



ArcGIS as a Tool for Developing Spatial DSS in the Context of Human Infection Disease Prevention: A Survey

Husam H. Abdulmughni^{1,2}, Ali A. AL-Bakhrani^{3,4}, Ratnadeep R. Deshmukh², Ramesh R. Manza²

¹Department of Information Technology, Faculty of computer and IT, Sana'a University, Sana'a, Yemen.

²Department of Computer Science and Information Technology, Dr. Babasaheb Ambedkar Marathwada University, Chhatrapati Sambhaji Nagar, India.

³Department of Computer Science, Technique Leaders College, Sana'a, Yemen.

⁴Faculty of Administrative and Computer Sciences, University of Albaydha, Albaydha, Yemen

ABSTRACT: Recently, various sorts of infections are spreading among humans and then, it was changed into a disease. It will be easier to prevent and get treatment for the infected disease if it is diagnosed initially like how much percentage is affected, and this could be done by employing the Spatial Decision Support System (SDSS). SDSS, which had been prolonged to offer knowledge workers with Decision-Making (DM) tools and support the data, is typically a Geographic Information System (GIS). DSS concept is grounded on Dialog, Data, and Model (DDM), and among these '3' capabilities, a well-design SDSS should have balance. The development of specific SDSS is facilitated by the DSS tools that could further be deployed for developing a variety of specific SDSS. Thus, human infection diseases, SDSS, SDSS for preventing human infection using ArcGIS, and the application of SDSS in other fields using Aeronautical Reconnaissance (ArcGIS) with its different models had been explained in this paper.

Keywords: Spatial decision support system, ArcGIS, Decision support system, Human infection, Diseases

1. INTRODUCTION

Usually, the average population density is 61 people per Km²; however, there are huge differences across nations (Nichols et al., 2022). The population density doesn't detect the ease with which infection spreads via a population. While the population raises to cause overcrowding, issues tend to arise initially. Several infections cause diseases in humans (Bhadra et al., 2021). Particularly, the infection doesn't cause disease. While viruses, bacteria, or else other microbes arrive in the body along with begin to grow, infections take



place. Usually, the disease occurs in a minor amount of infected people; also, while the cells are smashed due to infection, signs and symptoms of an illness appear (Sicking et al., 2021). In health care and community settings, for mitigating and controlling Infectious Disease (ID) risks of transmission, the implementation of suitable Infection Prevention and Control (IPC) measures are required (world health organization, 2022). A practical evidence-centric system that prevents patients and health workers as of being harmed by avoidable infection due to antimicrobial resistance is termed IPC. It is significant for making sure that human behavior concerning infection prevention is elucidated with diverse ID systems specifying the significance of person-to-person transmission in ID spread(Weston et al., 2018). As per epidemiological measures along with specific knowledge concerning a disease, SDSS could site out regions by precedence level in a geographical region for securing epidemiological outbreaks in human infection prevention. The SDSS centered on the epidemiological aspects is elucidated in figure 1 (De Lima et al., 2019).

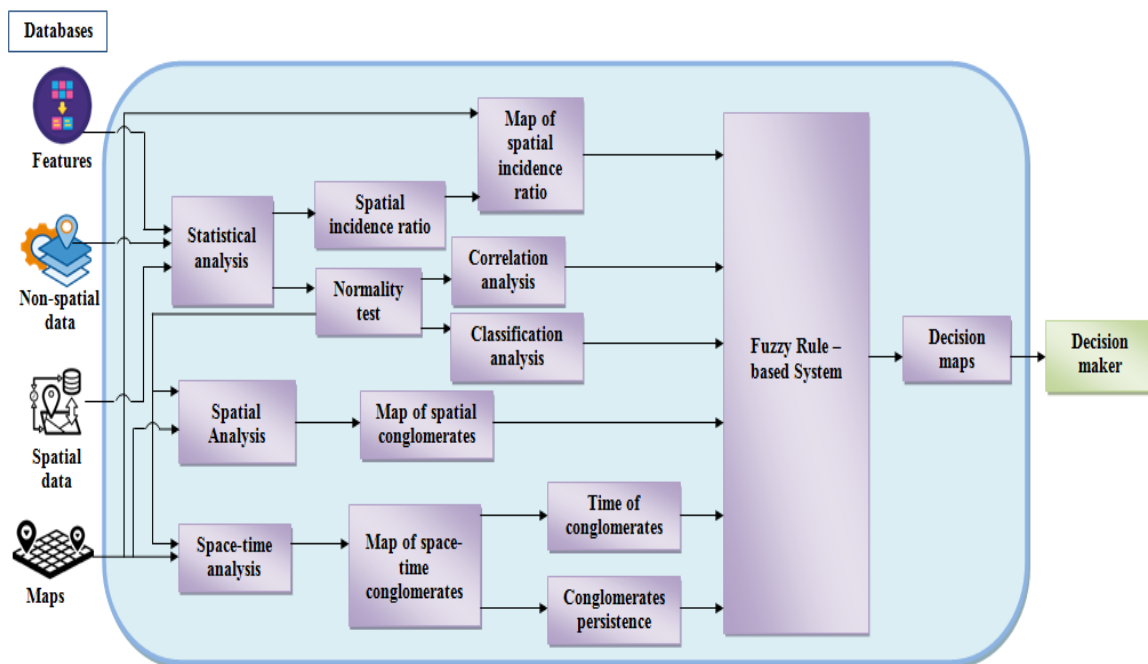


Figure 1. SDSS based on the epidemiological aspects

An interactive, computer-centric model built for assisting in DM when resolving a semi-structured spatial issue is termed an SDSS. To integrate analytical modeling abilities along with database facilities, SDSS offers a system for enhancing decision-making. To assist in detecting effectual decision paths, decisions might be employed (Governors, 2017). In specific domains, for computing the problem solution characteristics, SDSSs fuse (A) spatial as well as non-spatial data, (B) GIS evaluation and visualization operations, together with(C) decision systems. In human infection disease prevention, the SDSS is wielded. The spatial system also includes(Onari et al., 2022):



- ✓ Field investigations
- ✓ Data collection
- ✓ Transmission and analysis in real-time
- ✓ Epidemiological detection
- ✓ Customizing questionnaires
- ✓ Querying professional knowledge

For making decisions and policy recommendations, (A) healthcare officials with the data, (B) analytics, (C) information, (D) modeling capacity, together with (D) visual tools could be equipped with spatial decision support tools for enhancing public health outcomes (Imig et al., 2022). By using the software named “ArcGIS” (Aeronautical Reconnaissance), SDSS had been implemented (Aldrich, 2022). However, just the 1st 10,000 outcomes could be paginated; more than 10,000 outcomes can't be returned via pagination, which is the issue in SDSS for human infection prevention using ArcGIS. The originally returned outcomes might be more than 10,000 (Duclos et al., 2021).

The remaining part is arranged as: the survey on the SDSS in human infection prevention using ArcGIS is elucidated in section 2; the analysis is delineated in section 3; the paper is wound up with the future work in section 4.

2. Literature Review

Securing patients and healthcare personnel from attaining preventable infections in healthcare is the objective of IPC. With the development of life-threatening infections, effectual infection control practices for healthcare-related infections were even more serious. Using ArcGIS software; SDSS utilized for human infection prevention identifies the spots by the different regions at the geographical level and also helps to prevent outbreaks of infection. Here, human IDs are elucidated in section 2.1; the SDSS are described in section 2.2; the SDSS for preventing human infection diseases using ArcGIS are delineated in section 2.3; the application of SDSS in other fields using ArcGIS are explored in 2.4; the outcomes along with discussion are delineated in section 3.

2.1. HUMAN INFECTION DISEASES

A disease initiated by a pathogen or else its toxic product that emerges via transmission as of an infected person or else a filthy inanimate object to a liable host is termed infection disease (Rohr et al., 2019). Globally, in humans, they are the foremost reason of death, especially in lower-income nations and also in young children (Wiersinga et al., 2020). Recently, deaths as of IDs like Human immune deficiency virus (HIV) and tuberculosis have dropped considerably; in addition, they no longer seem on the list of top



‘10’ causes of death (Murray et al., 2022). The list of contagious diseases with their results and case fatality rate is elucidated in table 1.

Table 1. List of contagious diseases with their results and case fatality rate (CFR)

AUTHOR NAME	DISEASES	RESULTS	CFR(%)
(Baleanu et al., 2022)	Cholera	As per the outcomes, when analogized to other prevailing and fractional systems, the kernel along with $q=0.98$ were closer to the actual data; in addition, it was chosen for describing the vaccination effect on cholera.	$\approx[2-3]\%$
(Olson et al., 2022)	Influenza	63% (95% confidence interval [CI] was the efficacy against critical influenza. 75% (95% CI, 49% to 88%) was the efficacy beside life-threatening influenza vs 57% (95% CI, 24% to 76%) in contrast to non-life-threatening influenza.	$< 0.1-0.5\%$
(Mohanty et al., 2020)	Bird flu	As per the evaluation, for ring vaccination as of 16813 to 8722400, the outbreak’s calculated period as of 127 days to ‘eight’ years together with the number of vaccine doses were required.	56%
(Mastrangelo et al., 2022)	HIV / AIDS	In a few hyperendemic regions, outcomes were equal; in addition, severe paracoccidioido-mycosis (PCM) agrees to up to 26% of PCM cases.	90%
(Thornhill et al., 2022)	Monkey pox	Persons with infection were bisexual men(98%), White (75%), along with human immunodeficiency virus infection (41%); the median age was 38 years	less than 1 to 3%
(Moonsamy et al., 2022)	Hepatitis B (HBV)	As per the outcomes, from 2015 to 2019, HBV infection’s national prevalence rate per 100,000 population augmented from 56.14 to 67.76.	The death rate was 0.43% as of 2021
(Han & Yang, 2020)	Coronavirus Infection Disease	As per the evaluation, infected cases were available in 26 countries, particularly in Japan, and had a	0.5-1%



	(COVID-19)	maximal of 705 cases (from February nineteen).	
(Medhat & Aljanabay, 2022)	Typhoid fever	Analysis showed that there was a high incidence of typhoid fever in quarters three and two, which recorded 96 (30.8%) and 95 (30.5%) cases	[10–20]%
(Callaway et al., 2022)	Rabies virus	In the pre-fusion conformation, enhanced rabies vaccines centered on RABV-G depicted augmented stabilized outcomes.	100%

(Siribhadra et al., 2022)described antimicrobial stewardship in tropical IDs aimed at dengue along with malaria. For limiting the antibiotic prescriptions for dengue and malaria, Rapid Diagnostic Tests (RDTs) were presented. As per the outcomes, evidence of bacterial infection was not depicted in malaria patients (42%) who were treated with antibiotics; while, >10% of patients didn't receive them. 40% and 80% were the range of blood culture sensitivity for Salmonella spp. Also, it wasn't possible for attaining acute and convalescent sera in dengue or rickettsiosis; thus, the diagnosis might be delayed.

(Doyle et al., 2022)explained potently neutralizing along with defensive human monoclonal antibody isolation aiming at the Yellow Fever Virus (YFV). For screening for YFV-reactive antibodies veiled by transformed memory B cells, Peripheral Blood Mononuclear Cells (PBMCs) as of '4' subjects who established YFV vaccine formerly (differing as of months to years previous), were distorted in vitro with Epstein-Barr virus (EBV). As per the evaluation, in YFV infection and liver disease's susceptible hFRG mouse system, YFV-136 therapy provided at eight h post-infection was extremely defensive.

(Mamata Panigrahi et al., 2021)elucidated that miR-122 impacts Hepatitis C Virus (HCV) infections' initiation and maintenance. Analogizing transient along with stable miR-122-dependent vs. miR-122- independent HCV replication for detecting HCV genetic elements, which modulate HCVs addiction on miR-122 along with recognizing miR-122 roles in diverse HCV life cycle stages was the goal. As per the outcomes, since anti-miR-122 LNA usage in infected patients minimized HCV levels to untraceable levels, it has exhibited propitious outcomes as a therapeutic agent.

2.2. SDSS

A Decision Support System (DSS) where the data's spatial dimension is the basis for the decision evaluation is termed an SDSS (Brandt et al., 2022). The SDSS has a similar nature like the usual DSS; however, just pays extra consideration to spatial data and spatial issue acquisition along with resolution (Marques et al., 2021). Since augmented decision modeling is acquired by the relevant external data inclusion, data as of the exterior group



plays a significant role by employing the DSS in SDSS applications when weighed against prevailing DSSs (Keenan & Jankowski, 2019)(Indexed et al., 2018).

(Ghabour et al., 2019)elucidated theSDSS for Land Use (LU) management of freshly domesticated areas in arid regions. This system, which encompasses the land capability and suitability systems, was grounded on the ArcGIS environment database. As per the implemented SDSS, the deployed agricultural along with fish farming land might be augmented as of 48% to 71% of the entire area in which 60%, 11%, and 29% might be dedicated to field crop cultivation, deployed as a permanent fish farms, and given to residential along with industrial purposes or else any other recreational usage.

(Moghadam et al., 2018)explained the freshly incorporated SDSS in the urban context. Tackling the problems by implementing the incorporation of (A) Building Simulation (BS), (B) Multi-Criteria Analysis (MCA), together with(C) GIS to enhance SDSS in the urban context was the goal. As per the evaluation, every data were not entered; also, systems interoperability was essential; thus, the data might be communicated as of upstream systems and for downstream use.

(Fayoumi, 2018)analyzed the efficacy and SDSS with its findings and comparison. The extension of the prevailing DSS was exhibited in a more structured manner. For each measurement and criterion, this system aids the supportive component. As per the findings, each decision made was grounded on the gathered data, evaluated by SDSS tools, as well as relies on the presented systems.

(Idrees et al., 2018)implemented spatial intelligence for DSSs. As the details were associated with a special representation like longitude along with latitude, evaluating the spatial data was comprehensive. As per the evaluation, with 85% accuracy, this model got prospered to detect the disease distribution in 2015; in addition, elucidates that the distribution in 2014 attained fourteen% (entire death rate), along with fifteen% in 2015 was a growth of 1%, which leaves an error rate with the projected 15%.

(Rodela et al., 2017)examined knowledge integration along with learning with SDSS's social side. By employing 36 scientific paper samples regarding SDSS concerning conservational problems, the evaluation was done. As per the outcomes, the outcomes were not effectual as expected. Finally, for deploying the SDSS, the potential user required the required GIS expertise along with resources.

2.3. SDSS FOR PREVENTING HUMAN INFECTION USING ArcGIS

A novel field presented grounded on GIS and DSS is termed SDSS. In the future, SDSS will be a significant component of DSS applications. To control human IDs, SDSS is necessary by employing the software ArcGIS (Naguib et al., 2021). The SDSS studies for preventing the list of human IDs using ArcGIS are elucidated in table 2.



Table 2. SDSS studies for preventing the list of human IDs using ArcGIS in different locations

AUTHOR NAME	DISEASES	LOCATION	FINDINGS
(José et al., 2022)	COVID-19	Pernambuco, Brazil	As per the outcomes, famous along with higher-density areas were related to enhanced transmission rates; in addition, taking several attributes, which must assist in guiding DM associated with actions against COVID-19 was the implemented system's merit.
(Lessler et al., 2018)	Cholera	Sub-Saharan Africa	Per year, 141 918 mean cholera cases (95% credible interval [CrI] 141 538–146 505) were found. High cholera incidence was depicted in 4.0% (95% CrI 1.7–16.8) of districts, home to 87.2 million people (95% CrI 60.3 million–118.9 million).
(García et al., 2022)	Malaria	Bioko Island	As per the findings, the indoor residual spraying on Bioko efficacy was augmented by the fresh system for data collection and processing implemented by Campaign Information Management System.
(Moganoid et al., 2022)	Human rabies	South Africa	While the disease clusters were related to either several virus strains or else animal species, the Reproductive number (R_t) was high.
(Stopka et al., 2017)	HCV	United States (US)	HCV hotspots were independently along with negatively related to population percentage, which were high school graduates or else higher (adjusted odds ratio: 0.91; 95% CI: 0.89, 0.93)
(Al Manir et al., 2018)	Malaria	US	As per the evaluation, the access degree implements tedious queries required by the user community with minimal technical skill.



(Rezaei et al., 2020)	COVID-19	China	As per the evaluation, at the time of the epidemic or pandemic, ArcGIS maps might not be apt to control infection spread; also, other systems were essential.
(Pinto et al., 2021)	Hepatitis B virus (HBV)	Brazil	As per the outcomes, enhancing epidemiological data's data quality along with completeness was essential, which minimizes eventual errors that could make prevention together with control systems challenging.
(Ravinder et al., 2020)	COVID-19	United States of America (USA)	As per the evaluation, a considerably wider distribution ranging from ~2–14 and ~4–12 was depicted by the R_t values.

(Dong et al., 2017) described the Spatio-temporal pattern evaluation for appraisal of human infection spread with avian influenza A (H7N9) virus in China, 2013–2014. This approach identified 3 different epidemic phases of A (H7N9) human infection. In all phases, for analyzing disease spreading directional trend, standard deviational ellipse analysis was done; then, retrospective space-time permutation scan statistic was utilized. Analysis showed that in the first two phases, A H7N9 were clustering in space along with time with '5' important Spatio-temporal clusters ($p < 0.005$), yet in phase '3', there was no considerable cluster detected.

(Aturinde et al., 2019) explained HIV-TB co-clustering spatial analysis in Uganda. Tuberculosis along with HIV case data acquired as of the District Health Information Software 2 system, which is housed along with sustained by the Ministry of Health, Uganda, for the years 2015, 2016, and 2017 were used. Analysis indicated that across Uganda, relatively different spatial clustering patterns were exhibited by tuberculosis and HIV diseases while they were highly correlated (55-76%). Consistent hotspot clusters in districts nearby Lake Victoria along with northern Uganda were shown by the joint TB/HIV prevalence.

(Gwitira et al., 2020) described malaria cases' spatial along with Spatio-temporal in Zimbabwe. In passive malaria data collected from health facilities, GIS along with spatial scan statistics were applied as well as to detect the existence of spatial clusters, it is aggregated at the district level. Analysis showed that in malaria cases in the study area, there was a significant positive spatial autocorrelation. In addition, it had been found that as shown by the evidence of statistically important ($P < 0.05$) spatial along with space-time clusters of malaria in different geographic regions, malaria exhibited spatial heterogeneity.



Summary: SDSS, which offers clinical knowledge and information to physicians, nurses, and residents, as well as other people engaged in the care, is planned to collect, store, process, and examine data. At the point of care, for enhancing health along with healthcare delivery, information is intelligently provided. If the infection condition of humans is diagnosed early, human lives can be saved. Fundamentally, IDs were spread due to the crowd in the location. The implementation of automated tools was designed for promoting optimal DMlike SDSS. The information related to ID had been analyzed centered on the map in the location using SDSS. But for review, there are very few researches related to SDSS aimed at human infections as well as it is onerous for further discussion. On account of this reason, the common application of SDSS with its model has been discussed in the upcoming sections to identify the drawbacks and advantages. It will be helpful for future researchers for recognizing the drawbacks while concentrating on human infection research by identifying these advantages.

2.4. APPLICATION OF SDSS IN OTHER FIELDS USING ArcGIS

In several fields like credit (A) loan verification, (B) medical diagnosis, (C) business management, together with (D) analyzing bids on engineering, agricultural, or else rail projects, SDSS could be deployed other than human infection prevention (Sailaja et al., 2019). To deal with unstructured decision problems, a user-centered approach was offered by SDSS by incorporating predictive along with prescriptive systems with evaluation functions for assessing option quality (Jana et al., 2021). The application of SDSS in different fields using ArcGIS with its results achieved and disadvantages are elucidated in table 3.

Table 3. Application of SDSS in different fields using ArcGIS with its results achieved and disadvantages

AUTHOR NAME	FIELDS	FINDINGS	DISADVANTAGES
(Srisawat et al., 2017)	Transport	As per the evaluation, for transport logistics infrastructure development, Chiang Rai province (Northern region's Northeast part) includes the most potential efficacy.	A spatial DMtool entrenched in an ArcGIS with highly complex spatial data
(Y. Wang et al., 2017)	Urban Watershed	As per the outcomes, most sediments were engendered in a small area regarding small hotspots-coverage area; in addition, in the Watts Branch watershed, 80% of Hydrologic Response Units simulated less than 7 tons/ha of sediments per annum.	Information provided by the SDSS was clear, but some of the residents were not able to understand the properties



(Aghaloo & Chiu, 2020)	Agriculture	The Best-Worst Method (BWM) offered precise and stable outcomes with less uncertainty as per multiple criteria DM. The sensitivity outcomes of BWM + Fuzzy were superior in site-selecting techniques.	Sometimes, the method shows inaccuracy results that affect the performance
(Habibie et al., 2021)	Land	As per the evaluation, for the highly suitable areas, yield estimation was detected with normalized difference vegetation index (NDVI) (R2 = 77.81%) and SAVI (R2 = 72.8%).	On applying ArcGIS, it was not enough for suitability analysis
(Ioannou et al., 2018)	Biomass Energy Production	As per the evaluation, the biomass potential was estimated to be 25.5% of the entire biomass potential even though the chosen areas depict just 8% in the regional unit of Drama's total area.	There were several issues with biomass-associated projects that was funding

(Lombardi et al., 2017) described the multi-criteria SDSS for future urban energy retrofitting scenarios. Analyzing '2' different techniques for the definition along with the ranking of the evaluation criteria were the main aim. The outcomes indicated that when analogized with the environmental ones (Investments costs 30% together with PBP 27%), the topmost preference was given to the economic aspects. The applied method also constitutes valuable support in tackling values, which can't be quantified although it helps in a critical situation.

(Jayarathna et al., 2017) explained the GIS-centered SDSS to examine mining residential water demand. SDSS for residential water demand (SDSS-RWD) was developed by integrating the model with an SDSS. As per the outcomes, household size, presence of a pool, age over 65³, and income have a sturdy positive relationship with water demand. A weak positive relationship was depicted by 64 t toilets, secondary education, along with being born in Australia.

(Yao et al., 2017) described the ArcGIS-centered SDSS aimed at locust prevention along with control in China. By employing various programming languages, libraries, together with software, a fresh system was developed. Outcomes showed that for several years, Locust Prevention and Control DSS (LPCDSS) have been running successfully also recently it covers 22 provinces, encompassing 356 countries. A data source was provided by the weather open data to the service layer, though it was not present in the LPCDSS.



(Ahmed et al., 2017) examined the urban green space accessibility along with quality as a GIS-centric system as spatial decision support meant for urban ecosystem services in Brussels. To evaluate the proximity along with the quality of green spaces, a series of indicators was applied. As per the outcomes, with access to green spaces, 62% population resides in urban blocks with a lower when analogized to average quality score; thus, revealing a considerable margin for enhancement.

(Alexandridis et al., 2017) explained the incorporated system for promoting accuracy farming as a gauge towards minimized input agriculture in northern Greece employing an SDSS. For conducting several layers' evaluation, which elucidates study areas' (A) environmental, (B) social, together with (C) economic relevant data, GIS was incorporated. As per the evaluation, with some exclusions in the fresh Member States of Central and Eastern Europe, a high potential was shown in the central parts of Western Europe, while mainly medium in addition with low potential was shown on (A) Atlantic coast, (B) Balkans, along with (C) Mediterranean.

2.4.1. Models of the SDSS in the other fields using ArcGIS

The government could be assisted by the SDSS on epidemic diseases along with their application systems; in addition, it's public health institutions to apprehend disease monitoring along with surveillance (Vasquez et al., 2022). The superior public obtainability of spatial data along with the stretchy software was exploited by the SDSS; thus, it is made easier for incorporating modeling into ArcGIS (An EsriSoftware Security, 2021). The models of SDSS in the other fields using ArcGIS are elucidated in table 4.

Table 4. Models of SDSS in the other fields using ArcGIS

AUTHOR NAME	FIELD	MODEL	FINDINGS	LIMITATIONS
(Lan et al., 2020)	Water contamination	Web-based Spatial (WPS) model	As per the outcomes, navigation was easy in the interactive Well Water Risk Estimation Panel Component; whilst, the estimation maps were easy for interpreting.	Testing for kind I & kind II error testing outcomes of uncertainty weren't depicted on implementing the system.
(J. Wang et al., 2020)	Economic regional development	Fuzzy C-mean clustering model	Analysis showed that the Gross domestic growth rate increased by 0.105, 0.113, 0.134, 0.087 and 0.075	Decision-making science might be enhanced; in addition, it must guide the regional economy's healthy



				development while implementing the system.
(Li et al., 2020)	Agriculture	Multiphase flow substitution model	As per the outcomes, this system offered effectual along with practical support for managers meant for allocating land resources together with formulating sustainableLU policies rationally.	Spatial pattern optimization was not offered by the optimal LUstructure.
(Liu et al., 2020)	Land	System Dynamics (SD), Agent-Based Model (ABM), Cellular Automata (CA)	As per the outcomes, Beijing's population augmented as of 12.51 to 21.71 million, along with the GDP augmented as of 150.77 to 2368.57 billion yuan.	Incorporation's feasibility and operability were not satisfied completely.

(Guzman et al., 2020) described the cellular automata-centricLU model as an integrated SDSS meant for urban planning in developing cities. In the future, for simulating and evaluating '8' scenarios with transport infrastructure's diverse policy directions, Cellular Automata-centric (CA) systems were utilized. As per the evaluation, 11,104 pixels of available land (40 km²) were rehabilitated into middle-socioeconomic strata residential land; in addition, 2245 pixels (8.1 km²) of lower-SES residential land were transformed into middle-socioeconomic strata residential land.

(Belkacem et al., 2020) explained the ArcGIS-centric multi-criteria SDSS for tackling health facility resources. Enhancing a spatial system along with presenting the implementation possibility inside the GIS for tackling health resource issues was the main aim. As per the outcomes, 70 victims were evacuated; similarly, every health center was overloaded and maximum capacity was reached by 100%; in addition, the city needs reinforcement from outside the city in case of significant risk.

(Nguyen et al., 2020) described the development of an SDSS for real-time flood primary warning in the Vu Gia-Thu Bon river basin, Quang Nam province, Vietnam. This



approach presented a Hydrologic (SWAT) along with a hydraulic (HEC-RAS) model. The capability of fusing real-time meteorological along with hydrological systems for flood forecasting in the Vu Gia-Thu Bon river basin below a real scenario was demonstrated by the achieved SDSS results.

(Fernandes et al., 2020) explained the clinical SDSS (CDSS) for triage in the emergency department utilizing intelligent systems. CDSS, which was designed centered on intelligent methodologies, was encompassed in this technique. As per the evaluation, a lower average Area under the ROC Curve (AUC) of 0.73- 0.74 was depicted by the results of discharge disposition amongst medium acuity patients, mortality along with acute morbidity, employing LR, together with acute IDs, employing Naive Bayes. The disadvantages are the lesser availability of data along with less focus on the subjectivity of the system.

3. RESULTS AND DISCUSSION

Here, the count of annual malaria (one of the IDs) infection status is analyzed for the purpose of prevention and control from 2008 to 2018 based on SDSS using ArcGIS. The software tool, which supports the analysis of malaria-related information, is termed the SDSS. For risk analysis, ArcGIS-centric tools are essential in the field of controlling IDs. This was done for making use of GIS-centric evaluation, which could evaluate information in an intuitive and visible way (Ngo et al., 2019). The annual malaria infection status counts for prevention and control from 2008 to 2018 based on SDSS using ArcGIS is elucidated in figure 2.

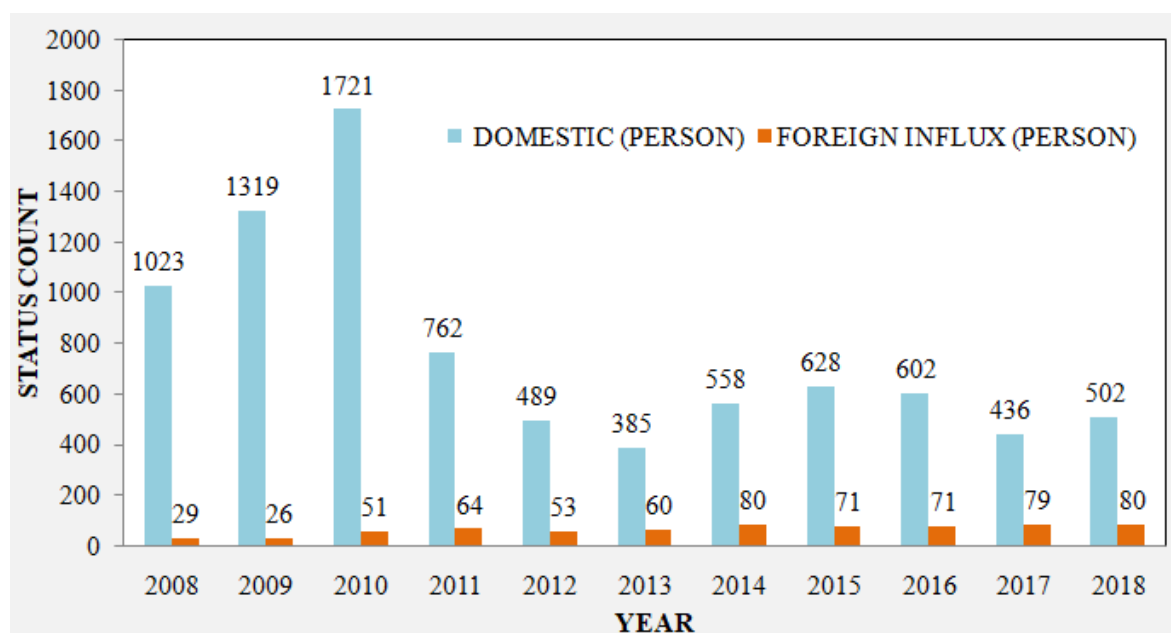


Figure 2. Annual malaria infection status count for prevention and control from 2008 to 2018 based on SDSS using ArcGIS



When compared with the foreign influx (person), the status of the infection count is extremely high in domestic (person). From 2007 to 2010, the count of infection status was fluctuating starting at 1023 in 2008; decreasing in the next year and again it increased up to 1721 count. The count is enhanced year by year 72 in foreign influx (Kim et al., 2018).

4. CONCLUSION

Man's capacity of controlling epidemic diseases to a huge extent is built by modern technological developments. Nevertheless, in recognizing disease spread at several spatial scales (that is. local, regional, along with global), recognizing highly contagious diseases, together with effectively detecting outbreaks before they occur, problems are faced by the human race. In detecting the spots, a significant role is played by the technologies like SDSS, which are employed for controlling the infection before it goes to the extreme. However, as mentioned before, there was limited research done on human infection regarding SDSS using the software tool ArcGIS. Thus, the application of SDSS in other fields using ArcGIS with its models had been explained for the purpose of future researchers to mention the disadvantages of SDSS for human infection. However, there was an information overload and cost of development when SDSS serves as a tool for any field like land, human infection, transport, agriculture, etc. Thus, when researchers focus on the work of SDSS for human infection, they should consider these limitations in the future.

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