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UDC [636.09:004.41]:303.722.4(045) **Research article**

Spatial analysis of rabies using ArcGIS Pro tools

Anar M. Kabzhanova, Sarsenbay K. Abdrakhmanov, Gulzhan N. Yessembekova, Temirlan G. Bakishev, Gulmira K. Murzakayeva, Zhanar S. Bakisheva

[1]Faculty of Veterinary and Livestock Technology,
S. Seifullin Kazakh Agrotechnical Research University, Astana, Kazakhstan

Corresponding author: Anar M. Kabzhanova: an_kab@bk.ru
Co-authors: (1: SA) s_abdrakhmanov@mail.ru; (2: GN) gulzhan_nk@mail.ru; (3: TB) bakishevt@mail.ru; (4: GM) m.gumika@list.ru; (5: ZB) bakiweva@mail.ru
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Abstract

Background and Aim. In line with the One Health concept, which recognizes the interconnectedness of human, animal, and ecosystem health, the global burden of rabies remains relevant given the current increase in zoonotic and vector-borne diseases. For successful rabies control, monitoring the changing patterns of infection spread is vital. This paper is devoted to the spatial analysis of the spread of rabies among animals in Kazakhstan.

Materials and Methods. The Spatial Autocorrelation (Moran's I) and Anselin Local Moran's I statistics of the Geoprocessing tool in ArcGIS Pro were used.

Results. Several types of spatial distribution were noted: clusters in the northeast, south, and west of the country; sparse type in the border areas of the north and northwest; and random distribution in the central and southwestern regions. High-Low Outliers indicating sporadic outbreaks of rabies caused by the migration of infected animals, as well as Low-High Outliers indicating the containment of the epizootic due to preventive measures or natural barriers were also revealed.

Conclusion. The study highlights the need to strengthen control over the spread of rabies, implement measures to prevent the migration of infected animals, and optimize vaccination and monitoring programs. The use of spatial analysis methods allows us to identify epidemiological patterns and develop effective strategies to combat the disease in regions with different risk levels.

Keywords: animal rabies; spatial analysis; clusters; geographic information system technology.

Introduction

Rabies is a major public health problem [1, 2, 3]. Despite significant progress in epidemiological surveillance and prevention, more than 55,000 people die from rabies every year worldwide, making it the deadliest zoonosis [4, 5]. In Kazakhstan, it remains a pressing veterinary and epidemiological problem, especially in rural and border regions. The main sources of infection are wild and stray animals, and the spread of the virus largely depends on natural [6, 7], climatic, and socioeconomic factors.

Modern methods of epidemiological monitoring, including spatial analysis using GIS technologies, make it possible to identify foci of infection, analyze patterns of spread, and develop effective preventive measures [6, 7].

Spatial analysis plays a key role in studying the spread of infectious diseases such as rabies, enabling the identification of patterns and clusters of disease incidence. As noted in the IMAJINE report: "Regional economic growth varies significantly across EU territories depending on local capacities, policies, and historical trajectories" (*Dax* et al., 2020, 15), ArcGIS Pro tools, including Spatial Autocorrelation (Global Moran's I) and Cluster and Outlier Analysis (Anselin Local Moran's I), are widely used to assess spatial autocorrelation and identify local clusters, respectively [8, 9].

Global Moran's I is used to measure overall spatial autocorrelation, determining whether the data are randomly distributed, clustered [10, 11, 12, 13], or dispersed. This tool calculates Moran's I, z-score, and p-value to assess the significance of spatial distribution [10, 11, 12, 13].

Anselin Local Moran's I identifies statistically significant hot spots, cold spots, and spatial outliers, providing detailed information at the individual site level [12, 13]. This method is useful for identifying areas with abnormally high or low disease rates.

The application of these methods in ArcGIS Pro allows researchers to effectively analyze spatial data on rabies, identify clusters of cases, and assess the influence of various factors on the spread of infection. The use of such tools contributes to a deeper understanding of epidemiological processes and the development of effective strategies for disease control and prevention [12, 13].

Materials and Methods

Spatial Autocorrelation (Moran's I). To perform Moran's, I index analysis in ArcGIS Pro, data from the rabies database for 2013-2023 converted into point data were used as the input, and the number of rabies cases was used as the identification attribute (Figure 1). The analysis generated a document with full identification characteristics and a corresponding diagram.

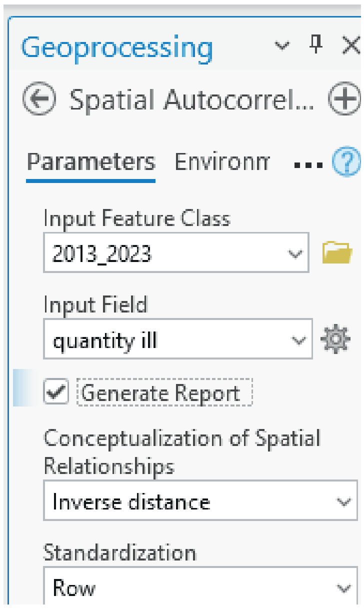

Figure 1 – Setting up the tool parameters: Spatial Autocorrelation (Moran's I)

Cluster and Outlier Analysis (Anselin Local Moran's I). This tool is used in geostatistics to identify [12, 13] spatial clusters and outliers. Anselin Local Moran's I can determine the presence of significant spatial patterns in the data, such as clusters of high or low values, and identify outliers that may indicate anomalies or interesting features [12, 13]. This method can help understand the spatial distribution of the data and identify areas that require further analysis or intervention.

In the context of spatial analysis with Anselin Local Moran's I [12, 13, 14, 15, 16], a High-High Cluster refers to an area where high values of a variable are surrounded by other high values [13, 14, 15]. This indicates positive spatial autocorrelation, where high values tend to cluster together. Similarly, a Low-Low Cluster refers to an area where low values of a variable are surrounded by other low values. This also indicates positive spatial autocorrelation, where low values tend to cluster together [13, 14, 15]. Such clusters may indicate areas of high and low activity or concentration of a particular phenomenon, respectively, that require further investigation.

In the same context, a High-Low Outlier refers to an area where a high value of a variable is surrounded by low values [13, 14, 15]. This indicates negative spatial autocorrelation, where the high value is an anomaly among the low values. Similarly, a Low-High Outlier refers to an area where a low value of a variable is surrounded by high values, indicating negative spatial autocorrelation wherein the low value is an anomaly [13, 14, 15]. Such outliers may indicate unusual or interesting features in the data that require further analysis.

Results and Discussion

Spatial Autocorrelation (Moran's I). The analysis of spatial autocorrelation using z-score (standardized critical value) and p-value (significance level) revealed the following spatial features:

High z-scores (>2.58, red zones) indicated the clustering of cases, probably [14, 15] related to sporadic outbreaks established among agricultural (western and northeastern regions) and domestic animals (southern regions), in which infection often does not go unnoticed [14, 15].

Low z-values (<2.58, blue zones) indicated a sparse distribution, reflecting the absence of coherent foci, possibly due to isolated cases of infection from migrating animals. This may correspond to rabies outbreaks in previously safe areas (northern regions).

Random distribution (yellow area) indicated the absence of clear patterns of viral transmission, reflected as sporadic outbreaks without obvious territorial references (central and northern regions). These data are shown in Figure 2.

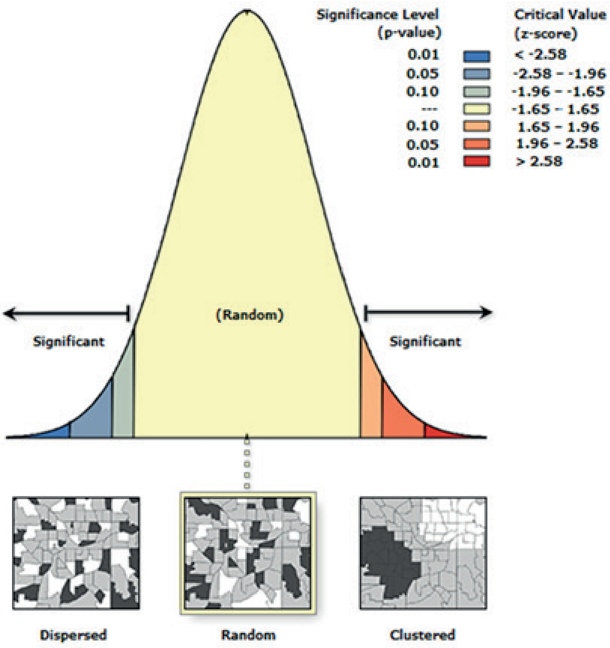

Figure 2 – Spatial correlation results (Moran's I index)

Cluster and Outlier Analysis (Anselin Local Moran's I). This analysis produced a map showing identified clusters and outliers of animal rabies cases (Figure 3).

High-High Clusters (pink dots) [13, 14, 15]. These clusters were identified in the western and northeastern regions, characterized by a high, established incidence of rabies "surrounded" by equally high values, indicating the presence of active natural foci of infection, wherein the virus is actively spread by wild animals among farm and domestic animals [13, 14, 15].

High-Low Outliers (bright red dots): These indicated areas where rabies was detected, surrounded by low values; that is [13, 14, 15], sporadic outbreaks of rabies were registered, brought into an area with overall low incidence.

Low-High Outliers (dark blue dots): These marked territories with a low number of infected animals, surrounded by areas with high infection, which may be due to the effectiveness of vaccination or the presence of natural barriers, such as mountains and rivers. These patterns were established in the territories of northeastern Kazakhstan.

Low-Low Clusters (blue dots): These territories were characterized by low incidence, surrounded by the same low values, which may indicate a controlled epizootic situation, a low population of infected animals, or the effectiveness of veterinary measures. These clusters occurred in southern Kazakhstan, where urban rabies is widespread, stemming from domestic animals. Regarding vaccination effectiveness, it is worth noting that here, domestic animals (cats and dogs) had the highest rates of rabies vaccination, which indicates a significant containment of the spread of rabies [14, 15]; nevertheless, gaps remain.

Not Significant (grey dots): In these territories, statistically significant spatial dependence was not established. These values indicated the predominant territory of the country.

No Neighbors (black dots): For these areas, the available information was insufficient to determine the corresponding characteristics.

Moran's scatterplot (analysis of spatial dependence) plots the relationship between the number of diseased animals and their spatial distribution, with more points located at the extremes of the plot indicating higher levels of clustering or outliers. $R^2=0$ indicates that the data may have low global spatial dependence, but local clusters are present.

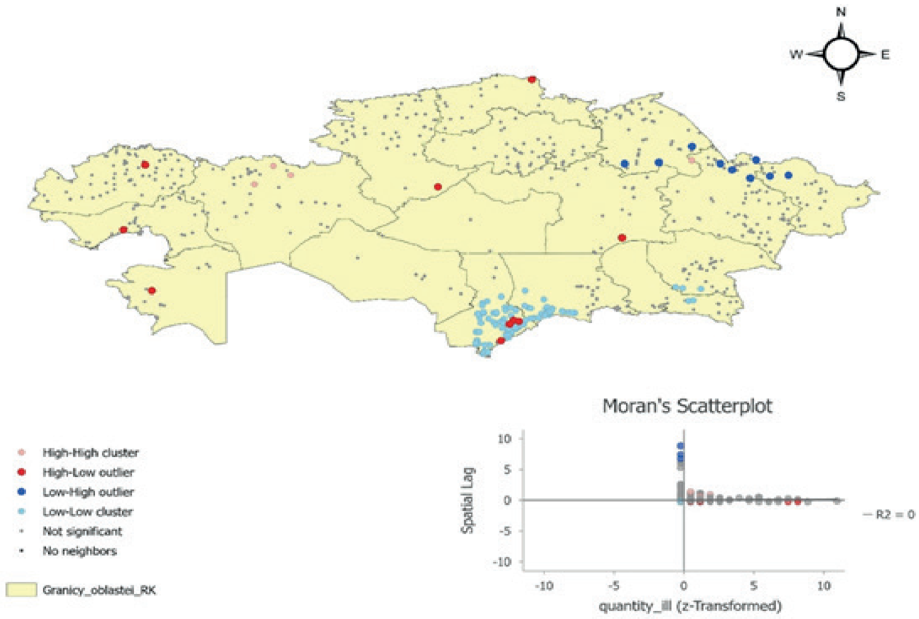

Figure 3 – Cluster and outlier analysis of animal rabies

Spatial autocorrelation (Moran's index 1) showed the following distributions of rabies cases in Kazakhstan:

- Cluster distribution: Foci in the northeast, west (among farm animals), and south of the country (among domestic animals), where infection spread probably occurred through companion animals (south) and wild animals (south, west, and northeast);
- Sparse distribution: Isolated cases of rabies in the border areas of the north and northwestern parts of the country;
- Random distribution: This included cases where the source of infection was migratory animals (central and southwestern regions), while a random, mutually unrelated distribution may have been due to the inaccuracy of epizootological characteristics given scant information about rabies among wild animals; this represents a significant barrier to the creation of an effective system of anti-epizootic measures.

For cluster-based cases, increased control, vaccination, and monitoring measures are needed in high-risk areas. In case of sparse distribution, it is important to monitor animal migration and prevent the introduction of infection into new regions. In cases of random distribution, studies of additional factors (e.g., climate, ecology, and contact with people) are needed.

The spatial analysis method (Anselin Local Moran's I) [12] along with rabies clusters revealed High-Low Outliers in the territories of the Mangystau, Atyrau, West Kazakhstan, Kostanay, North Kazakhstan, Karaganda, and Turkestan oblasts. These can be perceived as sporadic outbreaks of rabies in areas with low or no incidence as a result of accidental contact with infected migrating animals. One such example is the registered sporadic outbreak in the Mangystau oblast in the form of 18 foci with 19 rabies-infected animals (16 agricultural [camels], 1 domestic, and 2 wild animals) in 11 settlements (villages) from February 14 to March 20, 2018, where the infection source comprised wild fauna (wolves). Subsequently, the infection spread to the territory of the Atyrau region, with 7 outbreaks from March to September, also through a wild animal.

In areas with high disease incidence, Low-High Outliers were established [13], perceived as contained epizootics due to effective preventive measures or the presence of relief features like high mountains or mountain slopes, which impede animal movement.

Conclusion

Modern global trends in the study of problems related to animal and human morbidity are increasingly represented by a system of scientific analysis involving popular approaches such as the use of Big Data, ICT methods, AI, GIS, and other digital technologies; the growing popularity of online databases and the addition of research results to accessible online resources and libraries; the development of modern methods and platforms for widespread use; and the continuity of relevant research worldwide. This is evidenced by a significant increase in scientific publications and conferences in the field of veterinary medicine, frequent studies using molecular genetic methods to determine the genetic characteristics of pathogens, the active use of geospatial analysis methods with subsequent mathematical modeling, and forecasting disease outbreaks and foci. Along with increasing disease spread, the growth of these applications has been facilitated via active promotion by global organizations (e.g., FAO, WHO, OIE) of the One Health concept, which is based on the principle of close interconnection between the health of people, animals, and ecosystems.

The fundamental basis was a verified, reliable rabies database with complete information for the last 10-year period (2013-2023), with 942 rabies outbreaks and 1,243 infected heads among more than 10 animal species ranging from rats to deer. Outbreaks in 584 settlements reflected territorial characteristics, with the most unfavorable zones at various levels as follows: rural: Kokzhyra (Abay region), urban: Semey, district: Urzhar (East Kazakhstan oblast), and oblast: East Kazakhstan (181 outbreaks). The abovementioned unfavorable situation in the eastern part of the country, as well as in the southern, western, and northeastern parts, was expressed by clusters derived from spatial analysis using ArcGIS Pro, indicating a tense epizootic situation via comprehensive analysis along with other conditions.

Spatial autocorrelation analysis using Moran's I index and the Anselin Local Moran's I method allowed the identification of features of rabies distribution among animals in Kazakhstan. The epizootic process was found to have a clustering nature in several regions (northeast, west, and south), requiring the strengthening of preventive measures, including vaccination and monitoring. The sparse distribution in the border areas of the northern and northwestern parts of the country indicates the need to control animal migration to prevent the introduction of infection.

The random spread of rabies cases in the central and southwestern regions may be due to both the migration of wild animals and insufficient epizootological information, which emphasizes the importance of additional research and improved monitoring systems.

The identified High-Low Outliers in certain areas indicate sporadic outbreaks of rabies caused by accidental contact with infected migrating animals. Low-High Outliers in areas with high incidence may indicate the effectiveness of preventive measures or natural barriers limiting the spread of infection.

These results highlight the need for a comprehensive approach to combat rabies in Kazakhstan, including veterinary surveillance strengthening, animal migration control, regular vaccination, and further application of spatial analysis methods to optimize anti-epizootic measures.

Authors' Contributions

AK, BT: Conducted laboratory research and wrote the first draft of the manuscript. SA: Developed the aims, objectives, and methodology of the work; GM and ZB: prepared the article per the publication requirements. EG: Performed statistical analysis and reviewed the manuscript. All authors read, reviewed, and approved the final version of the manuscript.

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Conflicts of Interest
The authors declare no conflicts of interest.

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