International Journal of Mosquito Research

ISSN: **2348-5906**
CODEN: **IJMRK2**
IJMR 2020; 7(1): 45-50

Received: 23-11-2019
Accepted: 27-12-2019

Stavelin Abhinandithe K
Assistant Professor, Division of Medical Statistics, Faculty of Life Sciences, JSS AHER. Mysore, Karnataka, India

Madhu B
Associate Professor, community medicine, JSS Medical College, JSS AHER Mysore, Karnataka, India

S Balasubramanian
Dean & Director Research, Faculty of Life Sciences, JSS AHER Mysore, Karnataka, India

Sahana KS
M.Sc. Division of Medical Statistics, Faculty of Life Sciences, JSS AHER Mysore, Karnataka, India

Corresponding Author:
Stavelin Abhinandithe K
Assistant Professor, Division of Medical Statistics, Faculty of Life Sciences, JSS AHER. Mysore, Karnataka, India

Malaria incidences prognosis using climatic factors in Mysore, India: A time series approach

Stavelin Abhinandithe K, Madhu B, S Balasubramanian and Sahana KS

Abstract
Changing condition along with climatic components represent the greatest test in battling against the wellspring of intestinal sickness Malaria despite everything stays a general medical issue in creating nations. Utilizing climatic factors in Mysore as indicators this investigation was intended to estimate Malaria cases in Mysore, India. Strategies: the number of month to month malaria occurrences from January 2013 to December 2017 have been gathered from District health office, Mysore. Climatic information of month to month mean rainfall, least and most extreme temperature were from territorial meteorological focus, Mysore. Expert modeler of IBM SPSS version 22 was utilized to serve the purpose of splitting down the time arrangement information. Result: Autoregressive moving average, winter's additive model, which is comparable to ARIMA (0, 1, 0) $(0, 1, 0)_{12}$, was considered to be the best fit. Seasonal Adjusted Factor (SAF) for malaria incidences appears high during the long stretches of August and November. ARIMA models is a straightforward and solid instrument in creating dependable estimates for malaria in Mysore, India.

Keywords: Malaria, ARIMA, Temperature, Rainfall, Seasonal Adjustment Factor.

1. Introduction
Above one thousand million individuals are tainted and beyond 0.1 crore individuals pass on from vector-borne sicknesses consistently. World Health Organization (WHO) previously featured the genuine as well as expanding risk of vector-borne sicknesses. Malaria represents the greatest danger with about 40% of the total population in danger of contamination, among vector-borne diseases [1]. In endemic countries malaria diminishes monetary development by greater than single rate point for every year. For the most part, the malaria transmission season corresponds to brief periods of illness causing a substantial cost on the least fortunate areas in the world [2].

Changing condition and climatic variables represent the greatest test in battling against the wellspring of intestinal sickness. Malaria despite everything, stays a general medical issue in creating nations, disregarding different ongoing headways in symptomatic and treatment modalities [3]. It is an altogether avoidable and curable disease brought about by Plasmodium species parasites, transferred solely by the Anopheles mosquito chomps. In addition to this, it leads to noteworthy horrifying deaths, especially in asset substandard areas. After assessment it was found that 3,400 million individuals were endangered in 2013 with, 2070 lakhs expected instances in 2013 and on an average 0.63 million deaths in 2012 [4].

Among the malaria influenced areas, south eastern Asia, holds the second position with, extreme cases occurring in India, expecting twenty four million deaths every year. In contrast to a majority of infant deaths in Africa, in India, it is seen that mortality due to malaria is prominent in the financially favorable age interval of 15-44 years [5]. The disease stricken household has greater than one fourth of its salary as its expenditure on intervention [6]. Due to the extreme wellbeing effect of malaria, strategy development has become a necessary requirement that gives permission to determine the early attack with convenient case discovery can be actualized successfully [7].

Investigations of malaria prevalence demonstrated its relationship with patterns of rainfall, and temperature. In numerous spots, circulation is regular and topmost during and immediately after the stormy season [8]. Jungle fever diseases are regularly progressively basic during stormy seasons on account of increment in number of reproducing locales. Ideal condition for

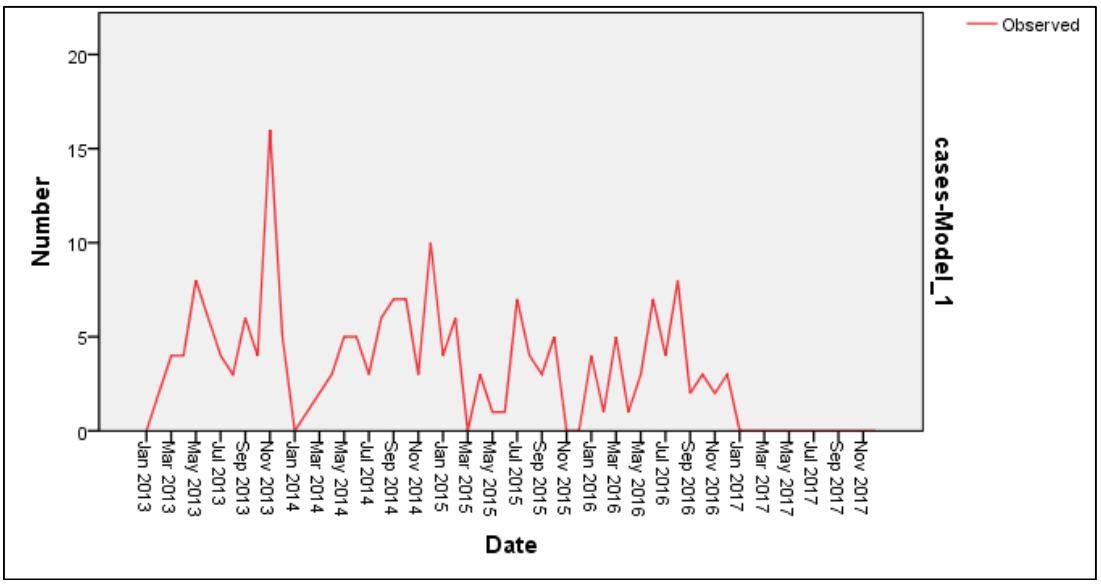
disease transmission occurs for the temperature within 20-30 degree Celsius and the relative humidity is at any rate sixty percentage on an average. Oceanic reproducing pattern length of the mosquito vector is under the water temperature management and its life span extends with elevated relative humidity [9]. Thus the main aim of this study is to understand the present patterns of malaria cases and hence to determine the frequency of future occurrences.

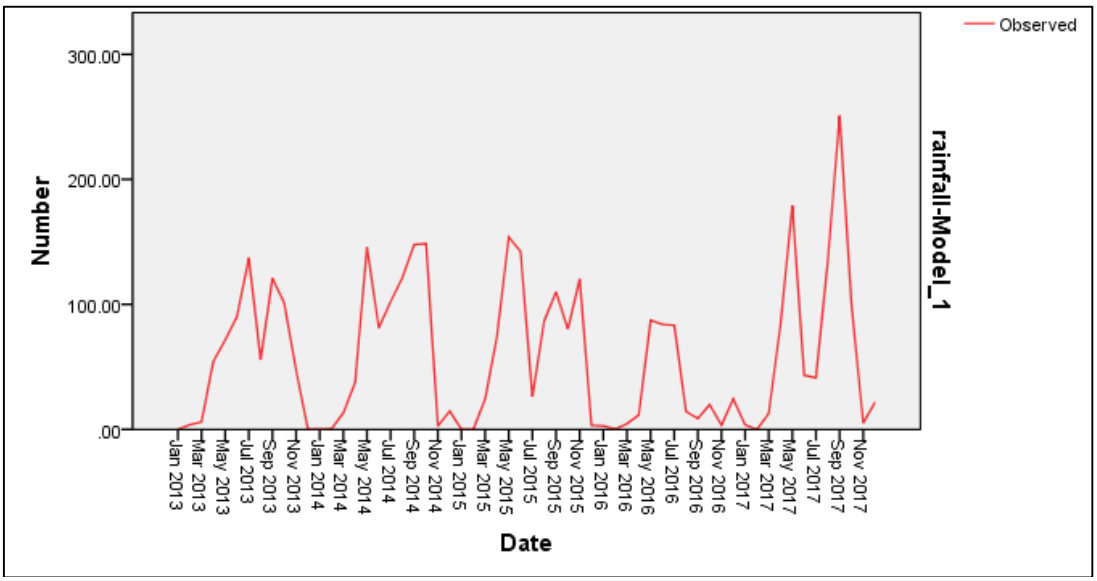
2. Materials and Methods

Data Collection: The legislature of India presented Public wellbeing framework. The health Department is giving human services administrations at the doorsteps through wellbeing laborers. Alongside giving general wellbeing the fundamental goal of the office is usage of different National level Programs to give health administrations to the general population through different health establishments. We got month to month Malaria cases from January 2013 to December 2017 in each taluk, in Mysore district, from the District Health Office, which is a government association.

2.1 Statistical Analysis: Employment of Expert modeler under SPSS ver.22 programming yielded most fitting reasonable model for the chronological series data. Information stationarity was examined through autocorrelation and partial autocorrelation function. Utilizing SAF decision was made on the pinnacle of regular variety. To confirm the accurate determination of the model, Ljung-Box test was very helpful. To address the puzzling elements, estimating of the occurrence of month to month incidences was finished including the climatic indicators utilizing the best fit model.

3. Results





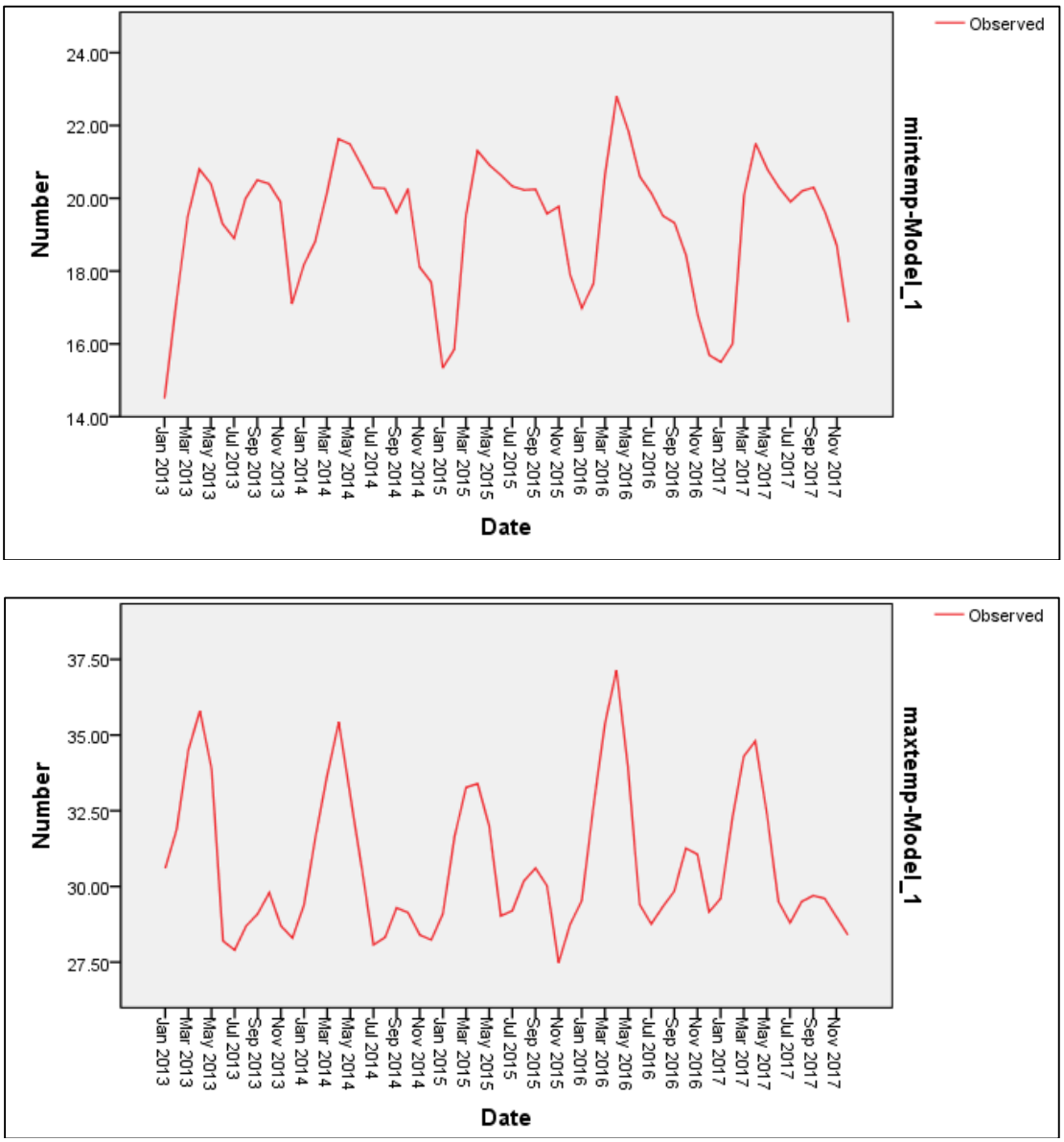


Fig 1: Monthly malaria case, rainfall, minimum and maximum temperature from January 2013 to December 2017 in the study area.

Table 1: Seasonal Adjustment Factor (SAF) for malaria cases.

Months	Observed cases	SAF
January	8	0.5
February	10	0.62
March	11	0.69
April	11	0.69
May	17	1.068
June	19	1.19
July	18	1.13
August	21	1.31
September	18	1.13
October	19	1.19
November	21	1.31
December	18	1.13

The sum of month to month affirmed instances of Malaria is most uplifted during 2013 as appeared in figure 1. Investigation of the Malaria contaminations, rainfall pattern, least and most extreme temperatures from 2013 to 2017 shows no reasonable pattern and recommends a seasonal dependence in the series. All series displayed various pinnacles other than small sized variations. The massive increases made from month to month in the sequence of malaria infections had all the earmarks of being isolated for more than a month. Observations with no seasonal variation have a null seasonal component. Table 1 shows that since May, Malaria's seasonal adjusted factor (SAF) has surpassed 1, that is, malarial diseases have been progressively over the usual months in these months. The aforementioned period, also matches the Mysore, August and November rainstorm season with the most notable 1.31 SAF. It indicates the peak of transmission occurs in this duration when the threat is 1.31 times greater than any normal month.

Table 2: Model Statistics for malaria, rainfall and temperature data.

Model parameter	Stationary R	Ljung-Box statistic			Model Type
		Statistics	df	P value	
malaria infections	0.838	7.493	15	0.29	Winter's Additive
Rainfall	0.78	28.461	16	0.028	simple seasonal
Max Temperature	0.683	59.071	16	0.001	simple seasonal

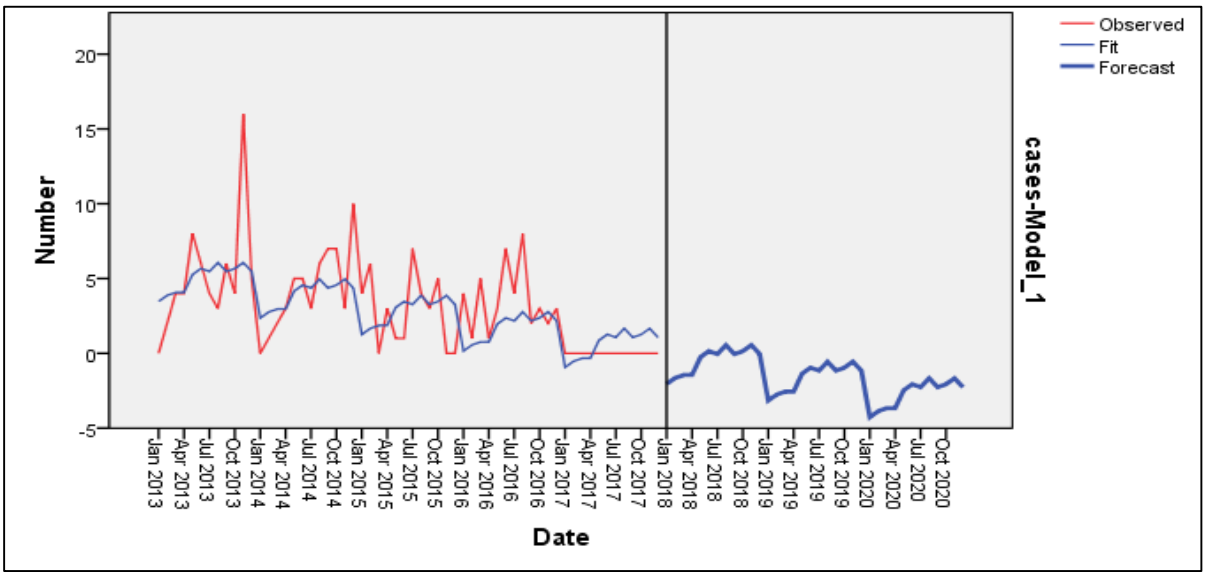


Fig 2: Observed and forecasted values for malaria cases

Expert modeler aided to locate the most appropriate model for anticipating disease occurrences utilizing rainfall average, least as well as the most extreme temperatures, all lagged down as covariates at one month, as shown in Table 2. It proposed autoregressive integrated moving average model, Winter's additive model, which is proportional to ARIMA (0, 1, 0)(0, 1, 0)$_{12}$ as the best fit measurable model for the given time series information. It was discovered that mean rainfall (p value= 0.028) and most extreme temperature (p value= 0.001) were the noteworthy disease indicators in the examination zone. Least temperature doesn't fundamentally foresee infections. The genuine watched and the anticipated values coordinated sensibly well. In spite of the fact that time series modeler offers various goodness of fit statistics, we utilize stationary R-squared an incentive as it gives an estimate of the extent of the total variation in the series that is clarified by the model. It is desirable over ordinary R-squared when there is pattern or seasonal pattern as on account of present data. The bigger estimations of stationary R-squared show better fit (up to a most extreme estimation of 1). An estimation implied that the model could clarify 83.8 % of the observed variations in the series.

The forecasted model proposed winter's additive model [ARIMA (0, 1, 0) (0, 1, 0) [12] which served useful in estimating monthly malaria occurrences for the future from January 2018 through December 2020. Rainfall showed up to be the most prominent predictor. The forecasts also depicts a seasonal pattern with high peaks during rainy seasons. (Figure 2)

4. Discussion

Malaria is identified with all of us, including guys, females, the old, and the youthful. The Malaria infection transforms effectively and rapidly, bringing about a Malaria pandemic consistently. This prompts huge clinical utilization and social weight. India, as a huge and crowded nation, has just done numerous preventive strategies and set up a wellbeing observation framework. Regardless of these measures, Malaria despite everything wins. There are, numerous components influencing Malaria occurrence including infection destructiveness, the environment, geographical area, population portability, preventive methodologies and financial status thus, we can't hinder or kill the infection, yet we can forestall it or limit the misfortune when the ailment happens. Right now, utilized measurable techniques that have been infrequently utilized in Malaria cases to develop models for anticipating Malaria frequency, in this way giving research ideas to Malaria counteraction and supporting direction for general wellbeing [11].

As a conventional general wellbeing undertaking, the study of disease transmission observation of irresistible illnesses is unavoidable, and model estimating will better use the reconnaissance information [12, 13]. It has been demonstrated that statistical models are useful in anticipating future transmittable illness rate, and it is critical for the cleanliness office to perceive epidemic conduct earlier [14]. The ARIMA model of time series analysis was initially imagined for financial matters yet has been broadly utilized in network of irresistible infection for number of various time dependent occasions. It is extremely helpful to fit time-series information and has been displayed to be the best way to deal with variety of time series [15, 16]. Time series models assume a noteworthy job in infection forecast, as they can foresee the future event of illness with rate information gathered month to month or yearly [17]. They have been utilized for the expectation of flu mortality [18, 19]. Malaria incidence [20, 21] hemorrhagic fever with renal disorder (HFRS) incidence [12] and other diseases [12, 22, 23]. The analysis of inspection data on the occurrence of various infections is helpful in development of theories to understand and predict the nature of the observed phenomenon, and then in creating a quality management mechanism and resource reallocation. ARIMA models are beneficial in designing the temporal dependency of a time series structure, taking into account changing patterns, periodic shifts, and random disruptions [12]. They have likewise been utilized in investigating the relationship among changes in national liquor strategies and suicide rate, etc.

It is big data period now, gigantic information are rising ordinary pervading into pretty much every aspect of our lives, and how to apply the information in general wellbeing is critical in disease avoidance and control [24]. Time series analysis of infection information is valuable to propose new speculations, envision pandemic patterns, and improve the avoidance framework. This examination develops an

occasional ARIMA model to conjecture malaria cases, adding to an early notice framework that can help general health approach workers take measures to keep it from spreading, improve open mindfulness, and migrate assets. This statistical technique proposed right now in this study is a great deal to profit general wellbeing.

In any case, there are likewise a few inconveniences of our examination. The SARIMA model is just utilized for momentary estimating, and it may not be hearty or exact for long haul determining. Continuous surveillance and observing are imperative. We ought to progressively change the model by including new observing information for Malaria cases. It is promising that, with progressively dependable malaria cases and further model refinement, these regular ARIMA models by time series analysis strategy could encourage increasingly adequate references for open authorities to plan for Malaria pandemics.

5. Conclusion

A seasonal pattern was seen in malaria frequency in Mysore region with changes during the long stretches of August to November. Winter's additive [ARIMA (0, 1, 0) $(0, 1, 0)_{12}$] model was seen as the best suited factual model for anticipating disease cases in Mysore. Rainfall and maximum temperature were seen as solid indicators, when contrasted with minimum temperature to forecast malaria incidence in the investigation region. This investigation will be increasingly valuable for open directors for arranging preventive and control measures.

6. Conflicts of interest

The authors declare no conflict of interest.

7. Statement for Human and Animal Ethics: Ethical approval has been provided by JSS Medical College, JSS AHER, Mysore, Karnataka, India.

8. References

1. World health organization (WHO) campaigns, world health day 2014: Preventing vector-borne disease, http://www.who.int/campaigns/world-health-day/2014/en/.
2. United Nations (UN) Millennium Project, “coming to grips with Malaria in the New Millennium”, Task force on HIV/ AIDS, Malaria, TB and Access to Essential Medicines, Working Group on Malaria, 2005
3. McMichael AJ, Woodruff RE, Hales S. Climate change and human health: present and future risks. The Lancet. 2006; 367(9513):859-69.
4. World Health Organization, “Factsheet on the World Malaria Report 2013”, http://www.who.int/malaria/media/world_malaria_report_2013/en/.
5. National Institute of Malaria research, “Estimation of True malaria burden in India”, http://www.mrcindia.org/MRC_profile/profile2/Estimation%20of%20true%20malaria%20burden%20in%20India.pdf.
6. The United Nations Children’s Fund (UNICEF), “Factsheet: Malaria, A Global Crisis”, http://www.unicef.org/media/media_20475.html.
7. World Health Organization (WHO), Malaria Epidemics: Forecasting, Prevention, Early Detection and Control. From Policy to Practice, Report of an Informal consultation, World Health Organization, Geneva, Switzerland, 2004.
8. Gomez-Elipe A, Otero A, Van Herp M, Aguirre-Jaime A. Forecasting malaria incidence based on monthly case reports and environmental factors in Karuzi, Burundi, 1997–2003. Malaria Journal. 2007; 6(1):129.
9. McGregor I, Wernsdorfer WH. editors. Malaria: principles and practice of malariology. Churchill Livingstone, 1988.
10. Kumar V, Mangal A, Panesar S, Yadav G, Talwar R, Raut D *et al*. Forecasting malaria cases using climatic factors in Delhi, India: a time series analysis. Malaria Research and Treatment, 2014.
11. Kevin Yin J, Salkeld G, Heron L, Khandaker G, Rashid H, Booy R. The threat of human influenza: the viruses, disease impacts, and vaccine solutions. Infectious Disorders-Drug Targets (Formerly Current Drug Targets-Infectious Disorders). 2014; 14(3):150-4.
12. Liu Q, Liu X, Jiang B, Yang W. Forecasting incidence of hemorrhagic fever with renal syndrome in China using ARIMA model. BMC Infectious Diseases. 2011; 11(1):218.
13. Nsubuga P, White ME, Thacker SB, Anderson MA, Blount SB, Broome CV *et al*. Public health surveillance: a tool for targeting and monitoring interventions. Disease control priorities in developing countries. 2006; 2:997-1018.
14. Earnest A, Chen MI, Ng D, Sin LY. Using autoregressive integrated moving average (ARIMA) models to predict and monitor the number of beds occupied during a SARS outbreak in a tertiary hospital in Singapore. BMC Health Services Research. 2005; 5(1):36.
15. García-Díaz JC. Monitoring and forecasting nitrate concentration in the groundwater using statistical process control and time series analysis: a case study. Stochastic Environmental Research and Risk Assessment. 2011; 25(3):331-9.
16. McGee VE, Jenkins E, Rawnsley HM. Statistical forecasting in a hospital clinical laboratory. Journal of Medical Systems. 1979; 3(3-4):161-74.
17. Kane MJ, Price N, Scotch M, Rabinowitz P. Comparison of ARIMA and Random Forest time series models for prediction of avian influenza H5N1 outbreaks. BMC bioinformatics. 2014; 15(1):276.
18. Reichert TA, Simonsen L, Sharma A, Pardo SA, Fedson DS, Miller MA. Influenza and the winter increase in mortality in the United States, 1959–1999. American Journal of Epidemiology. 2004; 160(5):492-502.
19. Dominguez A, Muñoz P, Martínez A, Orcau A. Monitoring mortality as an indicator of influenza in Catalonia, Spain. Journal of Epidemiology & Community Health. 1996; 50(3):293-8.
20. Gaudart J, Touré O, Dessay N, lassane Dicko A, Ranque S, Forest L *et al*. Modelling malaria incidence with environmental dependency in a locality of Sudanese savannah area, Mali. Malaria Journal. 2009; 8(1):61.
21. Hanf M, Adenis A, Nacher M, Carme B. The role of El Niño southern oscillation (ENSO) on variations of monthly Plasmodium falciparum malaria cases at the cayenne general hospital, 1996-2009, French Guiana. Malaria Journal. 2011; 10(1):100.
22. Luz PM, Mendes BV, Codeço CT, Struchiner CJ,

Galvani AP. Time series analysis of malaria incidence in Rio de Janeiro, Brazil. The American Journal of Tropical Medicine and Hygiene. 2008; 79(6):933-9.
23. Yi J, Du CT, Wang RH, Liu L. Applications of multiple seasonal autoregressive integrated moving average (ARIMA) model on predictive incidence of tuberculosis. Zhonghua yu fang yi xue za zhi [Chinese Journal of Preventive Medicine]. 2007; 41(2):118-21.
24. Khoury MJ, Ioannidis JP. Big data meets public health. Science. 2014; 346(6213):1054-5.