

Increasing MMR vaccination rates substantially reduces measles infections in Gaines County, Texas

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SUMMARY

In early 2025, Texas experienced its largest measles outbreak in decades, with Gaines County reporting 413 of the state's 762 confirmed cases. Despite an estimated 82% measles-mumps-rubella (MMR) vaccination rate, factors such as vaccine hesitancy, safety concerns, and philosophical or religious beliefs contributed to increased transmission. Our study hypothesized that simulations we generated using a Susceptible–Infected–Recovered–Vaccinated (SIRV) model would show that increasing vaccination coverage reduces both the total number of infections and the peak infection burden during an outbreak. Using county-level epidemiological data from the Texas Department of State Health Services, we implemented an SIRV model in Python to simulate measles transmission in Gaines County under different vaccination scenarios. Model results predicted approximately 528 infections at an 82% vaccination rate, decreasing to 261 infections at 85% coverage, and only 6 total cases with an expected outbreak duration of 33 days at 95% vaccination. The analysis revealed a strong inverse relationship between vaccination coverage and burden of infection. These findings indicate that predictive modeling can effectively simulate outbreak dynamics and show how increasing vaccination coverage substantially reduces disease transmission. Because measles outbreaks continue to occur in under-vaccinated communities, these results demonstrate how modeling can inform public health planning and highlight the real-world importance of maintaining high vaccination rates to prevent future outbreaks.

INTRODUCTION

Measles, also known as rubeola, is a highly infectious viral disease (1). It typically lasts about 10–14 days if other disorders do not complicate the infection, though it can lead to major complications and even death (2). The disease results in a generalized rash that can remain for up to two weeks, along with symptoms such as high fever, fatigue, sore muscles, gastrointestinal issues, and cough (2). Measles spreads primarily through contact with infected individuals via airborne particles, and respiratory droplets can remain airborne for up to two hours (1). Among unvaccinated people, just one infected individual can transmit the infection to approximately 9 out of 10 people in close proximity (1). Individuals at highest

risk of severe complications include those younger than five years, adults older than thirty years, pregnant individuals, and those with weakened immune systems; complications may include pneumonia, blindness, encephalitis with brain injury, and death (2). Blood tests detecting immunoglobulin M antibodies or viral isolation from respiratory samples confirm the diagnosis (2). Although there is no specific antiviral treatment option, vitamin A supplementation is recommended to reduce major complications in children (2). Two vaccines aid in the prevention of measles: MMR (measles, mumps, rubella) and MMRV (measles, mumps, rubella, varicella) (3). Public health organizations (like Centers for Disease Control and Prevention) strongly recommend two doses of either vaccine, with two doses of MMR providing approximately 97% protection against infection (3).

Measles became a disease of concern in the United States beginning in 1912 (3). During this decade, official records reported approximately 6000 deaths resulting from measles annually (3). By the mid-20th century, health agencies reported approximately 3–4 million infections each year, along with hundreds of deaths and cases of encephalitis. Blood samples collected by John F. Enders and Dr. Thomas C. Peebles led to the isolation of the measles virus, which enabled vaccine development (3). In 1968, Maurice Hilleman and his team developed a more efficient and less virulent measles vaccine, forming the basis of current MMR/MMRV vaccines. Continued vaccination efforts led to substantial declines in measles incidence, and in the year 2000, public health officials officially declared measles eliminated in the United States (3). However, sporadic outbreaks have continued to occur in under-vaccinated communities due to factors such as vaccine hesitancy, safety concerns, barriers to healthcare access, and philosophical or religious beliefs, which reduce vaccination uptake and create gaps in herd immunity that allow measles transmission to persist (4).

In January 2025, health officials reported new measles cases in Harris County, Texas, followed by additional cases in Gaines County. These cases marked the beginning of the state's largest measles outbreak since 1992. Texas reported approximately 762 cases during the outbreak, with 413 cases occurring in Gaines County despite an estimated MMR vaccination rate of approximately 82% (5). Approximately 94% of infections occurred among unvaccinated or under-vaccinated individuals, demonstrating gaps in community

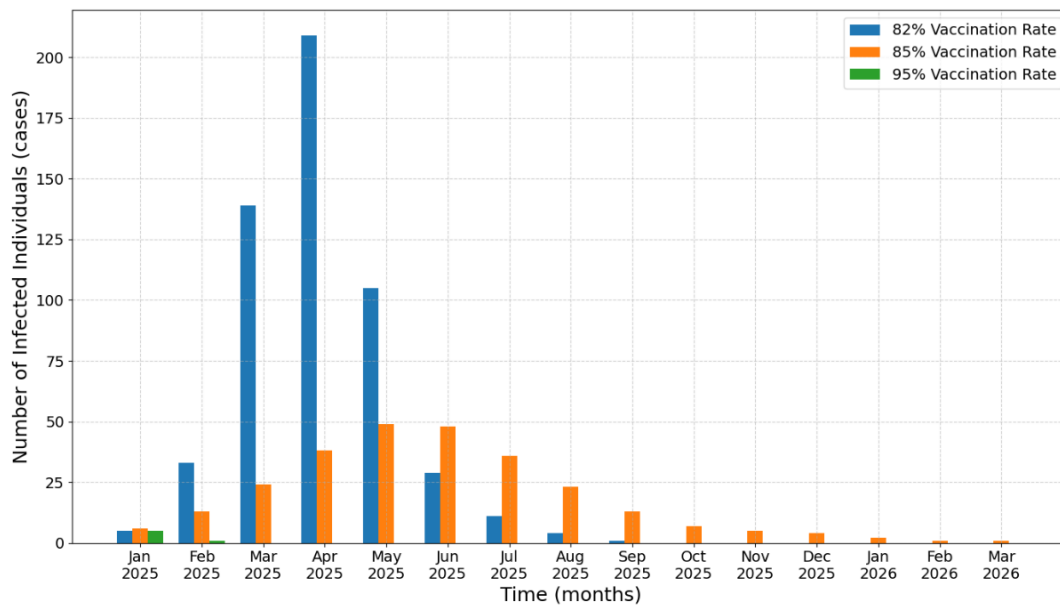


Figure 1: Infected individuals per month for 82%, 85%, and 95% vaccination rates. A Susceptible-Infected-Recovered-Vaccinated (SIRV) compartmental model was used to simulate measles spread from Jan 2025–Mar 2026. The y-axis represents the number of infected individuals (cases) for all three vaccination scenarios. No statistical testing was performed. Results are based on a single deterministic simulation per scenario.

immunity (6). After the spread drastically declined through May and June, the measles outbreak in Texas was officially declared over on August 18, 2025; however, ongoing outbreaks across North America have raised concerns regarding potential resurgence and the possibility that the United States could lose its measles elimination status.

The study hypothesized that simulations of the 2025 measles outbreak in Gaines County, Texas, calibrated to the specific population size, density, and demographic profile of the county during the affected period, would demonstrate that increasing vaccination coverage reduces both the total number and peak number of infected individuals during an outbreak (7). To evaluate this, the study used simulations conducted with a Susceptible-Infected-Recovered-Vaccinated (SIRV) model implemented in Python. This framework extends traditional epidemiological modeling by tracking how proactive immunization transitions individuals directly from a susceptible state to a protected state, thereby limiting viral transmission chains. This implementation enabled detailed analysis of disease dynamics and predicted outbreak trajectories. Rather than relying on generalized projections, the model calibrated these simulated timelines based on localized transmission parameters and baseline vaccine exemption metrics commonly utilized in the field for modeling small-scale outbreaks (8). The results demonstrate that relatively small increases in vaccination rates substantially reduce disease spread, highlighting the real-world importance of maintaining high vaccination coverage and illustrating how mathematical modeling can inform public health planning and prevention strategies (8).

RESULTS

To evaluate how changes in vaccination coverage influence measles outbreak dynamics, we used a Susceptible–Infected–Recovered–Vaccinated (SIRV) model to simulate infection spread and determine how increasing vaccination coverage influences total infections and peak infection burden during an outbreak.

We compared the predicted number of infected individuals over time across vaccination scenarios of 82%, 85%, and 95%, illustrating how increasing vaccination coverage alters

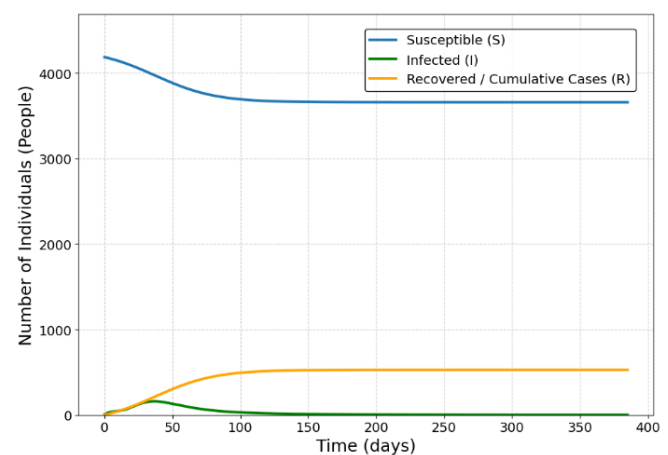


Figure 2: Expected trends of susceptible, infected, and recovered individuals across the outbreak period at 82% vaccination rate. Illustrative epidemic curves used to represent anticipated measles spread patterns based on observed outbreak characteristics. Y-axis represents the number of total individuals. X-axis represents time (in days) since the beginning of the outbreak; No statistical tests; single scenario visualization.

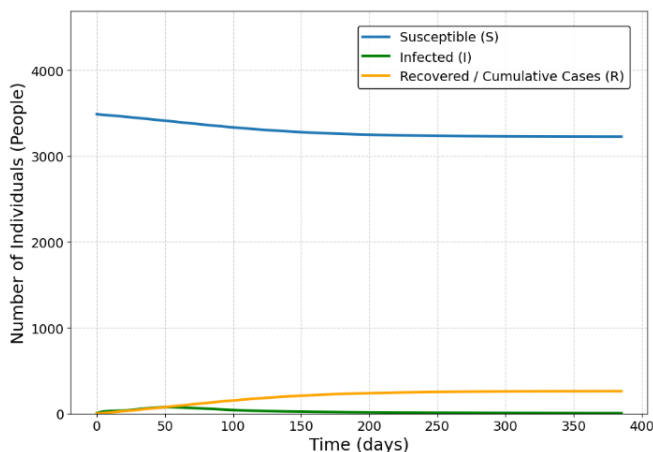


Figure 3: Expected trends of susceptible, infected, and recovered individuals across the outbreak period at 85% vaccination rate. Illustrative epidemic curves used to represent anticipated measles spread patterns based on observed outbreak characteristics. Y-axis represents the number of total individuals. X-axis represents time (in days) since the beginning of the outbreak; No statistical tests; single scenario visualization.

outbreak dynamics (Figure 1). Higher vaccination rates reduce both the peak number of infections and the overall duration of the outbreak, highlighting the strong influence of vaccination coverage on transmission patterns. At an 82% vaccination rate in Gaines County (representing the estimated MMR vaccination coverage during the outbreak period), the outbreak stabilizes around the beginning of July 2025 (Figure 2). This stabilization occurs because the number of individuals recovering increases during this period while the number of susceptible individuals (individuals who were unvaccinated and had not previously been infected) decreases as individuals either become vaccinated or gain immunity through recovery. In the model, the number of currently infected individuals peaks around April, consistent with reported epidemiological data from Gaines County, and then slowly decreases until reaching zero toward the middle of the summer. Actual case data support this trend, with reported cases declining substantially after the April peak, demonstrating agreement between the model and observed outcomes. The difference between the number of susceptible individuals and recovered individuals is greater in the 85% vaccination rate simulation compared to the 82% vaccination rate simulation (Figures 2, 3).

The model demonstrates that increasing vaccination coverage substantially alters outbreak dynamics. Increasing vaccination coverage from 82% to 85% decreases the total number of infected individuals while slightly increasing the duration of the outbreak. Increasing vaccination coverage to 95% produces the most favorable modeled outcome (Figure 4). This vaccination rate results in a predicted outbreak duration of approximately 33 days and about 6 infected individuals (Table 1). The total number of infected individuals decreases by over 97%, and the expected outbreak duration

decreases by approximately 352 days (Table 1).

We used a curve fitting model to calculate the beta (β) and gamma (γ) values for the SIRV model, where beta represents the transmission rate (the rate at which susceptible individuals become infected) and gamma represents the recovery rate (the rate at which infected individuals recover) (Figure 5). We observed an exponential relationship between the number of infected individuals and time. As the outbreak continued, case numbers declined, and a negative exponential relationship emerged.

We identified a negative exponential relationship between the monthly rate at which susceptible individuals become vaccinated and the peak number of infected individuals (Figure 6). If the proportion of Gaines County's population that remains vaccinated remains at a baseline of 82%, the peak number of individuals infected at a given time exceeds 200. However, when the vaccination rate reaches 0.006 (vaccinating 0.6% of the remaining susceptible individuals per month), the peak number of infected individuals decreases to fewer than 20. Increasing this monthly vaccination rate further to 0.010 (1.0% per month) reduces the peak infection burden to its lowest modeled levels (approximately 15 individuals). These results demonstrate that increasing vaccination coverage substantially reduces infection burden within the modeled population.

DISCUSSION

This study aimed to evaluate how varying levels of immunization impact transmission dynamics during localized measles outbreaks. We hypothesized that increasing vaccination coverage would significantly reduce the peak and total number of affected individuals. Our compartmental modeling supported this hypothesis, as higher vaccination rates saw fewer peak and total infected individuals. This demonstrates that proactive immunization campaigns effectively flatten the infection curve and interrupt transmission chains.

Understanding these localized dynamics has become increasingly critical given global immunization trends (8). Despite substantial progress toward measles elimination achieved through highly effective vaccines, the percentage of children receiving the first dose of this vaccine has declined

	82% Vaccination Rate	85% Vaccination Rate	95% Vaccination Rate
Total Predicted Number of Infected Individuals	528	261	6
Outbreak Duration (days)	266	385	33

Table 1: Total number of infected individuals and outbreak durations for 82%, 85%, and 95% vaccination rates for measles in Gaines County, TX. Data found from Center for Disease Control (CDC) and Prevention and Texas Department of State Health Services (DSHS); Outbreak duration and predicted number of infected individuals were calculated from SIRV (Susceptiblemodel); No statistical test; Single simulation run per vaccination scenario.

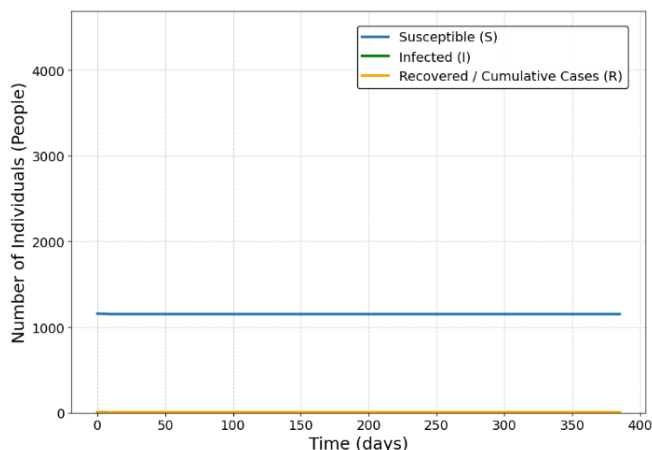


Figure 4: Expected trends of susceptible, infected, and recovered individuals across the outbreak period at 95% vaccination rate. Illustrative epidemic curves used to represent anticipated measles spread patterns based on observed outbreak characteristics. Y-axis represents the number of total individuals. X-axis represents time (in days) since the beginning of the outbreak; No statistical tests; single scenario visualization.

from 86% to 83% between 2019 and 2023 (9). Our simulation directly mirrors the consequences of this vulnerability, revealing that case counts increase exponentially during the first few months before gradually declining. While the Curve Fitting Model displays a clear exponential relationship between case count and time, our SIRV model offers deeper mechanistic insight by showing that slightly increasing the number of individuals vaccinated in a population decreases the number of infected individuals, though the outbreak may last longer (as seen in this study from the vaccination rate increase from 82% to 85%). This increase in duration is likely because increasing the vaccination rate decreases transmission among susceptible individuals, causing the virus to persist for a longer period as it gradually reaches the remaining unvaccinated individuals or those experiencing breakthrough infections. However, increasing the vaccination rate to 95% decreases both the expected number of infected individuals and the duration of the outbreak. A 95% vaccination rate is recommended to achieve herd immunity (9). This proportion of vaccinated individuals is crucial to protect those who are not vaccinated or are unable to receive vaccines, as it reduces measles circulation within the population and makes infection substantially less likely.

Comparison between model projections and real-world epidemiological data suggests that the model accurately captured key trends observed during the Texas measles outbreak. The model predicted stabilization around early July 2025, which aligns with reported data showing a sharp decline in cases following the April peak and the official declaration of the outbreak's end on August 18, 2025 (5). This agreement between modeled outcomes and observed trends supports the validity of the SIRV framework for evaluating vaccination strategies and understanding measles transmission dynamics.

The SIRV model used in this study yields similar results to previously published epidemiological models, including the epiEngage and CDC measles outbreak models (9,10). Although these models use different parameters and frameworks, they similarly demonstrate that increasing vaccination coverage reduces the total number of infected individuals and helps shorten outbreak duration. These consistent findings across multiple modeling approaches strengthen confidence in the conclusion that vaccination coverage above 90% is critical for controlling measles outbreaks.

Public health responses and increased community awareness during outbreaks may also influence vaccination behavior. If vaccination uptake increased during or following the Gaines County outbreak, this would be consistent with prior research showing that outbreaks can increase risk perception and motivate higher vaccination rates (9). Although precise post-outbreak vaccination rates for Gaines County have not yet been fully reported, prior research has shown that measles outbreaks are often associated with increased risk perception and temporary increases in vaccination uptake, suggesting that the outbreak may have influenced local vaccination behavior. These modeling results can support public health campaigns by illustrating how even small increases in vaccination coverage substantially reduce infection burden, providing evidence-based messaging to encourage community vaccination uptake. External factors such as healthcare access, socioeconomic status, vaccine cost, and local healthcare infrastructure may also influence vaccination compliance and contribute to variations in coverage across communities. Future research examining vaccination trends before and after the outbreak could provide additional insight into how outbreak dynamics influence community vaccination behavior and long-term disease prevention. For policymakers, these findings highlight the importance of targeted vaccination initiatives, improved access to immunization services, and early intervention strategies to maintain vaccination coverage above herd immunity thresholds and prevent future outbreaks.

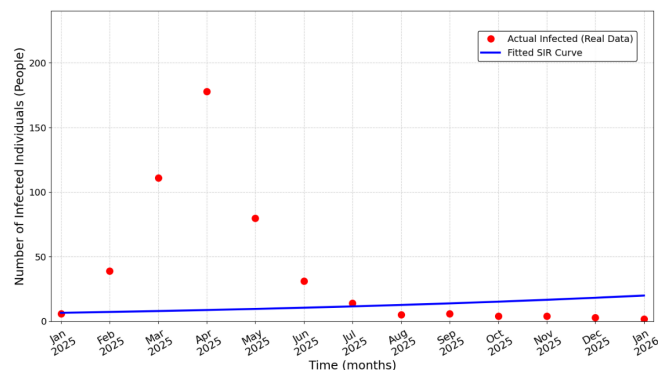


Figure 5: Susceptible-Infected-Recovered-Vaccinated (SIRV) Curve Fitting model. Used to showcase the spread of measles in Gaines County, TX and calculate the beta and gamma values for the SIRV model, based on real infection data. Regression line of best fit was used for this calculation. Single simulation run.

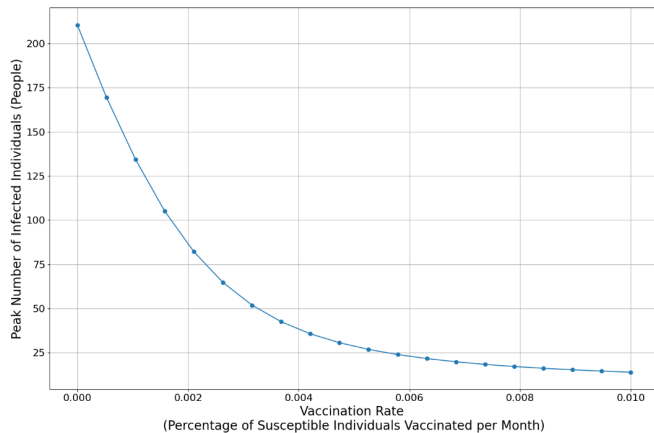


Figure 6: Graph of Vaccination Rate and Peak Infections. Data points generated from Susceptible-Infected-Recovered-Vaccinated (SIRV) model. Line of best fit was used to show the relationship. Single simulation run.

METHODS

Data Acquisition

This study utilized case data from the Texas Department of State Health Services (DSHS) (4). We utilized data from the first four months of the outbreak because this period captured the exponential growth phase necessary for accurate parameter estimation and provided sufficient variation to reliably fit model parameters. The analysis focused specifically on Gaines County, where most reported cases in the state occurred. Beginning in January, we compiled monthly case counts in Gaines County to estimate the outbreak trajectory using publicly available DSHS data (Figure 7) (5).

SIRV Model

Using the DSHS dataset, a Susceptible–Infected–Recovered–Vaccinated (SIRV) model was constructed in Python to simulate disease transmission dynamics (11). This compartmental model is commonly used in epidemiology to predict the spread of infectious diseases within a population (6). The model consists of four primary compartments: susceptible (S), infected (I), recovered (R), and vaccinated (V). Susceptible individuals are those who are not vaccinated and have not yet been infected but may become infected. The infected compartment represents individuals currently carrying and transmitting the disease. Recovered individuals are those who were previously infected and are assumed to have immunity. Vaccinated individuals are those who have received a vaccine against the disease. To govern the movement between these states, the model utilizes the parameters β (beta), γ (gamma), v , and μ to denote the transmission rate, recovery rate, vaccination rate, and loss-of-immunity rate, respectively. The loss-of-immunity rate represents the potential for immunity to decrease over time, allowing individuals to return to the susceptible category. Ultimately, the model assumes homogeneous mixing within the population and applies compartmental transitions

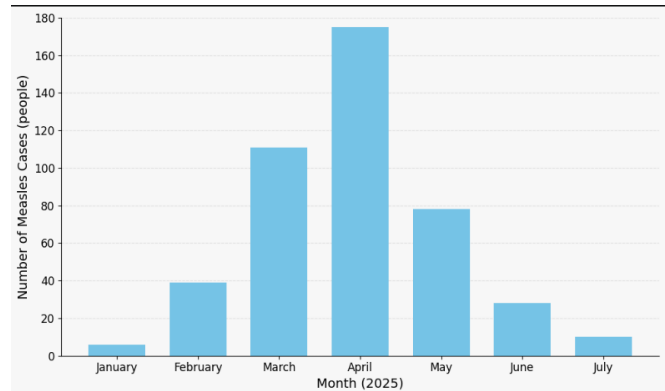


Figure 7: Bar Graph of Measles Cases by Month in Gaines County, TX. Measles cases by month in Gaines County from Jan 2025 to July 2025. Data collected from Center for Disease Control and Prevention (CDC) and Texas Department of State Health Services (DSHS). Infections peak in April with approximately 175, declining substantially after May. Single simulation run.

governed by these parameters to simulate outbreak dynamics under different vaccination scenarios.

Model parameters included the transmission rate (β), recovery rate (γ), vaccination rate (v), and loss-of-immunity rate (μ). The transmission rate (β) represents the rate at which susceptible individuals become infected after contact with infected individuals. The recovery rate (γ) describes how quickly infected individuals recover from the disease. The vaccination rate (v) represents the rate at which susceptible individuals become vaccinated. The loss-of-immunity rate (μ) represents the potential for immunity to decrease over time, allowing individuals to transition back into the susceptible category; although measles immunity is typically long-lasting, this parameter was included to maintain consistency with extended SIRV frameworks and to account for uncertainty in long-term protection assumptions.

The first equation describes how the number of susceptible individuals, $S(t)$, changes over time. Susceptible individuals may become infected through contact with infectious individuals or be removed from the susceptible group through vaccination.

$$dS/dt = -((\beta SI)/N) - vS \quad [\text{Equation 1}]$$

The second equation models the change in the number of infectious individuals, $I(t)$, over time. The term $(\beta SI)/N$ represents the inflow of newly infected individuals from the susceptible group, while the term $-\gamma I$ represents the outflow of individuals who recover from infection at a rate γ . This balance determines whether the infection spreads or declines within the population.

$$dI/dt = ((\beta SI)/N) - \gamma I \quad [\text{Equation 2}]$$

The third equation captures the rate of change of the recovered population, $R(t)$. Since recovery is assumed to confer lasting immunity, recovered individuals move permanently from the infectious class to the recovered class.

The term γI therefore reflects the rate at which infected individuals recover per unit of time.

$$dR/dt = \gamma I \quad [\text{Equation 3}]$$

Finally, the fourth equation describes the dynamics of the vaccinated group, $V(t)$. Individuals are added to this group when susceptible individuals receive a vaccine, represented by the term νS . The model assumes that vaccination provides complete and permanent immunity, meaning vaccinated individuals do not return to the susceptible class.

$$dV/dt = \nu S \quad [\text{Equation 4}]$$

Together, these four equations form the SIRV compartmental model, which tracks how infection, recovery, and vaccination interact over time in a constant-size population. This framework enables quantitative analysis of epidemic dynamics and evaluation of vaccination strategies under varying transmission and recovery conditions.

These equations were used to construct the SIRV model function in Python. All simulations and analyses were performed using Python (version 3.11.9). Scientific computing libraries included NumPy for numerical computations, pandas for data organization and processing, SciPy for parameter estimation (`curve_fit`) and numerical solution of the differential equations (`odeint`), and matplotlib.pyplot for visualization and graph generation. Simulations were executed in a deterministic framework using ordinary differential equation solvers.

The initial population (N) of Gaines County was set to 23,289. Because six measles cases were reported in Gaines County in January, the initial number of infected individuals (I_0) was set to 6. The initial recovered population (R_0) was set to 0 since none of these individuals had recovered during January. The vaccination rate in Gaines County remained approximately 82%, so the initial vaccinated population (V_0) was set to $0.82 \times N$. The number of susceptible individuals was calculated as:

$$S_0 = N - I_0 - R_0 - V_0 \quad [\text{Equation 5}]$$

Curve Fitting Model

To estimate the transmission and recovery rates, an additional program titled “Curve Fitting Model” was developed. In this model, I_0 and R_0 remained the same; however, vaccination effects were not included, resulting in an increased susceptible population. An SIR model was used to estimate the transmission and recovery parameters. Time, estimated transmission (0.2), and estimated recovery rates (0.1) were used as initial inputs. The Euler method was applied to approximate solutions to the differential equations by calculating expected changes in infections and recoveries over small time intervals. These calculated changes updated the compartment values (S , I , R , new infected, new recovered) for each interval. The rate of change at each interval was used to build an approximate trajectory of how S , I , and R evolved over the simulation period.

The `curve_fit` function implemented the Levenberg–Marquardt nonlinear least-squares optimization algorithm to determine optimal parameter values for β and γ , which were estimated as 1 and 0.1266, respectively. These values, along with the initial SIRV compartment values, time points, and vaccination rate, were used as inputs for the main SIRV model.

The `odeint` function served as the numerical solver for the system of differential equations, computing rates of change for S , I , R , and V across specified time intervals. Line graphs were generated using matplotlib to visualize the changes in compartment populations over time. Outbreak duration was estimated by counting the number of days during which the infected population (I) exceeded one active case. Beginning in January, the duration counter increased by one for each day in which $I > 1$. When the number of infected individuals reached zero, the counter stopped, and the total outbreak duration was recorded.

Additional visualizations included bar graphs representing monthly case counts and curve-fitting outputs displaying the relationship between time and number of infected individuals when the vaccination rate was set to zero. Using the same SIRV framework, an additional analysis examined the relationship between vaccination rate and peak infection levels. Vaccination rates were varied from 0.00 to 0.01 in increments of 0.0005, generating 20 distinct vaccination scenarios. An array, `peak_infections`, stored the maximum number of infected individuals for each vaccination rate. The β and γ values remained constant throughout this analysis. For each simulation, `odeint` generated a two-dimensional array in which rows represented time points and columns corresponded to S , I , R , and V values. The array was transposed using Python’s `.T` method to extract the infected population as a one-dimensional array, allowing the maximum infection value to be calculated. This procedure was repeated for each vaccination rate to generate the final dataset.

Received: June 13, 2025

Accepted: March 22, 2026

Published: October 26, 2026

REFERENCES

1. Cleveland Clinic. “Measles (Rubeola).” Cleveland Clinic, 2025, <https://my.clevelandclinic.org/health/diseases/8584-measles>.
2. National Library of Medicine. “Overview: Measles.” National Institutes of Health, Sept. 2023, <https://www.ncbi.nlm.nih.gov/books/NBK564984/>.
3. Centers for Disease Control and Prevention. “History of Measles.” Centers for Disease Control and Prevention, 9 May 2024, <https://www.cdc.gov/measles/about/history.html>.
4. Kuppalli, Krutika, and Trish M. Perl. “Measles in Texas: Waning Vaccination and a Stark Warning for Public Health.” *The Lancet Infectious Diseases*, May 2025,

- [https://doi.org/10.1016/S1473-3099\(25\)00162-8](https://doi.org/10.1016/S1473-3099(25)00162-8).
5. Texas Health and Human Services. “Measles Virus Measles Outbreak in Texas.” Texas Health and Human Services, 2024, <https://www.dshs.texas.gov/measles>.
 6. Texas Department of State Health Services. “Measles Outbreak in Gaines County, Texas.” Texas Health and Human Services, 5 Feb. 2025, <https://www.dshs.texas.gov/news-alerts/measles-outbreak-gaines-county-texas>.
 7. Schlickeiser, Reinhard, and Martin Kröger. “Key Epidemic Parameters of the SIRV Model Determined from Past COVID-19 Mutant Waves.” *Pathogens*, vol. 3, no. 4, 2023, pp. 42–56. <https://www.mdpi.com/2673-8112/3/4/42>.
 8. Minta, A. A., et al. “Progress Toward Measles Elimination — Worldwide, 2000–2023.” *MMWR. Morbidity and Mortality Weekly Report*, vol. 73, no. 45, 2024, pp. 1036–42. <https://doi.org/10.15585/mmwr.mm7345a4>.
 9. epiEngage. “epiENGAGE Measles Outbreak Simulator.” Texas Advanced Computing Center, 2025, <https://epiengage-measles.tacc.utexas.edu>.
 10. Masters, N. B., et al. “Real-Time Use of a Dynamic Model to Measure the Impact of Public Health Interventions on Measles Outbreak Size and Duration — Chicago, Illinois, 2024.” *MMWR. Morbidity and Mortality Weekly Report*, vol. 73, no. 19, 2024, pp. 430–34. <https://doi.org/10.15585/mmwr.mm7319a2>.
 11. Sinha, Aarush. “Gaines County Measles Outbreak SIRV Model Code.” GitHub, 2025, <https://github.com/Aarush-ai288/Gaines-County-Measles-Outbreak>.

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