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Biostatistical approaches for early identification of influenza trends in the United States using CDC surveillance data

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Abstract

The U.S. still faces significant challenges related to seasonal flu as evidenced by considerable annual variation in both disease transmission, disease-related hospitalizations, and onset times of epidemics. To facilitate an effective public health response and optimal use of resources during these outbreaks, timely information on emerging increases in the level of influenza activity is critical. The purpose of this paper is to apply a well-defined statistical methodology to better understand how we can detect influenza trends early using national surveillance data collected through the CDC's ILINet system from 2010-2024.

Data from weekly reports of the number of patients who present with symptoms associated with Influenza Like Illnesses (ILI), were examined in detail to provide a description of baseline levels of ILI, describe seasonal patterns in the number of cases reported per week, examine the degree of correlation in influenza transmission over successive weeks. Statistical analytical techniques employed include descriptive statistics; smoothing of short-term variability in weekly ILI incidence rates via application of a three-week moving average; temporal dependency in weekly ILI trends was evaluated via AR (1) model fitting; and the presence or absence of epidemic level ILI was identified based on thresholds defined historically as two standard deviations above the sample mean ($\mu+2\sigma$).

Performance of each analytical method used to generate predictions of ILI incidence at future points in time was evaluated by applying epidemiologic metrics that included measures of accuracy (sensitivity, specificity) and predictive values to measure the practicality of using early warnings to predict upcoming outbreaks.

We found evidence of strong seasonality in influenza incidence patterns, a high degree of short-term temporal dependence among weekly ILI trends, and consistency in detecting peak levels of ILI via threshold-based statistical methods. We also demonstrated that statistically-based early detection methods utilizing moving averages provided quantifiable lead-time to detect increases in transmission rates prior to when they would have been detected using traditional threshold-based methods alone.

Overall, the results indicate that transparent, replicable, and easily implemented computational/statistical methodologies will be valuable additions to existing

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surveillance systems designed to monitor for early signs of influenza outbreaks. Utilizing such methodologies within ongoing public health monitoring activities could potentially enhance the timeliness and effectiveness of outbreak detection efforts and preparedness strategies and consequently contribute to decreased overall influenza morbidity and enhanced national public health preparedness.

Introduction

Despite several decades of public health initiatives, seasonal flu is still a serious public health problem in the U.S. Many people suffer from flu-related illness each year and some die from it. In addition to the loss of life and suffering, flu causes significant economic costs. Flu disproportionately affects those who may be most at risk for severe illness due to age (older adults), underlying medical conditions (young children, chronic diseases) or immune status (immunocompromised). National estimates indicate that influenza contributes to tens of thousands of deaths and hundreds of thousands of hospitalizations each year, underscoring its continued relevance as a major public health concern [1-3].

The role that effective surveillance can play in reducing the adverse effects on public health associated with influenza includes being able to detect rising transmission early; monitor how the flu season progresses over time; and develop appropriate intervention strategies based upon current information. The Center for Disease Control and Prevention (CDC) oversees influenza surveillance in the U.S., using a multi-faceted approach. This system utilizes several different sources of influenza-related data including ILI (influenza like-illness) indicators; laboratory-based virological surveillance; influenza-related hospitalizations; and mortality from all causes. The most commonly utilized source within this network of surveillance is the CDC's Influenza-Like Illness Network (ILINet). ILINet provides an indicator of outpatient visits that are due to influenza-like illnesses at a national level. These surveillance systems provide the empirical foundation for situational awareness and evidence-based public health decision-making at national and regional levels [4,5].

Seasonal influenza activity is driven by a variety of factors that interact with one another. They include virus evolution, as well as levels of immunity among populations due to infection or vaccination; climate variability; and the nature of human behavior, which also can have significant variability both temporally (across different seasons) and geographically (across various parts of the country). Due to this complexity, it often can be difficult during the initial phase of an outbreak's increase to differentiate between normal variability and actual unusual increases in activity. This difficulty in differentiating normal and abnormal seasonal activity demonstrates the need for robust methods to detect statistically significant changes in surveillance indicator values (e.g., number of reported cases), while providing sufficient transparency regarding methodology and being practical for use in current public health surveillance activities.

Influenza Trends Early Identification Using U.S. National CDC ILINet Surveillance Data was developed using a biostatistics approach to identify influenza trends in the United States. The analysis uses ILINet data collected by the U.S. Centers for Disease Control and Prevention (CDC) on a weekly basis over multiple influenza seasons, from 2010-2024. Temporal patterns, smoothing methods, autoregressive models, and statistical threshold values were evaluated to determine how they could assist in detecting increased influenza activity outside of typical seasonal patterns. The goal of these analyses was to provide additional statistical strength to influenza surveillance activities and improve national situational awareness, preparedness plans, and rapid responses related to increased influenza activity.

Background and related work

Seasonal influenza surveillance has long been a central component of public health practice in the United States, providing essential information for monitoring disease activity and guiding preventive planning. The Centers for Disease Control and Prevention (CDC) coordinates a comprehensive surveillance system that integrates clinical, virologic, hospitalization, and mortality data, creating a national framework for evidence-based decision-making and situational awareness [4]. Among these systems, the Influenza-Like Illness Surveillance Network (ILINet) provides a widely used indicator of outpatient visits associated with respiratory illness, enabling continuous monitoring of influenza activity across geographic regions.

Research using CDC surveillance data has documented substantial variability in epidemic timing and intensity across seasons, as well as significant contributions to morbidity and mortality nationwide [2,3]. These analyses demonstrate that population-level surveillance indicators are essential for understanding influenza burden and for evaluating the impact of vaccination programs and other public health interventions. Long-term surveillance datasets also enable comparative analyses across seasons, supporting the identification of consistent epidemiological patterns and deviations from expected activity.

Despite these advances, interpreting early-season surveillance signals remains challenging due to baseline variability, reporting delays, and fluctuations in healthcare-seeking behavior. Regional heterogeneity in influenza transmission may further complicate national surveillance indicators, as epidemic activity often emerges at different times across states and metropolitan areas. When surveillance data are aggregated at the national level, localized increases in disease activity may initially be difficult to distinguish from routine background variation [5,6].

To address these challenges, researchers have increasingly applied biostatistical and time-series approaches to improve interpretation of surveillance data and strengthen early detection of epidemiological changes. Methods such as smoothing techniques, baseline comparisons, autoregressive modeling, and statistical outbreak detection algorithms have been widely explored to reduce short-term variability while preserving meaningful epidemiological signals [7]. These approaches aim to improve early warning capabilities while maintaining methodological transparency and interpretability for public health practitioners.

Previous work also emphasizes the importance of analytic methods that rely on routinely collected surveillance indicators, allowing findings to be readily integrated into existing monitoring systems. Public health agencies frequently require statistical approaches that are computationally efficient, reproducible, and easily interpretable, particularly when supporting rapid situational assessment during evolving influenza seasons

[8]. As a result, practical statistical frameworks that can be implemented using standard surveillance data remain an important area of methodological development.

Although earlier studies have advanced influenza monitoring, fewer analyses have focused specifically on integrating multiple statistical techniques to evaluate temporal persistence, smoothing-based trend detection, and threshold-based outbreak identification within a unified analytic framework. Continued refinement of such approaches may enhance the capacity of surveillance systems to identify early deviations from expected influenza activity and support more timely public health responses.

The present study builds on this body of work by applying a biostatistical framework to national CDC ILINet surveillance data to evaluate temporal patterns, trend smoothing, autoregressive dynamics, and statistical threshold detection of influenza activity. By examining weekly surveillance indicators across multiple seasons, this analysis seeks to strengthen early identification of influenza trends and contribute to improved situational awareness and preparedness planning in the United States.

Data sources and methods

Data sources

This study employed publicly available influenza surveillance data collected via the U.S. Influenza Surveillance System, developed by the Centers for Disease Control and Prevention (CDC). The CDC collects data from a variety of sources that are each used to assess influenza activity throughout the United States. Specifically, the CDC has established several complementary data sets to track influenza; these include Outpatient Influenza-like Illness Surveillance Network (ILINet); virological laboratory data; hospitalizations; and death reporting systems [4].

The major data set of interest within this study was ILINet. The ILINet system reports weekly data regarding the percentage of patients who present with symptoms consistent with an influenza-like illness at outpatient facilities. The CDC defines an influenza-like illness as either fever (greater than or equal to 100 degrees F) and cough and/or sore throat. Since many patients presenting with symptoms of an influenza-like illness do not receive a test for influenza when they visit their health care provider, ILI is often used as an indicator for tracking community-level influenza virus activity and for identifying trends in transmission [9].

In addition to using ILINet data, this study also incorporated additional laboratory-based data to provide further context on how influenza viruses circulated during the years studied. These laboratory-based data included the proportion of respiratory samples that tested positive for influenza viruses and specifically for A and B subtypes. By incorporating laboratory-confirmed data into the study's data set it allowed researchers to distinguish between cases of influenza-related illnesses and those caused by other respiratory pathogens [4].

All data collected for the period from 2010 through 2024, representing multiple flu season cycles were analyzed to account for inter-seasonal variations in rates of infection and patterns of recurrent epidemics. All data collected were retrieved from publicly available databases managed by the CDC allowing researchers to utilize uniformly collected data and thus facilitating complete replication of the study's analytical framework.

Study design

This research used an observational, retrospective study design employing secondary U.S. influenza surveillance data.

Data for this research were organized using a descriptive/analytic (epidemiological) model in order to investigate the time-dependent characteristics of influenza activity among a number of different years in which influenza activity occurred in the U.S.

The overall goal of this research was to develop statistically-based indicators that could support the detection of increases in the levels of influenza transmission at times when seasonal epidemics are beginning.

In particular, weekly surveillance indicators were analyzed to provide information about typical influenza activity during the base-line season, during periods when influenza activity is increasing, and during peak periods of influenza transmission.

Additionally, by examining a large number of influenza seasons simultaneously, the research attempted to assess variability with respect to the timing, magnitude, and duration of each epidemic.

Using a comparative seasonal approach allows for the assessment of whether or not the observed influenza activity varies significantly from what would be expected under normal conditions, as well as provides additional support for identifying early warning signals within the surveillance system.

Epidemiologic measures

Standard epidemiologic measures were used to characterize influenza burden and support interpretation of surveillance patterns.

Incidence rate was estimated using the general epidemiologic formulation:

$$IR = \frac{New\ Cases}{Population \times Time}$$

This measure reflects the rate at which new influenza cases occur within a population over a defined time interval [10].

Prevalence was estimated as:

$$P = \frac{Existing\ Cases}{Population}$$

Prevalence provides a snapshot of disease burden at a given point in time and supports interpretation of population-level influenza activity during specific surveillance periods [10].

These measures allow comparison of disease frequency across time periods and contribute to understanding influenza transmission dynamics within national surveillance systems.

Statistical analysis

Time-series analytic methods were employed to assess temporal pattern trends among various Influenza Surveillance Indicator. Statistical Smoothing was applied to weekly influenza surveillance data (since influenza activity has a clear seasonal trend) to eliminate short term random fluctuation and to help better define longer-term trends [7].

Weekly Moving Averages of the same Flu Indicators as above were calculated to provide an indication of long-term sustained influenza activity:

$$MA_t = \frac{1}{k}\sum_{i=0}^{k-1} Y_{t-i}$$

where Y_t represents the observed influenza activity at time t, and k denotes the window length used for smoothing.

Autoregressive modeling was used to evaluate temporal dependence between successive observations:

$$Y_t = \mu + \phi_1 Y_{t-1} + \epsilon_t$$

This approach captures short-term persistence in influenza surveillance indicators and helps characterize the progression of seasonal influenza activity.

Regression analysis was further applied to assess temporal changes in influenza indicators over time:

$$Y = \beta_0 + \beta_1 X + \epsilon$$

where X represents time and Y represents influenza activity.

To support early outbreak detection, threshold detection methods were implemented to identify unusual increases in influenza activity relative to baseline conditions:

$$\text{Threshold} = \mu + z\sigma$$

where μ represents baseline activity, σ represents the standard deviation of historical activity, and z corresponds to the standard normal threshold used to define abnormal increases.

All analyses were conducted using the R and Python statistical computing environments following reproducible research practices.

Ethical considerations

This analysis used only publically available data from U.S. flu surveillance systems. No identifiable health care information about individuals was obtained, nor did the researchers have direct involvement with humans. Thus, institutional review board approval was not required for this work.

Results

Descriptive statistics of influenza activity

Beginning with analysis of National Influenza Surveillance Data provided by the Center for Disease Control and Prevention's Influenza Like Illness Surveillance Network (ILINet) (n=1482 weekly timepoints) demonstrates considerable variation within each season in the proportion of patients that report symptoms of Influenza Like Illness (ILI). The average weighted percent of ILI is 1.93 % (standard deviation=1.49%) with an average of 1.49% and a maximum of 8.28% as shown above to illustrate the large variations in seasonal outbreaks.

As seen with all other respiratory viruses, when there are no epidemics, ILI will be at or below baseline levels; however, ILI can increase substantially during each seasonal peak, which follows what has been well documented regarding the epidemiology of influenza and the cycling nature of the respiratory viruses. As such, these summary statistics demonstrate the very dramatic difference between the amounts of respiratory illnesses at baseline vs. amounts experienced during the onset of each influenza epidemic as evidenced by surveillance data.

Table 1: Descriptive statistics of weekly influenza-like illness (ili) activity.

Measure	Value
Number of weekly observations	1,482
Mean ILI (%)	1.93
Standard deviation	1.49
Median	1.49
Minimum	0.00
Maximum	8.28

Temporal patterns and seasonal dynamics

Time series analysis indicated clearly defined and recurring seasonal patterns for influenza transmission. The patterns demonstrated high levels of influenza activity in the winter months (peaks) and much lower baseline activity outside of these peak months. Temporal clustering was observed to be significant among the various influenza seasons. Rapid increases in influenza activity were noted at the beginning of each season that gradually decreased to baseline levels throughout each subsequent season.

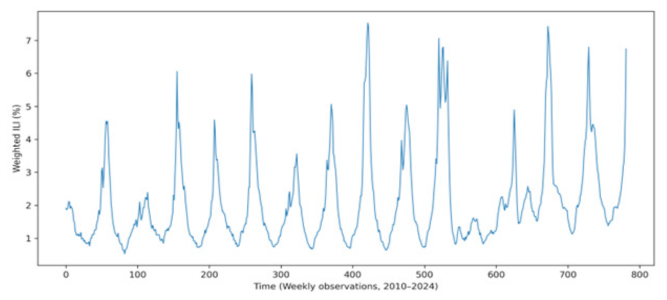

Figure 1: Weekly weighted Influenza-Like Illness (ILI) activity across epidemiological weeks based on CDC ILINet surveillance data (2010–2024).

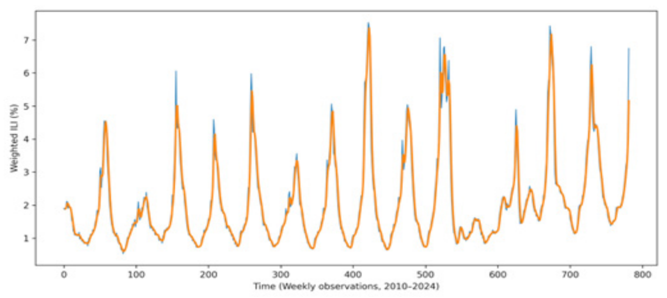

Figure 2: Observed weekly Influenza-Like Illness (ILI) activity and three-week moving average smoothing demonstrating underlying seasonal transmission trends (CDC ILINet, 2010–2024).

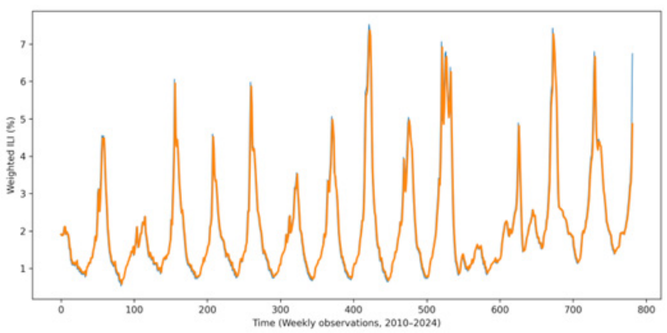

Figure 3: Observed versus autoregressive (AR(1)) predicted Influenza-Like Illness (ILI) activity demonstrating temporal dependence in surveillance data (CDC ILINet, 2010–2024).

Threshold detection and early outbreak identification

Baseline influenza activity was estimated using the overall historical mean (**μ=1.93%**) and standard deviation (**σ=1.49**). A statistical detection threshold defined as:

$$\mu + 2\sigma$$

identified abnormal influenza activity at:

$$ILI > 4.92\%$$

Weeks exceeding this threshold aligned with historically recognized high-activity influenza periods. This finding supports the utility of simple statistical monitoring approaches for surveillance-based outbreak detection using routinely collected public health data.

Table 2: Threshold detection parameters for influenza activity.

Metric	Value
Baseline Mean (μ)	1.93
Standard Deviation (σ)	1.49
Detection Threshold (μ + 2σ)	4.92

Early-signal performance (Operational validation)

To assess how well two alerting criteria (early-signal and alarm) performed in practice based on an operational definition of “epidemic” — that is, weeks when the number of reported cases of ILI was greater than the threshold (μ + 2σ), or 4.92%, — the performance of these criteria was evaluated by comparing them to the operational definition.

The Alarm Rule used the same threshold as the operational definition; it triggered alerts for each week when the weekly ILI data was above the threshold (μ+2σ).

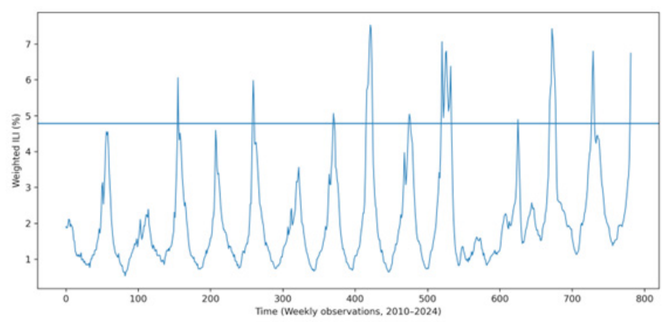

Figure 4: Threshold-based detection of influenza activity using μ+2σ and identification of epidemic-level exceedances (CDC ILINet, 2010–2024).

Table 3: Alert performance for epidemic-level weeks.
Reference definition: Epidemic-level week defined as observed ILI > 4.92% (μ+2σ).

Panel A. Classification counts

Alert Rule	Threshold (%)	True Positives (TP)	False Positives (FP)	False Negatives (FN)	True Negatives (TN)
Weekly threshold on observed ILI	4.92	87	0	0	1,395
3-week MA > μ + 1σ (early signal)	3.42	87	117	0	1,278
3-week MA > μ + 2σ (smoothed signal)	4.92	69	19	18	1,376

Panel B. Classification counts

Alert Rule	Sensitivity (%)	Specificity (%)	Positive Predictive Value (PPV, %)	False-Positive Rate (%)	Median Lead Time (weeks)
Weekly threshold on observed ILI	100	100	100	0.0	0
3-week MA > μ + 1σ (early signal)	100	91.6	42.6	8.4	1
3-week MA > μ + 2σ (smoothed signal)	79.3	98.6	78.4	1.4	—

MA: Moving Average; μ: Mean; σ: Standard Deviation; TP: True Positives; FP: False Positives; FN = False Negatives; TN: True Negatives; PPV: Positive Predictive Value.

A second rule, referred to as the Early-Signal Rule, provided alerts at an earlier point in time by triggering an alert when ILI rose above a lower threshold calculated as a three-week moving average (μ+1σ), which corresponded to 3.42% ILI.

According to this operational assessment of the early-signal rule, it demonstrated 100% sensitivity since it captured every week identified as an epidemic according to the ILI thresholds. It also had a specificity of 91.6%, resulting in a false positive alert rate of 8.4%. The median lead time across epidemic episodes for the early-signal rule was one week ahead of the first identified epidemic week. Thus, there appears to be some potential use in providing earlier situational awareness and preparedness through the use of the early-signal rule as part of public health surveillance systems.

Discussion and public health implications

This study clearly illustrates how biostatistics are able to assist in identifying influenza trends at an early stage through national surveillance programs. Biostatistic analysis of Centers for Disease Control and Prevention (CDC) surveillance data of influenza from 2010 to 2024 shows that the combination of temporal tracking of flu-like illness indicators, along with statistical smoothing, autoregression modeling and threshold-based detection, provides valuable knowledge about the pattern of seasonal influenza. As such, the results of this study clearly indicate that statistical analysis of surveillance data is a crucial part of national preparedness for public health emergencies and providing real time situational awareness [4-6].

A key finding in this study is the level of seasonal variability seen in the amount of influenza activity seen in the various surveillance periods. Each season was different based on differences in time of onset, peak levels and rates of epidemic growth (Figures 1 & 2). The fact that there is so much variation suggests that it would be beneficial for national surveillance systems to have the ability to detect deviations from normal influenza activity rather than just relying on predetermined expectations. Temporally dependent and historically variable statistical monitoring methods (i.e., see Figure 3) could add significantly to situational awareness during the initial phases of influenza spread [7-9].

There are several practical benefits for public health agencies in incorporating statistically trending detection into their current surveillance systems. Early warning of an increase in influenza activity (as shown by a threshold-based detection approach; Figure 4) enables public health officials to alter their preparedness strategies, inform healthcare providers and the general public regarding risks associated with increased influenza activity and implement preventive measures such as vaccination campaigns and resource allocations. Therefore, enhanced analytical tools can result in better-timed public health actions and potentially reduce the negative impacts associated with seasonal influenza outbreaks [10-12].

Strengthening U.S. influenza surveillance is a high priority for public health security. Influenza causes significant amounts of morbidity and mortality each year and places considerable stress on healthcare resources. Tools for analyzing surveillance indicators to better understand disease patterns will allow for earlier identification of emerging outbreak conditions. In this context, using clear and reproducible statistical models has the potential to make national-level influenza surveillance programs more reliable and scalable [1-3].

This study's demonstration of how to combine epidemiological logic with mathematical modeling techniques illustrates the necessity of doing so. Surveillance data contain useful information related to disease activity but does not necessarily identify true epidemiologic signals or normal variability in reported data. Methods such as using moving averages, autoregressive models, and threshold-based detection used in this study demonstrate how basic analytical tools can be applied to enhance interpretation of surveillance trends without having to access complex computerized equipment [7,13].

In terms of broader applications beyond the realm of monitoring seasonal influenza, this study demonstrates that the methodologies developed herein can serve as templates for designing surveillance plans for other respiratory pathogens and emerging infectious diseases. The COVID-19 pandemic demonstrated the critical need for timely surveillance data and rapid epidemiologic trend assessment. Thus, analytical frameworks that enable early detection of changes in disease transmission may contribute to improved readiness for future public health threats and improve national response capacity [14-16].

Additionally, utilizing publicly available CDC surveillance data illustrates the critical nature of developing open data systems to foster public health research. Independent analysis, method development and inter-institutional collaboration, all are enabled by open surveillance data and contribute to strengthening national epidemiologic capacity. Ongoing investment in surveillance infrastructure and analytical capability will continue to be needed to maintain effective disease monitoring systems [4,17].

Limitations exist relative to the interpretations of findings generated from this study. ILI indicators are proxies for actual influenza activity and thus may include data from patients infected with non-influenza respiratory viruses presenting clinically similarly. Additionally, variations in patient presentation behaviors (e.g., seeking medical attention), reporting behaviors (e.g., self-report vs. physician report) and regional participation in surveillance networks may affect observed trends. Finally, aggregate surveillance data may obscure local variations in transmission dynamics. Notwithstanding these limitations, national surveillance indicators are valuable sources of information regarding trends in influenza activity and can provide valuable insights when analyzed appropriately [4,8].

Future studies may build upon the methodologies developed in this study by expanding on the inclusion of additional surveillance indicators, e.g., hospitalizations due to influenza, laboratory confirmed cases of influenza, and genomic sequencing data. Developing advanced predictive modeling approaches (including those employing machine learning) may further improve early detection capabilities and support real-time public health decision-making. Methodology advancement will be necessary for continued improvement in the effectiveness of national-level surveillance systems and preparedness for both seasonal influenza and emerging infectious disease threats [18-21].

Overall, the study demonstrates that integrating biostatistical monitoring into routine surveillance of influenza can enhance the early recognition of transmission trends and lead to more effective public health decisions. Strengthening the analytical underpinnings of national surveillance systems through these types of methodologies can help lead to better preparedness, more prompt implementation of intervention strategies, and decreased overall burden of influenza in the United States [22-25].

Conclusion

This research shows how using biostatistics as an analytic tool on National Influenza Surveillance Data is helpful in identifying early seasonality of influenza in the U.S.

Using a structural analytical framework on CDC ILINet Data from 2010-2024, the authors of this paper demonstrate the benefit of combining Descriptive Statistics, Time Series Smoothing, Autoregressive Modeling and Threshold Detection Methods to provide better insight into the interpretation of Flu Activity Trends.

ILINet's Influenza Like Illness (ILI) data has significant Temporal Dependence and Seasonal Patterns that can be utilized to detect early indicators of increased flu transmission. The use of Moving Average Smoothing and Statistically Defined Thresholds to distinguish routine variation from Meaningful Epidemiological Change was found to be a useful and practical way to interpret trends in influenza activity. Additionally, the authors show that Early-Signal Detection Methods have been able to identify changes in influenza activity with significant lead times, and thus could be beneficial in real world Public Health Surveillance Applications.

At a larger scale, this study emphasizes the importance of developing Analytical Frameworks to be used within current surveillance systems to allow for timely and effective Public Health Decision Making. As previously stated, Systems that are Transparent, Reproducible, and built upon Routine Collection of Data are most beneficial for National Infrastructure for Disease Surveillance, due to Rapid Interpretation and Operational Feasibility being Key Considerations.

Utilizing Biostatistical Monitoring Techniques within Routine Influenza Surveillance will have the capability to Enhance Situational Awareness, Improve Preparedness Strategies, and Support Earlier Intervention Efforts; These Improvements May Contribute to Reducing the Public Health Burden of Seasonal Influenza and Strengthening National Readiness for Recurring Epidemics and Emerging Infectious Diseases.

To summarize, this Study Provides Evidence That Accessible and Interpretable Biostatistical Methods Can Provide A Stronger Analytical Foundation For U.S. Influenza Surveillance Systems. Further Development and Application of these types of methods will be Critical to Advancing Population Level Health Monitoring Through Enhanced Situational Awareness of Disease Trends and Increased Effectiveness.

Summary box

What is already known on this topic?

Seasonal influenza remains a major public health burden in the United States, and CDC surveillance systems are essential for monitoring influenza-like illness activity and detecting outbreaks.

What is added by this report?

This study demonstrates how statistical smoothing, autoregressive modeling, and threshold-based detection methods can improve early identification of influenza transmission trends using CDC ILINet surveillance data from 2010–2024.

What are the implications for public health practice?

Integrating transparent and reproducible biostatistical methods into routine surveillance systems may strengthen national situational awareness, support earlier outbreak detection, and improve preparedness planning.

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