Modeling RSV Transmission in Delhi Using a SIRS Framework: Integrating AQI-Based Recovery and Density-Driven Spread via Social Network Analysis

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Introduction

Respiratory Syncytial Virus (RSV) is a highly contagious respiratory pathogen that poses a significant health risk, particularly to infants, the elderly, and individuals with underlying respiratory conditions. Its transmission is strongly influenced by contact with respiratory droplets, rendering densely populated areas especially susceptible to rapid spread. Additionally, recent research highlights the adverse effect of air pollution on infection outcomes, with elevated Air Quality Index (AQI) levels associated with prolonged recovery times. Mathematical modeling has long been used to study the dynamics of infectious diseases, offering insights for predicting outbreaks and formulating intervention strategies. The SIR (Susceptible-Infected-Recovered) model remains one of the most widely used frameworks for understanding epidemic behavior. However, classical SIR models often assume homogeneous mixing and fixed transmission rates, which may not hold true in complex, real-world settings. In this study, we extend the classical SIR model to a SIRS framework to incorporate the temporary loss of immunity, and introduce two key modifications: the transmission rate is modeled as a function of local population density, reflecting the increased transmission potential in crowded environments, while the recovery rate is defined as AQI-dependent, accounting for the observed impact of pollution on recovery dynamics. These enhancements allow the model to better capture the combined influence of social structure and environmental conditions on RSV outbreaks in urban settings such as Delhi.

The Model

Effect of AQI Levels on Recovery Rates

Currently, no mathematical model incorporates the impact of AQI levels on recovery rates. In light of this, we propose a modified SIRS model where the recovery rate is a function of a district's AQI. Let AQI_0 represent a baseline AQI level, and AQI the AQI level in a specific district. Let d_0 denote the number of days required to recover at AQI_0. Previous research has shown that every 10 μg/m³ increase in lag03 PM2.5 corresponds to a 4.13-day increase in hospital stay (Cao et al., 2021). We calculate the relative increase in AQI per 10-unit increase as:

$$\frac{AQI - AQI_0}{10}$$

Because recovery rate cannot be negative, we take max $(0, (AQI - AQI_0)/10)$.

As we calculated based on data, we have found that a 1-unit increase in PM2.5 corresponds to a 1-unit increase in AQI (Calculations shown in the supporting document). Based on this, the relative increase in recovery time due to AQI is derived using the formula above. This value is

then multiplied by the reported 4.13-day increase per 10-unit rise in PM2.5, giving us the estimated increase in recovery days for each district. Accordingly, the updated recovery rate for node *i* is:

$$\gamma_i = \frac{1}{\frac{1}{\gamma} + 4.13 \times max(0, \frac{AQI - AQI_0}{10})}$$

Effect of Distance Between Nodes on Infection Rates

To model the influence of physical distance on infection rates, we implemented a distance decay function. These functions assume that as the distance between two locations increases, the interaction strength between them decreases (de Smith, Goodchild, & Longley, 2024). We used a standard exponential distance decay function, defined as follows:

$$\beta_{ij} = \beta \cdot e^{-\lambda d(i,j)}$$

β_{ij} is the transmission rate between individuals/houses *i* and *j*

β is the baseline transmission rate, which is the maximum transmission rate when distance is zero

λ is the decay parameter. It controls how fast the transmission probability drops off with distance.

d(i,j) is the distance between *i* and *j* based on longitude and latitude.

Differential Equations

Thus, the differential equations used in the model, using the updated recovery and infection rates, will be:

$$\frac{dS}{dt} = -\beta_{ij} SI + \delta R$$

$$\frac{dI}{dt} = \beta_{ij} SI - \gamma_i R$$

$$\frac{dR}{dt} = \gamma_i R - \delta R$$

Where *i* is a node which is connected to node *j* and β_{ij} and γ_i are defined as above.

Methodology

To model the spread of RSV in Delhi, we constructed a social network-based SIR model that incorporates environmental sensitivity to AQI levels, using Python. To generate the nodes, we

first allocated a maximum of 1000 houses (nodes) across Delhi's districts in proportion to their population densities. For instance, districts with higher population densities, such as North East Delhi, were assigned more houses. We then defined approximate bounding boxes for each district based on their geographical coordinates.

Figure 1: House Distribution in Delhi

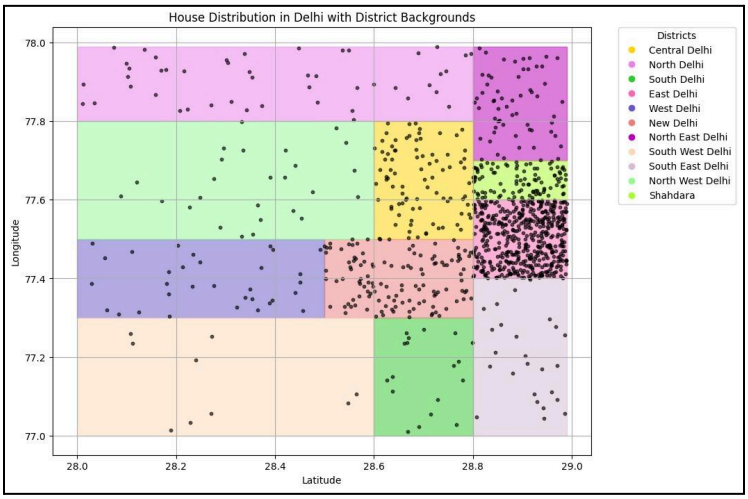


Figure 2: Delhi District Map

Source: NRIOL.com

Within each district, household coordinates were randomly generated within the corresponding bounding box. In total, 995 nodes were created, each representing a household (or individual).

To simulate a social network, the edges in the graph represented a simplified version of real-world contact. This was done by first choosing a district radius of 5000 metres for all districts. For each node, we identified the in-district and out-of-district neighbourhood. We then filtered out the in-district neighbours to the ones within the specified radius of 500 metres and chose up to eight of the closest distance-wise neighbours using the Python library *Geopy*. This was done to simulate real-world neighbourhoods where the rate of contact is likely to be highest amongst households that are closest to each other. To also take into account connectivity between people living further from each other, we connected each house to two random out-of-district neighbours. Thus, each node could have a maximum of ten neighbours. Weights were assigned to each edge based on the geographical distance between the two connected nodes. This network structure allowed us to capture how localized social interactions contribute to disease propagation.

The initial infection, recovery, and waning immunity rates were chosen to be, $\beta = 0.2$, $\gamma = 1/14$, $\delta = 0.01$, respectively. To initialize the graph, 5 individuals are randomly selected to be infected, and the others are susceptible. During each simulation tick, the state of every node is updated based on its current status and the status of its neighbors. If a node i is susceptible, it can become infected if it is connected to an infected neighbor j. The infection probability decreases with increasing geographical distance calculated via β_{ij}. Within β_{ij}, we

took λ = 0.001 to reflect the reality of urban mobility in a densely connected city like Delhi – not only are neighbours close by likely to interact, but people also travel across the city for work, education, and other purposes. Our λ value allows for significant infection transmission across several kilometers. If *i* is infected, it can recover based on a recovery rate that is adjusted according to the AQI of the node's district, which is calculated by γ_i. We assumed $AQI_0 = 150$ since that is the current average AQI in Delhi. Recovered nodes can return to the susceptible state based on a constant probability. This continuous update process models the spread and control of infection over time, with the current state of the population visualized on a dynamic network graph.

To contrast our results with the traditional SIRS model, we also ran a simulation using the standard differential equations. Thus, in this case, there was no network but only disconnected edges. The model parameters were the same as the initial parameters in our modified model.

Results and Analysis

Figure 3: SIRS Model with AQI-Based Recovery and Density-Driven Spread Simulation

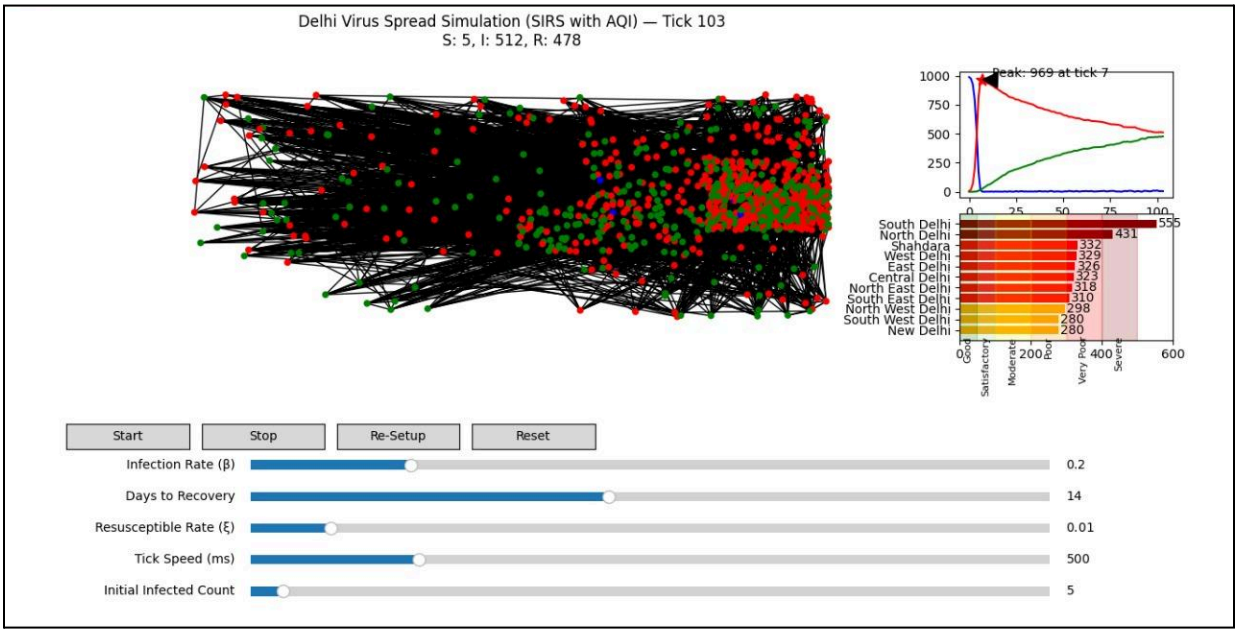


Figure 4: Traditional SIRS model simulation

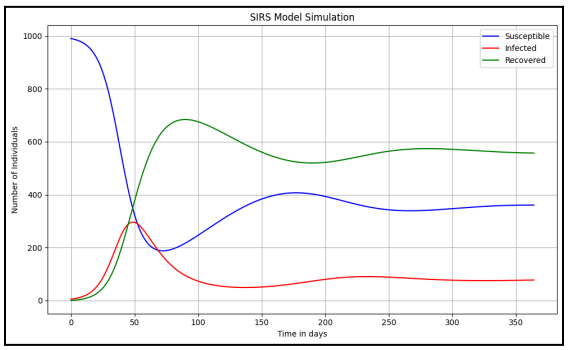
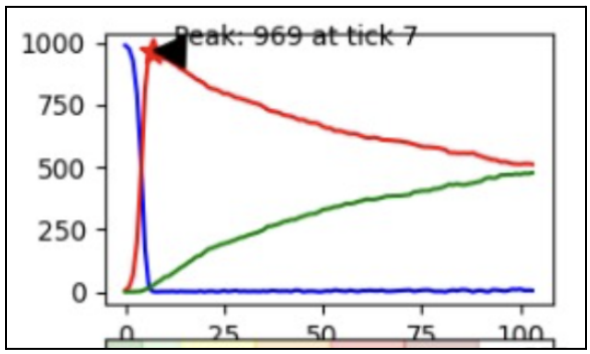


Figure 5: Modified SIRS model simulation



The simulation of RSV spread in Delhi, visualized using a network graph, revealed an epidemic curve typical of the SIRS model, but with key differences compared to the traditional SIR model. In the traditional SIRS model, the peak occurred at around day 49, showing a more prolonged epidemic curve, as shown in Figure 4. In contrast, our network-based model exhibited a sharper peak at day 7, as can be seen in Figures 3 and 5. This sharp peak in our model is a result of incorporating geographical proximity and district-based AQI levels into the network structure, which accelerated the spread of the infection in densely connected neighborhoods, and because recovery rates are lower in these regions. The high AQI values, typical of the November-December Diwali season, demonstrated how air pollution exacerbates RSV transmission. During this period, AQI levels often exceed 400, which is among the worst possible conditions for respiratory health. Further, the introduction of distance-based network connectivity allowed the disease to spread more quickly compared to the traditional SIRS model, which does not account for these local transmission dynamics.

Discussion

The simulation reveals that districts with persistently high AQI levels, particularly North Delhi, North East Delhi, and Shahdara, experience longer infection durations and slower recovery rates. When AQI increases by 10, recovery rates decline, with an increase of 4.13 days longer in recovery compared to moderate air quality conditions, indicating a potential threshold beyond which pollution significantly impairs health outcomes (Surit et al., 2023; Cao et al., 2021).

This effect is rooted in well-established biological mechanisms. Exposure to elevated levels of pollutants such as PM2.5 impairs respiratory function by triggering lung inflammation and reducing oxygen transfer efficiency (Adamkiewicz et al., 2020). Pollutants that enter the bloodstream induce body-wide inflammatory responses and oxidative stress, causing the production of free radicals and damaging cells that are responsible for healing (Gilmour et al., 2003). Moreover, the immune system is burdened as it diverts resources toward combating pollutant stress, further slowing recovery from infections like RSV (Zhang et al., 2020)

Incorporating geographical proximity into our network model uncovered distinct transmission patterns as well. Initial infections rapidly spread through densely populated neighborhoods, forming localized clusters. These clusters persisted longer in regions where high population density coincided with severe pollution, and long-range edges in the network helped bridge infections between districts, amplifying spread. It is important to note that while our peak is much lower, the reason for its significantly low value (day 7) is that the sample size considered is only 1000 houses.

While our findings underscore the importance of air quality in disease modeling, several limitations must be acknowledged. First, our model assumes a homogenous population, despite RSV disproportionately affecting infants, the elderly, and those with pre-existing conditions.

Second, although evidence suggests that air pollution can also increase susceptibility to respiratory infections, we chose to modify only the recovery rate parameter due to stronger empirical support. Our model does not yet capture pollution's effects on transmission probability. There are also structural simplifications in our network construction. We based interaction probabilities on geographical proximity, which overlooks real-world contact patterns shaped by workplaces, schools, and public transport. The use of square district boundaries, fixed interaction radii, and sampling only a small subset of Delhi's households introduces additional abstraction. Furthermore, our model assumes a linear relationship between AQI and recovery impairment, though this approximation requires validation through future field studies.

Despite these limitations, our findings emphasize that air quality is an important modifier of disease transmission. As air pollution worsens in many urban centers, especially in a developing city like Delhi, it becomes essential to adopt integrated health strategies. Our model suggests that improving air quality during RSV season could reduce both pollutant-related health burdens and infection severity. In high-risk districts, targeted policies, such as temporary school closures, mask mandates, and preemptive hospital resource allocation, could reduce strain on healthcare systems during pollution peaks (like during Diwali season).

For future work, longitudinal cohort studies tracking recovery time under varying AQI conditions could help establish more accurate quantitative relationships. Model improvements could also involve incorporating community-level transmission, age-structured populations, and mobility networks. By refining these parameters, we can better forecast infection trends in polluted cities and craft timely, data-driven interventions.

Author Contributions

All group members contributed equally to the research, modeling, coding, and report writing, with each member focusing more intensively on specific components.

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Conceptualization	Yes	Yes	Yes	Yes
Coding/Calculations	Yes	Yes	Yes	Partial
Analysis / Interpretation of model outcomes	Yes	Yes	Yes	Yes
Writing – Original Draft	Partial	Yes	Partial	Yes
Writing – Review & Editing	Yes	Yes	Yes	Yes
Visualization	Yes	Yes	Yes	Partial
Project Management	Yes	Partial	Yes	Yes
Preparing Slides	Partial	Partial	Partial	Yes
Organizing Meetings	Yes	Yes	Yes	Yes

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