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*Original Article*

# A Scaling Analysis of Influenza Transmission in Nepal

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## ABSTRACT

This research provides a detailed scaling analysis of Influenza transmission in Nepal by applying time series methods and the Hurst exponent. Examining monthly incidence across the most impacted districts from July 2022 to June 2024, the study evaluates the fractal characteristics—specifically self-similarity and self-affinity—of the data. By distinguishing between long-term and short-term memory patterns, the analysis determines whether the disease spread is persistent or anti-persistent. These insights offer a robust framework for public health officials to refine forecasting models and optimize intervention strategies.

**Keywords:** scaling analysis, Influenza transmission, Nepal

## INTRODUCTION

Over the last few decades, Influenza has emerged as a significant public health threat in Nepal, marked by a consistent rise in infection rates. To develop successful mitigation strategies, it is vital to understand the underlying mechanics of how these outbreaks evolve. One sophisticated way to study these trends is through **scaling methods**, which utilize mathematical concepts like scaling exponents and self-similarity to map the behavior of the virus. **Self-similarity** occurs when a structure is composed of smaller parts that statistically mirror the whole. In simpler terms, the pattern looks the same regardless of how much you "zoom in" or "zoom out." In the context of Nepal's Influenza data, self-similarity suggests that the fluctuations we see on a small scale (daily or weekly case counts) reflect the broader patterns seen on a large scale (seasonal or yearly cycles). By identifying these recurring structures, health officials can:

- **Improve Forecasting:** Predict future outbreaks by recognizing small-scale signals.
- **Optimize Resources:** Allocate medical supplies more efficiently based on recognized patterns.
- **Refine Interventions:** Create strategies that address both sudden spikes and long-term trends.

In epidemiology, **memory** refers to how much previous data points influence future trends. This is often categorized into two types:

**1. Long Memory (Long-Range Dependence)**

This occurs when current infection rates are significantly shaped by events from months or even years ago. If Influenza has a "long memory," it suggests that the disease is driven by persistent factors such as:

- Deep-rooted social behaviours.
- Long-standing environmental conditions.
- The lasting impact of historical public health policies.

**2. Short Memory (Short-Range Dependence)**

In this scenario, current cases are only influenced by the very recent past. The correlation between data points fades quickly. If an outbreak has "short memory," it implies the disease is highly sensitive to immediate changes, such as a sudden weather shift or a recent localized event, rather than long-term trends. Nygård and Glattre (2003) utilized fractal analysis to reveal hidden patterns in epidemiological time series, an approach useful for detecting trends in Influenza case data. Eco-epidemiological analyses by Chakravarti and Kumaria (2005) and Raheel et al. (2011) provided insights into the factors influencing

**Relevant conflicts of interest/financial disclosures**: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Influenza spread in India, essential for understanding the context of scaling analysis. Dias (2013) discussed self-affinity and self-similarity in ecological contexts, aiding in the modeling of self-similar Influenza case distributions. Saha et al. (2019) examined the relationship between irregularity and scaling indices in self-similar and self-affine signals, offering insights into the irregularities and scaling properties of Influenza trends. Ghosh (2020) applied scaling analysis to COVID-19 cases, demonstrating the effectiveness of these techniques in epidemiological studies. Time series forecasting using machine learning has also been explored by Bodapati et al. (2020) and Lestari et al. (2022), who employed Long Short-Term Memory (LSTM) networks to predict COVID-19 and Influenza cases, respectively. LSTM networks' ability to capture temporal dependencies makes them suitable for predicting future Influenza cases. Abdulwasaa et al. (2021) and El-Dessoky and Khan (2022) applied fractal-fractional models to epidemic forecasting, showing their potential for predicting Influenza outbreaks. Li et al. (2022) enhanced Influenza forecasts by integrating geospatial big data and historical information, highlighting the importance of comprehensive data for accurate predictions. Raubitzek et al. (2023) investigated scaling exponents in time series data through machine learning, providing methodologies relevant to analyzing Influenza trends. These studies collectively offer a robust foundation for using scaling approaches to analyze Influenza trends, demonstrating the applicability of various methods to understand and predict the spread of Influenza, crucial for developing effective public health strategies in Nepal. This research examines the daily fluctuations of Influenza cases in Nepal through a scaling framework, specifically focusing on **self-similarity** and **self-affinity**. By utilizing scaling analysis and calculating the **Hurst exponent (H)**, the study identifies latent patterns within the time series that conventional statistical methods often overlook. The Hurst exponent serves as a critical metric to quantify the "memory" and "roughness" of the data, revealing the extent to which past trends influence future outbreaks. Our findings confirm that daily incidence rates follow self-affine patterns, providing a more nuanced understanding of Influenza epidemiology. These insights are then discussed in the context of public health, offering a scientific basis for more robust monitoring and targeted intervention strategies in Nepal.

## 2. Theory:

### 2.1 Hurst Exponent

The Hurst exponent (H) measures the memory of a self-similar time series reflecting its tendency either to regress strongly to the mean or to cluster in a certain direction. For a self-similar time series, it ranges between 0 and 1. The following are its implications at different ranges.

**H = 0:** Represents white noise, where data points are completely uncorrelated.

**0 < H < 0.5:** Indicates anti-persistent behaviour (negative autocorrelation), where the time series exhibits short memory.

**H = 0.5:** Indicates a true random walk (Brownian motion), with no memory.

**0.5 < H < 1.0:** Indicates persistent behaviour (positive autocorrelation), suggesting long-term memory.

**H = 1:** Represents a perfectly smooth time series.

### 2.2 Scaling Analysis and Estimation of Hurst Exponent

Scaling analysis investigates how statistical features of data change with the scale of observation. It is employed to comprehend the fundamental patterns and behaviours that hold true throughout various temporal or spatial ranges. For a given finite time series $x(t_n)$ (where n=1,2, $N$ and $t$ represents time), The finite Variance Scaling Method (FVSM), specifically Standard Deviation Analysis (SDA), is used to estimate H. The sequence of cumulative standard deviations $D(t_j)$ associated with the partial time series $\{x(t_n)\}$ (for n=1,2, j) is calculated as:

$$D(tj) = \left[\frac{1}{j}\sum_{n=1}^{j} x^2(t_n) - \left(\frac{1}{j}\sum_{n=1}^{j} x(t_n)\right)^2\right]^{\frac{1}{2}}$$

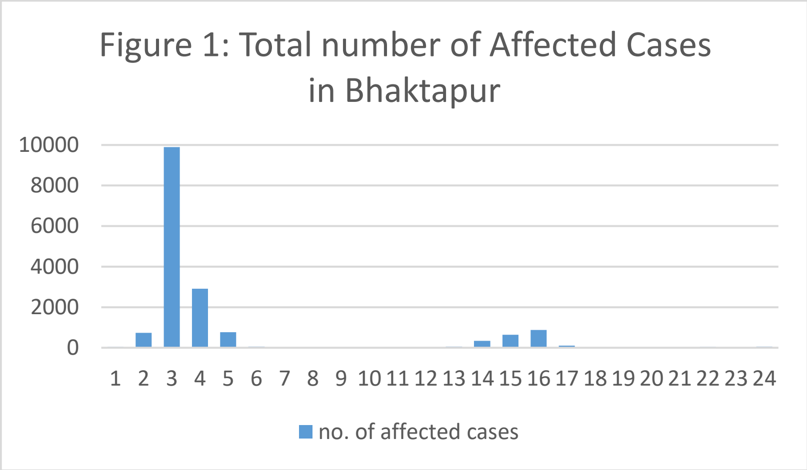
For self-similar time series, $D(t)$ follows a power law:

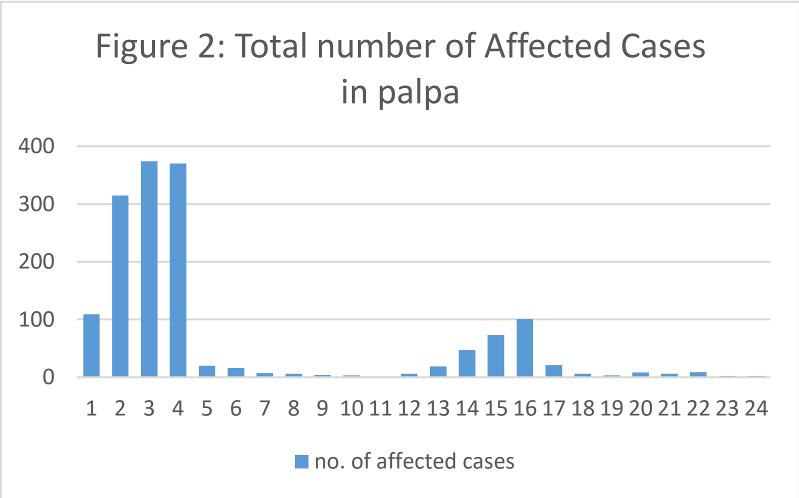
$$D(t) \propto t^H$$

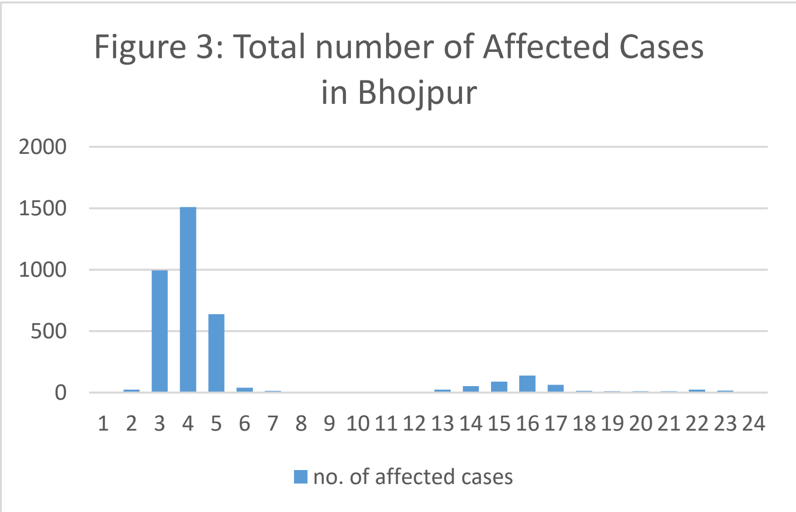
Here, H can be estimated from the slope of the best-fitted straight line in the log-log plot of D(t) versus t.

## RESULTS

In this study, we analyze the monthly number of new affected cases of Influenza in the most affected Districts of Nepal: Bhaktapur, Palpa, Bhojpur, Dhading, Makwanpur, Chitawan, Rupandehi, Katmandu. The data for this analysis has been sourced from the Ministry of Health and Population Department of Health Services Epidemiology and Disease Control Division ([14]). Figures 1-8 illustrate the monthly profiles for states namely Bhaktapur, Palpa, Bhojpur, Dhading, Makwanpur, Chitawan, Rupandehi, Katmandu in Nepal from July, 2022 to June, 2024.



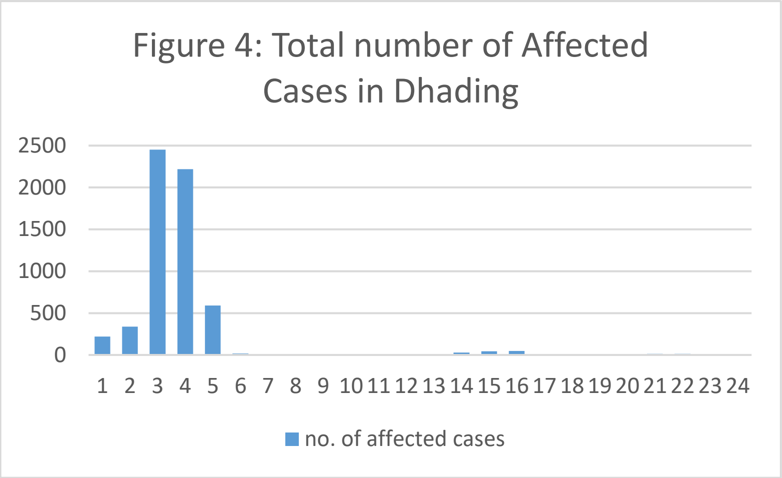


Figure 4: Total number of Affected Cases in Dhading
2500
2000
1500
1000
500
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
no. of affected cases

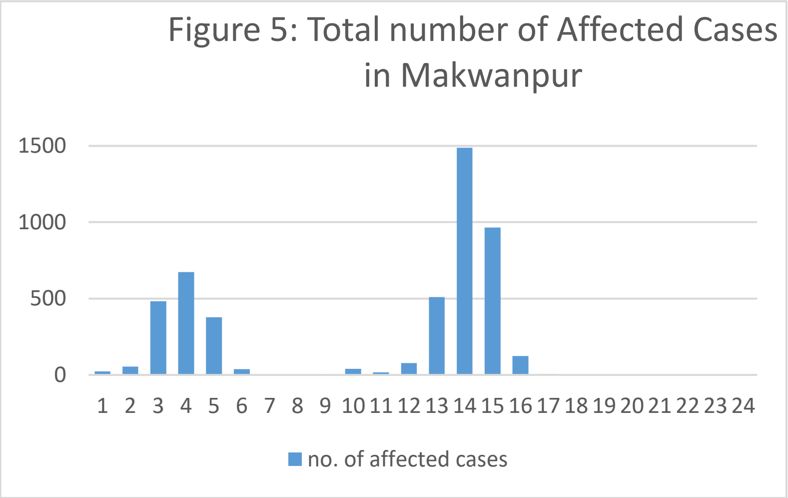


Figure 5: Total number of Affected Cases in Makwanpur
1500
1000
500
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
no. of affected cases

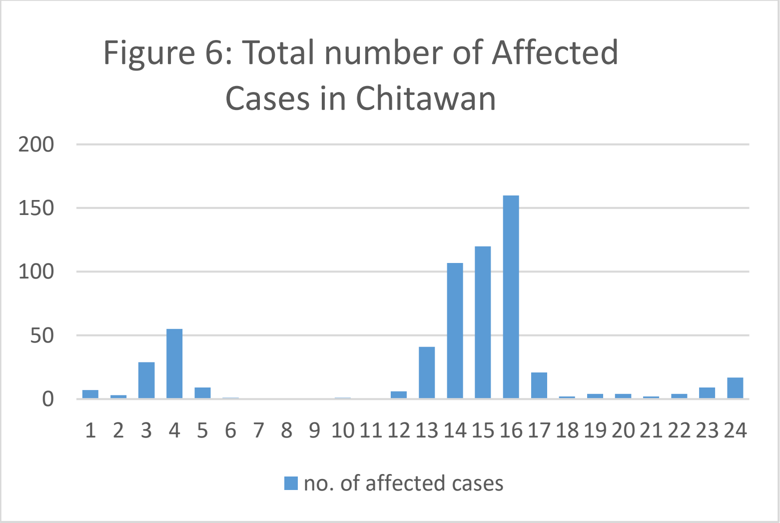


Figure 6: Total number of Affected Cases in Chitawan
200
150
100
50
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
no. of affected cases

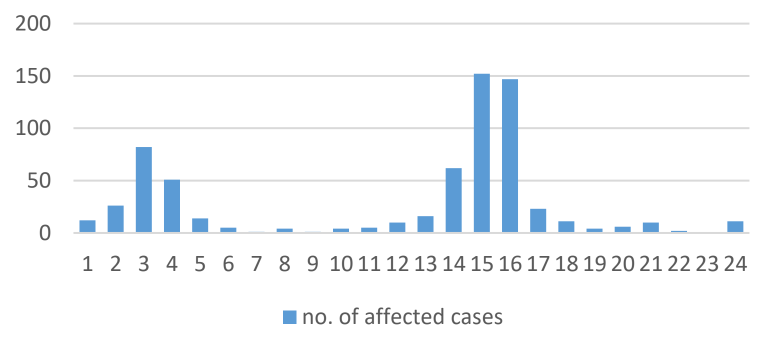



Figure 7: Total number of Affected Cases in Rupandehi

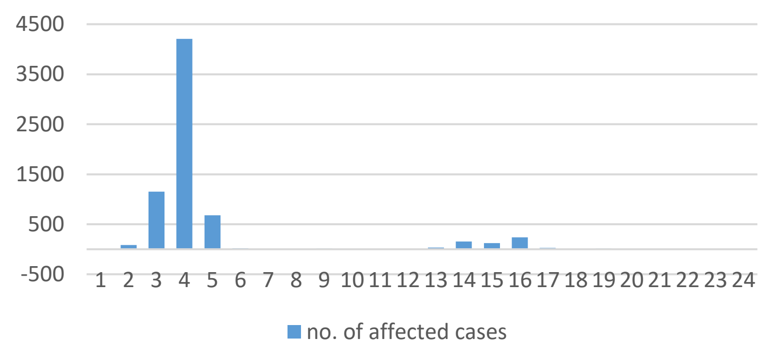



Figure 8: Total number of Affected Cases in Katmandu

The Finite Variance Scaling Method (FVSM) has been utilized on these ten distinct time series. The resulting log-log graphs, which depict the cumulative standard deviation plotted against time (in months), are shown in Figures 9 - 16.

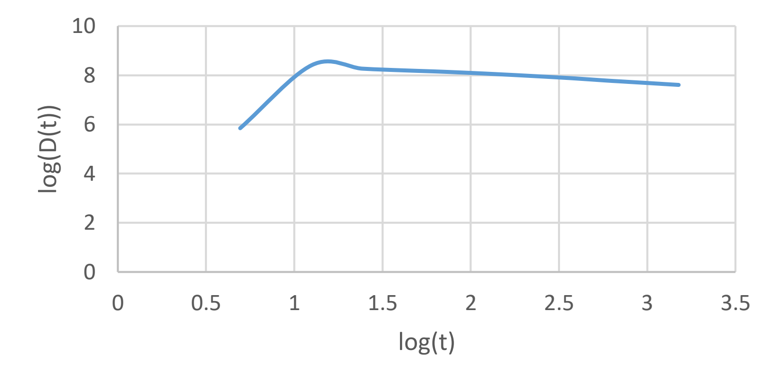



Figure 9: Scaling Analysis of New Cases of Influenza in Bhaktapur

Figure 10: Scaling Analysis of New Cases of Influenza in Palpa

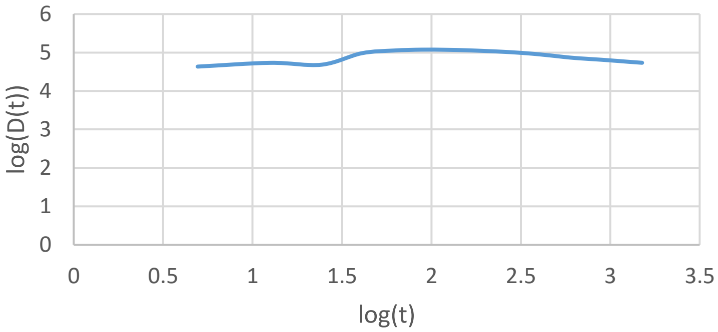



Figure 11: Scaling Analysis of New Cases of Influenza in Bhojpur

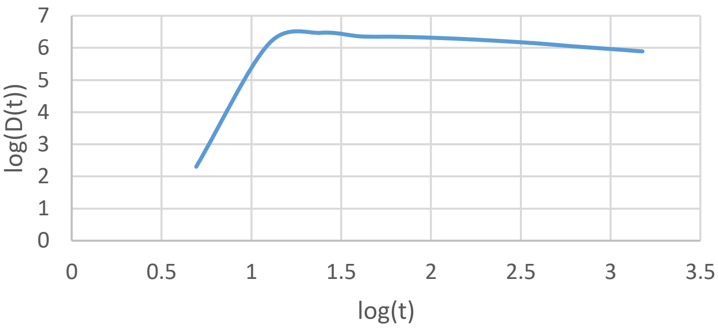



Figure 12: Scaling Analysis of New Cases of Influenza in Dhading

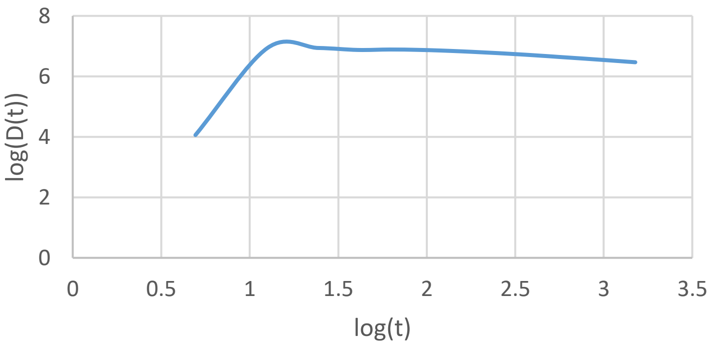


Figure 13: Scaling Analysis of New Cases of Influenza in Makwanpur

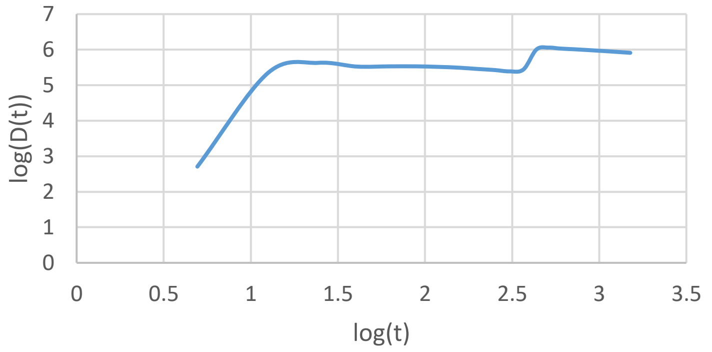



Figure 14: Scaling Analysis of New Cases of Influenza in Chitawan

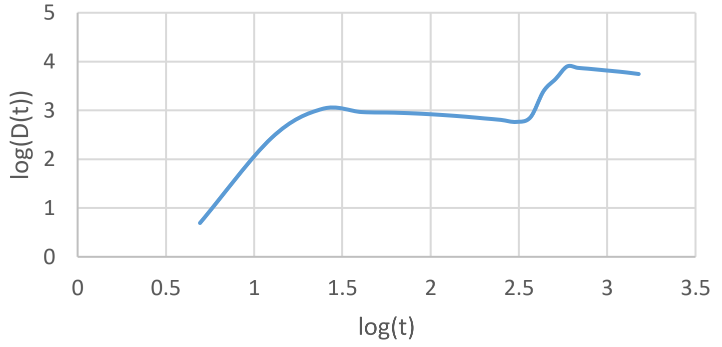
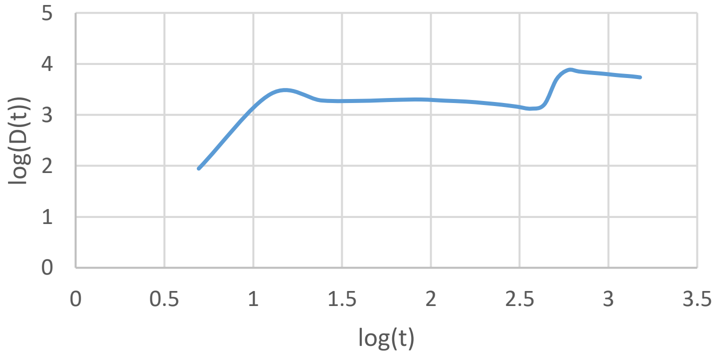



Figure 15: Scaling Analysis of New Cases of Influenza in Rupandehi



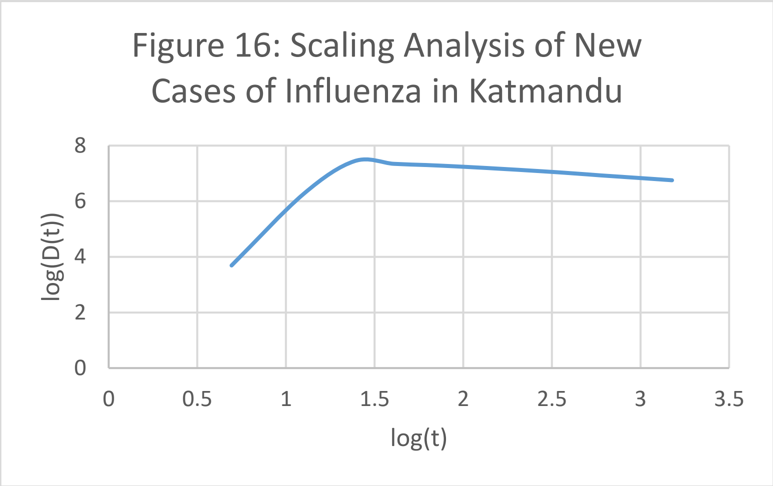



**Table 1: Estimation of Hurst exponent of affected cases due to Influenza in mostly affected Districts of Nepal:**

| States | Hurst Exponent (H) (for Affected cases) | Memory Status (for Affected cases) |
|---|---|---|
| Bhatkapur | 0.0613 | Short or anti-persistent memory |
| Palpa | 0.0013 | Short or anti-persistent memory |
| **Bojpur** | 0.4150 | Short or anti-persistent memory |
| Dhading | 0.2502 | Short or anti-persistent memory |
| Makwanpur | 0.7236 | Long or persistent memory |
| Chitawan | 0.9021 | Long or persistent memory |
| Rupandehi | 0.4739 | Short or anti-persistent memory with a hint of randomness |
| Katmandu | 0.4307 | Short or anti-persistent memory |

## DISCUSSION

In the present work, the scaling analysis of the monthly new cases of Influenza has been performed in some severely affected districts namely Bhaktapur, Palpa, Bhojpur, Dhading, Makwanpur, Chitawan, Rupandehi, Katmandu in Nepal. The data were log-transformed to calculate the Hurst exponent, followed by calculating the cumulative standard deviations. By plotting the log of the rescaled range against the log of the time and fitting a linear trend, the slope of this line provides the Hurst exponent. Makwanpur and Chitawan with high standard deviations and significant fluctuations, likely exhibit high H values indicative of persistent behavior. Bhojpur, with moderate trends, is expected to show intermediate H values, while Dhading with more stable trends, likely has a lower H value, suggesting less persistence, while Bhaktapur and Palpa, with stable trends, indicates a low H value. Rupandehi and Katmandu shows moderate persistence H values. Understanding these memory dynamics is crucial for designing predictive models, resource planning, and targeted public health strategies. Regions with persistent memory patterns may require continuous intervention efforts. Future research may examine environmental factors—like rainfall, temperature, and humidity—and their correlation with Influenza spread.

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