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Research Paper

GIS Based Spatial Modeling to Mapping and Estimation Relative Risk of Different Diseases Using Inverse Distance Weighting (IDW) Interpolation Algorithm and Evidential Belief Function (EBF) (Case study: Minor Part of Kirkuk City, Iraq)

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Abstract

The health of the individual is one of the most important indicators of good living and quality of life for the community. Therefore, the contribution of developing of public health sector management and monitoring of diseases related to the cultural, economic, and social progress of any society. Moreover, the diseases occur from spatial factors where the distribution and concentration differ in diverse positions. Hence, GIS can be used as a decision support system in order to help the mangers, assess and monitoring of various types of diseases. Thus, this research aims to define a spatial distribution, prediction of risks and analysis of disease hazard areas in Kirkuk city, north east of Iraq using two models evidential belief function (EBF) and Inverse distance weighting (IDW). IDW determines the correlation between conditioning factors and disease occurrence. Consequently, EBF can be used to assess the effect of each class of conditioning factors on diseases occurrence. The result shows that Al-Wasity quarter reports the highest range of the patients who have the blood diseases (D89-D50) in 2017. Contrary, the northern parts of the city and some quarters in the center of the city (Tessen, Bagdad road, Al-Mansor) reflect the lowest range of the patients in blood diseases. Eye diseases (H59-H00) and its accessories have the same spatial distribution. The result also demonstrated that the GIS based spatial techniques is provided a prospect to simplify and measure the epidemic state of different diseases within specific areas(minor part of Kirkuk city), and lay a base to pursue future surveys into the environmental factors responsible for the augmented disease threat.

Keywords: *Spatial analysis; diseases analysis; evidential belief function, empirical Bayes approach.*

1. Introduction

Analysis of infectious diseases aids to recognize the source of the disease, its progress over time, the role of habitation and area in the development of the disease and the level of its spread(Wilkinson et al., 1997). Predicting the sequence and geographic spread of a disease is considering critical as the basis of the disease is which involves high mathematical modeling and empirical surveys of diseases infection(Bailey, 1975). Disease mapping presents a visual image of more difficult geographical data, which would support to create numerous hypotheses about different purposes such as etiology, detecting risk areas, and to help policy making and effectiveness of resources. They are also useful in classifying disease clusters of the precise group(Wilkinson et al., 1997). The importance of disease mapping can be seen in various applications such as cholera disease (Jayakumar and Malarvannan, 2013; Ali et al., 2006), the investigation of cancer(Zayeri et al., 2015), spreading study of HIV infection(Srinivasan and Venkatesan, 2014),temporal and spatial patterns of diarrheal disease (Emch and Ali, 2001; Jepsen et al., 2009; Kumar et al., 2017).

Spatial interpolation using IDW is presented to study of local disease of cholera and dysentery data collected in Bangladesh(Ali et al., 2006). Geographic extent Lyme disease in the United States was studied by performing spatial and spatiotemporal cluster analyses for characterizing Lyme disease development (Lantos et al., 2015). Spatial analysis is also used in field of diseases to analysis the Relative Risks resulted by skin cancer, the Baisan approach is applied in this studied and conclude that the rate of disease may vary with geographical situation and environmental conditions(Roche et al., 2015). Inverse distance weighting (IDW) is employed to examine and forecast the pattern of kala-azar disease in Vaishali region (India), which is reflected the spatial heterogeneity in the occurrence rate of this diseases in the city (Bhunia et al., 2013).

The spatial distribution of Epidemic Trends of Hepatitis E is applied in Zhejiang Province(china), spatial-temporal methods such as IDW were implemented to examine the epidemiological tendencies and detect high-risk districts of hepatitis E infection(Liu et al., 2016). Moreover, spatial analyses and geographic information system (GIS) techniques are influential tools to define epidemiological patterns, identify, describe and predict groups of diseases in any area and time(Tami et al., 2016). These techniques have been applied increasingly to detect prevention and control actions of different virus and to display the importance of public health (Tami et al., 2016; Ajaj et al., 2017; Shareef et al., 2014).

This study presents a disease risks assessment of minor part of Kirkuk city, Iraq by the combination of evidential belief function model and GIS models representing by IDW. For this goal, a detailed diseases dataset were prepared, and two conditioning factors were considered in a GIS environment. After the diseases maps prepared by evidential belief function model are validated, the area under the curve (AUC) method will be applied to find the area for the study area.

2. Materials And Methods

Methodology: Based on the interpolated maps, the spatial patterns were described of all related disease to perform the methodology including IDW. The produced interpolated maps were converted to raster's images (30 m resolution) and classified to represent the distribution of the number of patients in the study area. The obtained raster images are used to generate a map of the various diseases. Furthermore, we produced three maps to represent the effective weights of two main factors which are the population of each sector and distance from each health care center. The combination of these two effective weights maps was the disease risk potential prediction index map and it is clearly in figure 8. AHP was used to calculate the weights of population as well as distance from health care centers. Another method such as EBF model that depends on conditional factors representing by distance and population density is used here in this work. The EBF extracts the mass functions represented by Bel, Pls, Unc, and Dis.

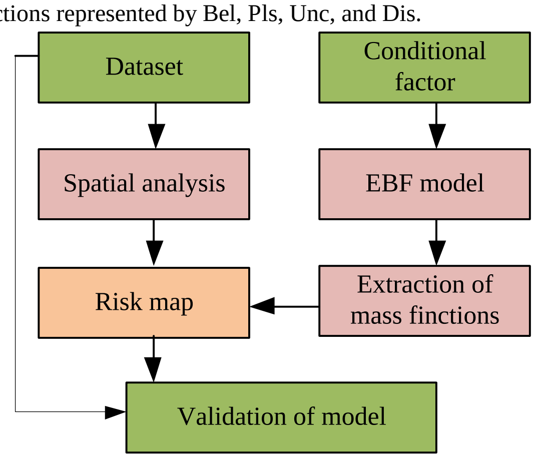


Fig. 1: General methodology adopted in the study

Study area: Kirkuk city or Kirkuk governorate is a city situated in the north of Iraq. It is located by Zagros mountains from the north and the Hamreen mountains in the south, the lower Zab from west and al-Sulaymania city in East at longitude 44˚00′E to 44˚50′ E and latitude 35˚13′ N to 36˚29′ N .The area of this city is about 9,679 Km2 or 2.2% of Iraq(AI-Taei and Nader, 2017). It is distance 250 kilometers (155 miles) approximately from Baghdad(Kane, 2010).The population was estimated in 2017 about 1,259,561 people. It is divided into four districts. In this study, we focus on the Kirkuk city center district which extends between 44° 24' 6.9552" E longitude and 35° 28' 42.8340" N latitude. On the other hand, Kirkuk discrete is also divided in to two parts: the major or grand part is situated from Al-Khasa River to the east boundary of the city. And the minor or small part is extending from Al-Khasa River to the west boundary of the city. Specifically, in this study we will deal with data that obtained to the minor part of Kirkuk city as shown in Fig.2.

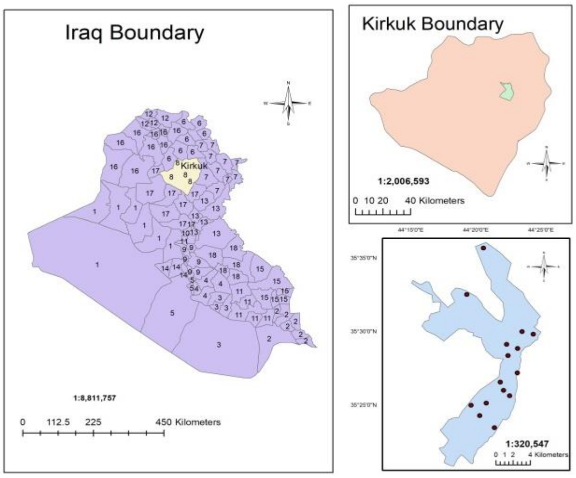


Fig. 2: Location of study area

Data description and disease occurrence characteristics: The disease data such as diseases names, number of disease, types of diseases, symbols of each disease, number of patients in each health center were obtained from health office of Kirkuk, Iraq. The data is including the monthly reports of residential quarter such as Al-Akhaa, Badir, Baglar, Sarchinar, Sikanian, Al-Salam, Arafa, Al-Mansour, Teseen, and Athar in a minor part of Kirkuk (see Fig.3). Moreover, the data provided contains monthly patient statistics tables for each sector and quarter, type of health organization if it was: outpatient or public clinic, consulting clinic, primary and secondary health care center, specialized center, health insurance clinic, popular clinic, and elderly clinic. The data used also included age groups and patient sex (male and female). Many diseases in the data base have been included sub diseases, some of these diseases had taken in the consideration due to frequently existence of patients to the health centers and others have not noticed, for this reason, in this paper, we focused on the diseases that have the number of patients and excluding diseases that have not been recorded patients.

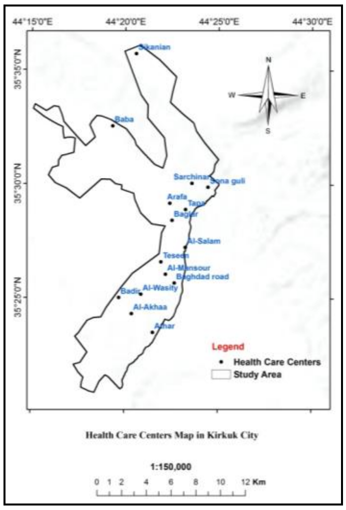
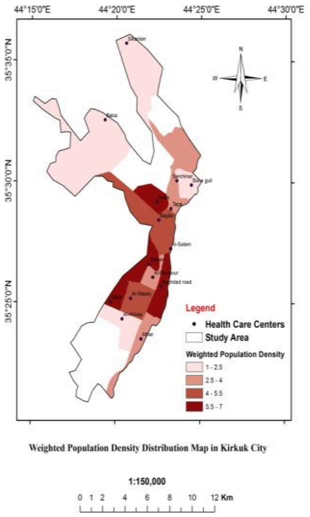


Fig. 3: The disease locations of the study area

Disease conditioning factors: In general, diseases are not limited to specific areas; it may include poor areas and rich areas of the city. Various reasons may control human parasitic diseases. rural and urban population growth areas without conforming enhancements in the public health infrastructure which leads to the augmented occurrence of vectors and pathogens (Meyer and Birbeck, 2007). Generally, the occurrence and movement of diseases in a given area are governed by various conditioning factors. many parasitic diseases affected by Environmental effects such as climate and agricultural practices (Liang et al., 2007). Disease conditioning factors are responsible for the occurrence of disease in the study area, which was collected from available resources. These factors are population density, distance, climatic condition. To create a disease potential map, the spatial database was considered to be a set of related spatial conditioning factors that influence disease occurrence. In this study, a total of two conditioning factors are used. Those conditioning factors in this study are: population density and distances (see Fig.4). The population and distance from health care centers were weighted according to the analytic hierarchy process (AHP).



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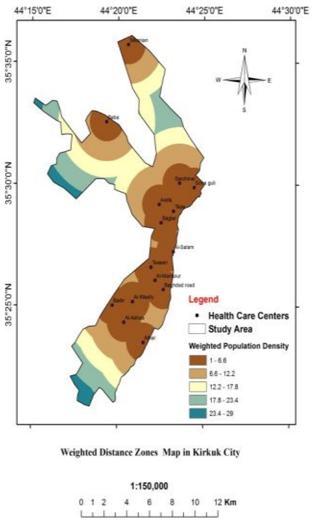


(b)

Fig. 4(a, b): The population and distance map of the minor part of Kirkuk city

Evidential belief function: The evidential belief function (EBF) is essentially derived from the Dempster–Shafer theory of evidence (DST) (Dempster, 1967; Shafer, 1976). The DST is mainly generated from a probability of Bayesian theory including lower and upper probabilities(Dempster, 2008).The upper and lower probabilities refer to the plausibility (Pls) and the belief (Bel) degrees, respectively. EBF also contains other components of probabilities representing by the degree of disbelief (Dis) and the degree of uncertainty (Unc) (Carranza and Hale, 2003; Althuwaynee et al., 2012), as illustrated in Fig.5. This method is derived from basic analysis of probability assignments or by using mass function (bpa or m) which describes a mapping of the power set to (0–1).

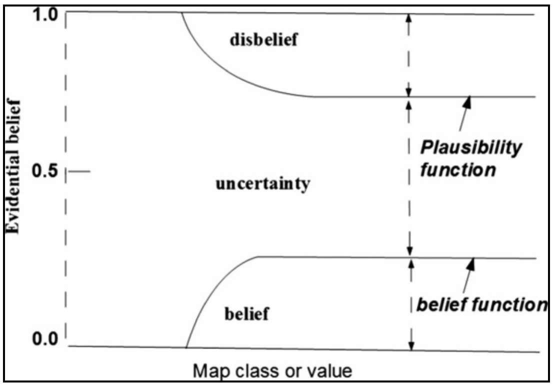


Fig.5 : Belief function components after modification by Bonham-Carter (Wright and Bonham-Carter, 1996) ; Carranza et al. (Carranza et al., 2005) and (Althuwaynee et al., 2012).

In this study, the mass functions are primarily obtained from likelihood ratio functions which can be determined using the following equations:

$$T_p = \frac{N(L \cap E_{ij})/N(L)}{N(E_{ij}) - N(L \cap E_{ij})/N(A) - N(L)} \tag{1}$$

Where $N(L \cap E_{ij})$ refers to the number of diseases occurred in E_{ij} ; $N(L)$ is a total number of the diseases in study area the ; $N(E_{ij})$ refers to the total number of pixels in the area of study. Thus, Bel function can be given as:

$$\mathrm{Bel} = \frac{(T_p)_{E_{ij}}}{\sum (T_p)_{E_{ij}}} \tag{2}$$

The opposite target proposition can be supported using the likelihood ratio as follows:

$$\overline{T_p} = \frac{N(L) - N(L \cap E_{ij})/N(L)}{\frac{N(A) - N(L) + N(E_{ij}) - N(L \cap E_{ij})}{N(A) - N(L)}} \tag{3}$$

For this consequent, the Dis can be calculated as

$$\mathrm{Bel} = \frac{(\overline{T_p})_{E_{ij}}}{\sum (\overline{T_p})_{E_{ij}}} \tag{4}$$

The uncertainty (Unc) can be calculated in Eq (5):

$$Unc = 1 - Dis - Bel \tag{5}$$

And also the plausibility (Pls) values area can obtain using Eq(6):

$$\mathrm{PLs} = 1 - \mathrm{Dis} \tag{6}$$

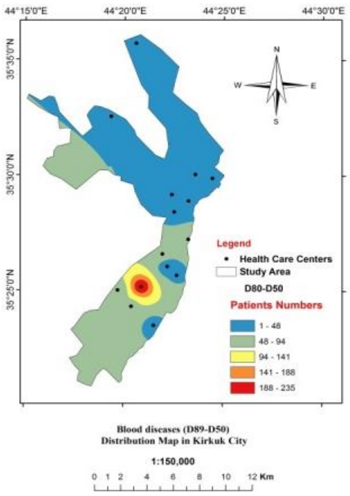
Inverse distance weighted: Inverse distance weighted (IDW) is conserved as one of the most common interpolation methods. It is used to predict the values for any unmeasured location, by measuring the surrounding values predicted location(Childs, 2004). It is primarily based on two assumptions: first, the influence of unknown value of a point is increased directly to the close control point than far points. Second, the influence degree point is directly proportional to the inverse of the distance between points. It can give the following equation(Bartier and Keller, 1996; Huang et al., 2011):

$$Z = \frac{\sum_{i=1}^{n} w_i Z_i}{w_i} = \frac{\sum_{i=1}^{n} Z_i / D_i^p}{1/D_i^p} \quad (7)$$

Where Z refers to the interpolated value of unknown point, $w_i$is the weighting function that control the significance of control point Z_i, and Z_i is the observed value at the control point i which represent the nearest neighborhood of produced interpolated point and it is ranging between 20 to 30. n is the nearest neighborhood of control points that is usually required time consummation. D_i^p refer to the distance between I and interpolated point, p is a weighting exponent which is an arbitrary positive real number, p is equal to 1 in inverse distance weighting (Guan and Wu, 2008).

3. Results And Discussion

Various map diseases of the patient's infections during 2017 in Kirkuk governorate were mapped (Fig.6), and the interpolation using IDW was achieved for the prediction of all the expansion of the diseases in the city. These maps interpret the number of the patients and the extended zone of the disease around the care center. Nine diseases were studied in the city depending on the care center distribution. According to the IDW, we classified the raster pattern of the Blood diseases to the five classes. These classes expose the spatial distribution of the disease relative to the care center, regardless of the population and environmental factors that may control the patient distribution. As an exploratory analysis, Al-Wasity quarter reports the highest range of the patients who have the blood diseases (D89-D50) in 2017. For this reason, blood diseases maps suggest that extreme the incidence of blood diseases cases was from a southern part of the city. The northern parts of the city and some quarters in the center of the city (Tessen, Bagdad road, Al-Mansor) reflect the lowest range of the patients in blood diseases. Eye diseases (H59-H00) and its accessories have the same spatial distribution, where the observed increase in patients is concentrated in southern areas of the city with some minor distributions to patients in the center and north of the city.



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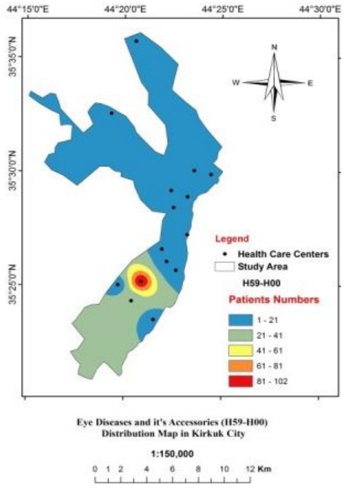

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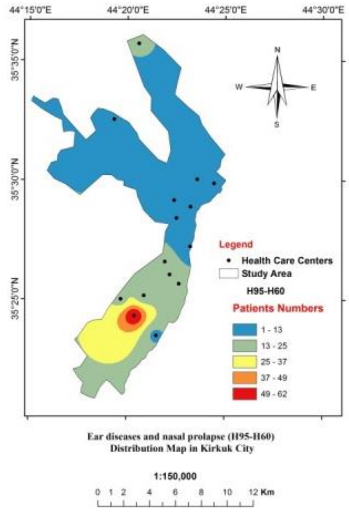

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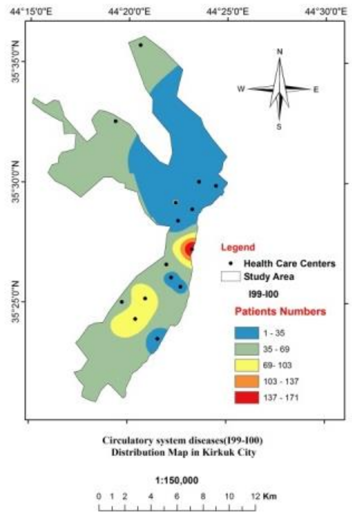

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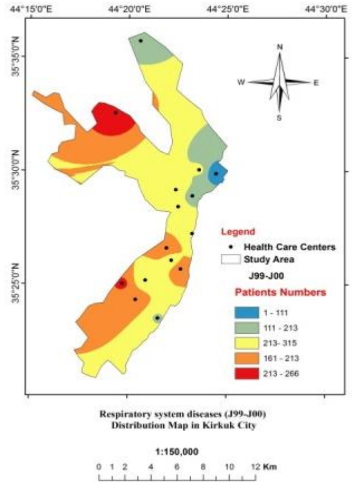

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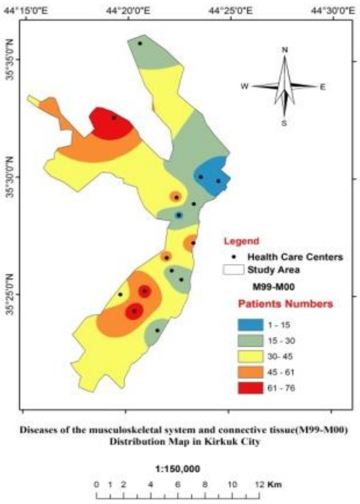

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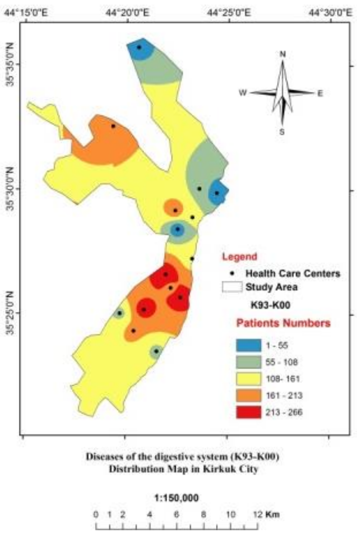

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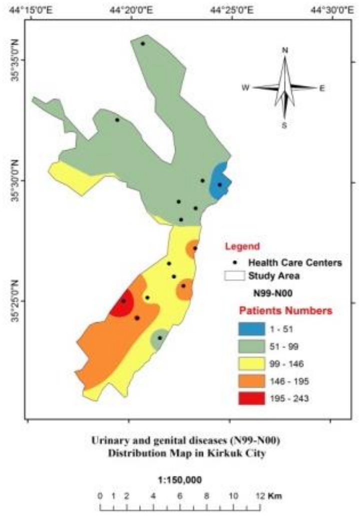

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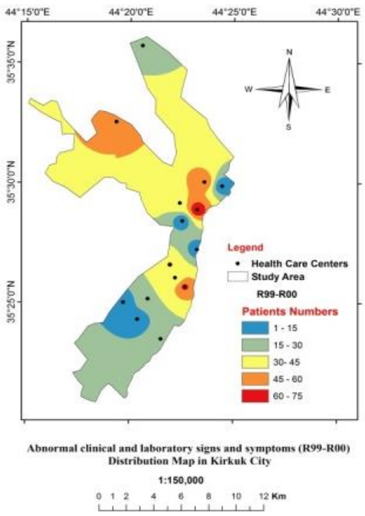


(i)

Fig. 6(a-i): Patient distribution using IDW

Thus, Al-Wasity quarter has also demonstrated the increasing in H59-H00. Ear disease displays a spatial distribution concentrated in Al-Akhaa quarter which is situated in the southern part and extend to the manufacturing part in the city. However, all red tones of the diseases represent the very high prevalence of disease appears in minor part of Kirkuk city, and other colors present the density of the patients founded in or near by the care center. Respiratory system diseases (J99-J00) presented different behavior of spatial distribution, the highest distribution of the diseases recorded in northwest areas, especially in Baba quarter which represents the highest number of patients. The moderate distribution observed in various parts in the northern to the south part of the city. Besides, comparable incidence rates were observed in the northwest area whereas low index rates in another area. Some diseases are fast moving among people including diseases and others are not. However, each disease is exposure a behaviors differ from another depending on the space factors, environmental factors, etc. the overall patients during one year (2017) of the care centers can be illustrated in Fig.6.

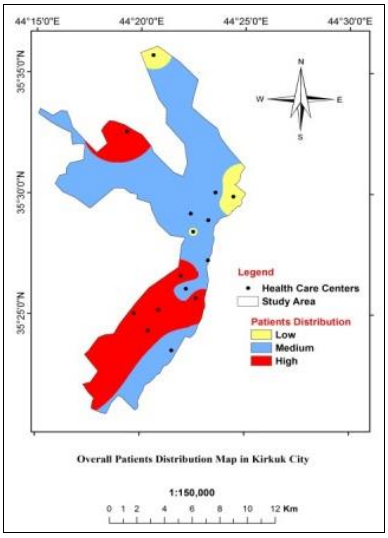


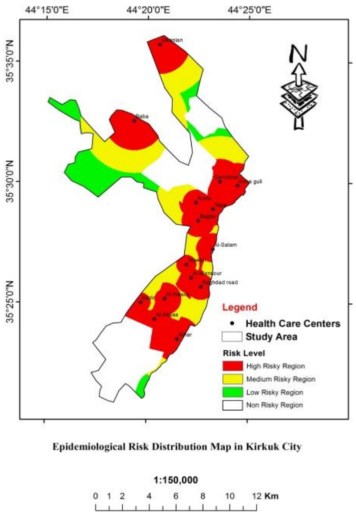
Fig. 7: Overall patient distribution using IDW

From the Fig.7, the number of the patients is classified into three classes. First class displays the maximum number of the patient happened in the care center which is noticed in several residential quarters, one in the area of Baba and the others in the southern quarters of the Kirkuk city. Moderate and low class occupied in the city center and northern part of the city.

Table 1 : Evidential belief function result

Factor	*classes*	*Count*	*Bel*	*Dis*	*Unc*
Population Density (per/Km^2)	4000	54212	0.208	0.208	0.755
	6000	4047	0.134	0.134	0.697
	5000	15940	0.139	0.139	0.775
	7000	4635	0.125	0.125	0.580
	8000	19550	0.133	0.133	0.762
	9000	10092	0.132	0.132	0.733
	10000	7932	0.129	0.129	0.699
Distance (m)	250	146491	0.015	0.015	-0.015
	500	193943	0.241	0.241	0.759
	750	204618	0.245	0.245	0.755
	1000	223921	0.251	0.251	0.749
	1250	213286	0.248	0.248	0.752

The lowest concentration of the patient observed in Sikanian and Sona Guli. The demonstrating results of EBF in Table 1 introduced the values of the four EBFs Such as belief, disbelief and uncertainty and plausibility indices. The values of these index range between 0 and 1. The values four mass functions were resulting during the spatial relationship among the Care health centers locations and conditioning factors. A reasonably high value of *Bel* indicates a higher probability of disease risk potential, while a low value indicates a lower probability of disease risk potential. The belief degree displays a higher value of diseases potential risk with close distances and high population density. Meanwhile, the *Bel* function is the best determined mass series function of all other index functions obtained, it was reflected as the index that powerfully demonstrates the presence of the potential diseases risks prospective zones in the area. Henceforth, the disease potential index was produced based on the belief function index as given in Fig.8.



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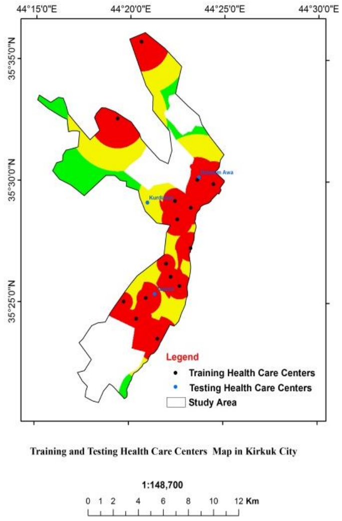

(b)

Fig. 8(a, b): Disease risk potential prediction index map

The reliability to create effectiveness and support the environmental decision, the assessment of produced spatial predictive model is considered highly important. The predictive model is compared with another group data not used in producing disease risk model. One group data was employed as a training data set to build a probable prediction index model map created and other group data is testing data which is used to compare with predicated diseases map. Kurdistan, Al-Taaesh, Raheem Awa health care centers consider as testing points to validate the interpolation process. This study exposes the spatial analysis characteristics of many kinds of disease in Kirkuk City (Iraq) using GIS spatial analyst method. Generally, this study presents a first attempt to perform GIS mapping to study the distribution of many types of disease patterns together.

Limitations: The limitations of this study were the absence of many information or variables. Information can be included variables of socio demographic and socio economic status which considers as lifestyle factors, toilet facility, the source of drinking water, and hygienic practices, environmental parameters such as temperature, types of the nutrition, were not available in hospital or care center records, registries, or other common sources of data.

4. Conclusions

This study examined the diseases spreading in spatial distribution pattern, in Kirkuk City. GIS based spatial techniques provided a prospect to simplify and measure the epidemic state of different diseases within specific areas, and lay a base to pursue future surveys into the environmental factors responsible for the augmented disease threat. Spatial distribution patterns and statistical analysis may present valuable information to sustain epidemiologist to monitor and predict disease spread over small and large areas. The methodology is depended on concepts on general principles of spatial distribution and statistics which may use the produced model to plot a strategy to monitoring and controlling diseases for various months or seasonally. Thus, in this paper, a GIS-based spatial modeling using interpolation IDW integrated with EBF model was performed to define the potential disease risk assessment in the Kirkuk City (Iraq). As a first step, employing many field surveys and database of health care centers yield to a descriptive map of data, which was divided the data into two data sets, training and testing data. Then, the contribution layers of two (2) conditioning factors (distance from each health care center and population density) were prepared. Secondly, the spatial interpolation IDW analysis layers and evidential mass of conditioning factors were also prepared. Validation results have established the strength and the effectiveness of the proposed method in the detection and prediction of diseases risk assessment potential in an area. The results obtained in this study might be suitable for associated agencies for comprehensive evaluation of diseases expansion and environmental controlling in the study area. Moreover, the proposed method permits not only the predictive mapping of satisfactory zones for different health care center, but also permits demonstrating of the degrees of uncertainty in the prediction which may be moveable to other regions with related distance and density characteristics.

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