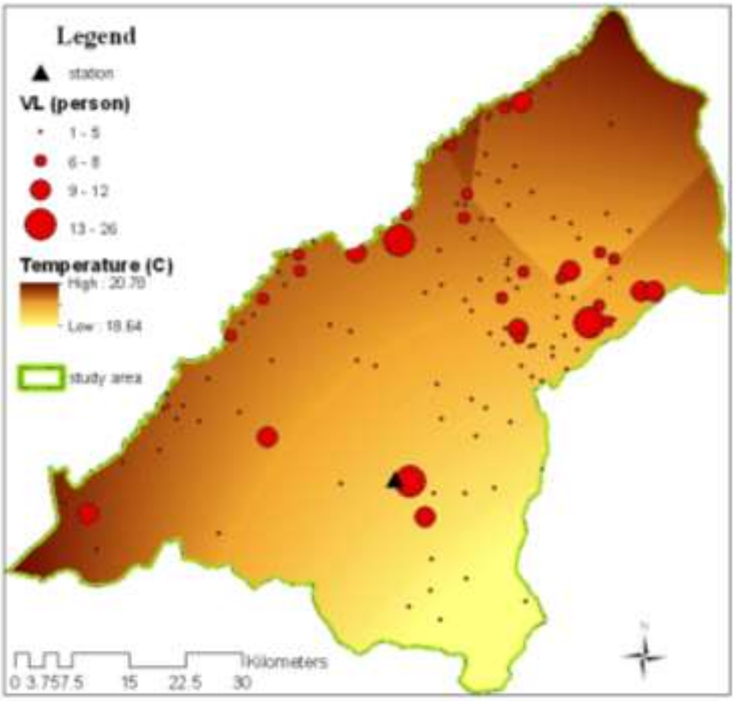

Fig. (5): Continuous surface of air temperature, VL rates in villages and meteorological station of Kalaybar and Khoda-afarin districts

شکل (۵): سطح پیوسته از دمای هوا، نرخ VL در آبادیها و ایستگاه هواشناسی بخشهای کلیبر و خداآفرین

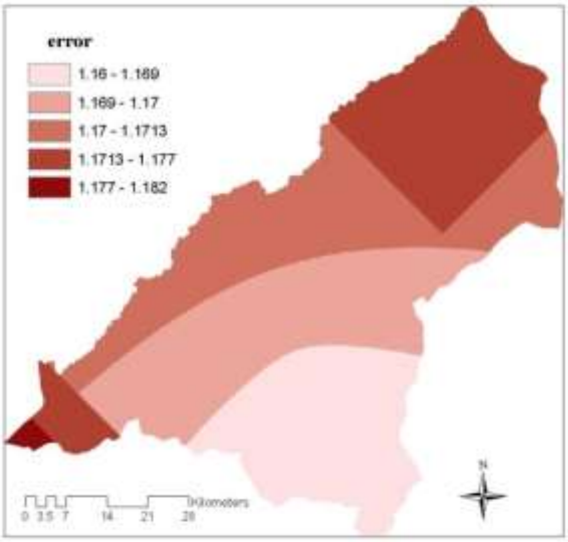

Fig. (6): Map of prediction standard error

شکل (۶): نقشه خطای استاندارد پیش‌بینی شده

In Fig. 5, darker colors indicate higher temperature value. Temperature of each pixel has been specified in this surface at 100 meters per pixel dimension. Meanwhile there is only one meteorological station available in this region and as shown in Fig. 1, there are only 10 meteorological stations around the region. Therefore, in endemic regions for VL, it is sometimes necessary to know the temperature value for purposes of planning, and, air temperature surface can follow it.

Fig. 5 shows the frequency of VL disease in villages during 1998 - 2012 along with metrological data from the station of Kalaybar and Khoda-afarin districts. As show in Fig. 5, in this region, air temperature was measured only by this station with no expanding to other villages. After intersecting maps of temperature with VL incidence map, Pearson coefficient was calculated for the correlation between VL incidence and air temperature in 123 villages (Table 3). The VL incidence in endemic villages appeared to be significantly and positively correlated with the air temperature (P = 0.027) at the 95 % confidence interval.

Table (3): Correlation of incidence of Visceral Leishmaniasis (VL) with Temperature of 123 study villages in Kalaybar and Khoda-afarin districts

جدول شماره (۳): همبستگی بین بیماری VL با دمای هوا در ۱۲۳ آبادی در بخشهای کلیبر و خداآفرین

Environmental variable	Mean readings	Standard deviation of readings	Minimum readings	Maximum readings	Pearson’s coefficient of correlation with VL incidence	P value	N
Temperature	19.96279	0.330342	18.9	20.56	0.21*	0.027	123

*Significance level: 0.05

4- Discussion

The hot spot and spatial auto-correalation analysis of VL disease pattern was evaluated. Furtheremore, this study was designed on grounds of the lack of meteorological stations, requird knowledge of the effects of temperature on VL disease and achieving more accurate predicted temperature values in endemic areas. Temperature measurement in specific areas and also in the whole related region will be costly and time consuming. Therefore, using different methods of spatial interpolation can provide proper estimates of temperature values for specific locations. Accordingly, this research was addressed to assess methods and determine more precise and suitable approaches for estimating unknown temperature quantities and achieve the above objectives.

The hot spot and spatial auto-correlation analysis of VL disease determined by Getis-Ord Gi* statistic and global Moran's I. I found VL disease cluster pattern with the more intense the clustering of high values spatially, and also, the pattern of VL disease in this county is clustered significantly by 2.221723, 0.026302, and 0.062107 as the z-score, p-value, and Moran׳s index, respectively.

Considering the distribution of point samples (meteorological stations), spatial interpolation was used to produce a continuous surface. Temperature degrees were also determined everywhere in the produced continuous surface. Meanwhile, temperature value was only determined in meteorological stations as point values, which allows for estimating temperature values over the whole studied region by means of interpolation methods. Prior studies suggested that Kriging methods on data with normal distribution had better results (ESRI, 2023). Moreover, in recent researches, kriging methods in producing a continuous surface of climatic factors such as temperature, precipitation and humidity, were assessed to determine the appropriate method, even with the lack of strong spatial correlation of data (e.g, Njoku et al., 2023). On the other hand, considering that the study area was a mountainous region, accounting for the effects of elevation on estimating temperature in the surface is favourable. Also, the normal distribution of data in this study has shown that the kriging methods can achieve better results. Considering the low number of sample points in the region, the cokriging method was also applied. By evaluating errors obtained by the four methods, namely, Ordinary Kriging and Ordinary Cokriging methods were evaluated as appropriate procedures; 1.9958 and 1.9897 in MAE, 2.737 and 2.714 in RMSE and 13.83 and 13.72 in PE (%), respectively. As per the results, ordinary Cokriging with MAE=1.9897, RMSE=2.714 and

PE(%)=13.72 values was the more suitable option. The study indicates that in regions with low number of data, cokriging provides better results as opposed to kriging. The findings also indicate that for temperature interpolation, the results of kriging method may provide less accurate prediction values than that of the cokriging method. This research also concludes that in areas with low-sample points, despite the average amount of correlation between temperature and the station elevation (0.63), cokriging method produces relatively higher accuracies than other methods.

The findings allude to the fact that air temperature is the environmental variable dependently associated with the distribution and incidence of VL in Kalaybar and Khoda-afarin districts. The results of the present research are in line with the previous research (such as Li and Zheng, 2019, Gutiérrez et al., 2024, Subramanian et al., 2024) and confirm their results, so that the air temperature has a direct and positive role in the spread of VL disease. Hence, using continuos surfaces can predict potential areas of disease incidence, such that by knowing the effective temperature range on disease in each region of the world and its comparing with the continuous surface, disease prone areas can be predicted for prospective years. However, in preventing disease incidence, temperature cannot be controlled for its natural nature, but the incidence of disease can be decreased by preventive actions such as identifying and treatment of VL patients, controling vectors and animal parasite reservoirs, enhancing health and environmental improvement through health centers and institutions and in collaboration with other governmental institutions and cooperation with NGOs and public participation, proper disposal of wastes from residential area (Joafshany et al., 2005).

The relation between air temperature and VL incidence studied due to its critical role to the development of sand fly. Of course, the role of other climatic and geographical factors in VL disease should also be investigated in this study area. VL is a vector born parasitic disease in Iran, a zoonotic disease with a life cycle that targets female sand flies (vector), dogs (reservoir) and children (host) (Maruashvili and Bardzhade, 1966; Zakeri et al., 2004; Sabzevari et al., 2020). Humans are the host in this disease and are not vectors, but the density and age of the host, whether it is related to the distribution of VL or not, can also be investigated.

5-Conclusion

Visceral leishmaniasis caused by leishmania donovani, is a significant parasitic disease affecting large populations in the tropics (Zakeri et al., 2004). To decrease the overall death toll from this disease requires knowledge of how this disease behaves. VL disease is clustered significantly and hot spot patterns were found based on hot spot and auto-correlation analysis in this study. VL is a vector-borne disease highly influenced by environmental factors. One of the geographical factors affecting VL is air temperature. Often times, meteorological stations in target regions are scattered (i.e., just one meteorological station in kalaybar city). To know the rate of air temperature in endemic areas, field measurements are too time-consuming and expensive. So, it is suitable to use geostatistical methods in GIS for producing a surface representation (raster maps) of air temperature in all parts of a given region. Therefore, this study proceeded with the comparison of certain methods for producing continuous surfaces of air temperature via GIS and data from meteorological stations. This surface data can be used to estimate correlations between VL disease and air temperature in GIS in order to decrease VL. In the mentioned period of sandfly activity, in 30 out of 123 villages stricken by this disease were confronted by 19.8 – 20.47 °c and 6-26 people as air temperature and VL number, respectively. Also, it is interesting that VL incidence is correlated with air temperature as Pearson's coefficient of correlation and appeared positively significant.

Temperature can therefore be said to affect the disease vector in the metamorphosis period as well as their abundance, with further effects on the abundance reservoir by impacting vegetation and relative humidity. Accordingly, after predicting the air temperature in endemic areas as a surface, epidemiologists should focus on other villages with similar conditions to the involved disease-stricken villages in terms of air temperature. Of course, in the case of these villages, the probability of sand fly activities and VL incidence are higher than others, and so preventative activities seem to be necessary. VL incidence can be decreased by reducing the chance of sand fly bites via activities including the use of net curtains and mosquito nets installments in houses and wearing traditional covering clothes for children.

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تجزیه و تحلیل نقاط تمرکز بیماری لیشمانیوز احشایی و بررسی ارتباط آن با دمای هوا در GIS

چکیده

لیشمانیوز احشایی (VL) یک بیماری ناقل زئونوز است. چندین عامل خطر جغرافیایی بر بروز VL تأثیر می‌گذارند، از جمله دمای هوا، که برای توسعه پشه خاکی حیاتی است. تعداد کمی ایستگاه‌های هواشناسی پراکنده اقدام به ثبت دمای هوا می‌کنند و اندازه‌گیری‌های میدانی پرهزینه و زمان‌بر است، اگر چه ارزیابی دمای هوا برای فعالیت‌های پیشگیرانه برای اپیدمیولوژیست‌ها بسیار مهم است. دما را می‌توان با سطوح پیوسته استخراج شده از طریق سیستم اطلاعات جغرافیایی تعیین کرد. این سطوح با استفاده از روش‌های زمین‌آماری شامل کریجینگ/ کوکریجینگ معمولی، کریجینگ /کوکریجینگ سراسری در مناطق کلیبر و خداآفرین ایران تولید شد. با استفاده از آمار Getis-Ord Gi* و Moran's I جهانی، نقاط تمرکز یا داغ و تجزیه و تحلیل خود همبستگی مکانی بیماری VL تعیین شده است. با توجه به z-score و p-value به ترتیب ۲,۲۲ و ۰,۰۲۶، کمتر از ۵ درصد احتمال دارد که این الگوی خوشه‌ای بیماری می‌تواند نتیجه شانس تصادفی باشد. برآورد MAE=1.9897، RMSE=2.714 و PE=13.72 نشان داد که روش کوکریجینگ معمولی روش برتر در این مطالعه بوده است. بروز VL با دمای هوا از طریق ضریب همبستگی پیرسون ارتباط نزدیکی داشت. اپیدمیولوژیست ها باید مطالعات خود را بر روی سایر روستاهای مشابه روستاهای مبتلا به بیماری از نظر دمای هوا گسترش دهند. در این روستاها احتمال فعالیت پشه خاکی و بروز VL بیشتر از سایر روستاهاست، بنابراین انجام اقدامات پیشگیرانه ضروری به نظر می‌رسد.

کلمات کلیدی: لیشمانیوز احشایی، تجزیه و تحلیل نقاط تمرکز و خودهمبستگی مکانی، دمای هوا، زمین آمار، سیستم اطلاعات جغرافیایی.