

# Key Factors Driving Malaria Prevalence



## Key Observations

### Strong Correlations

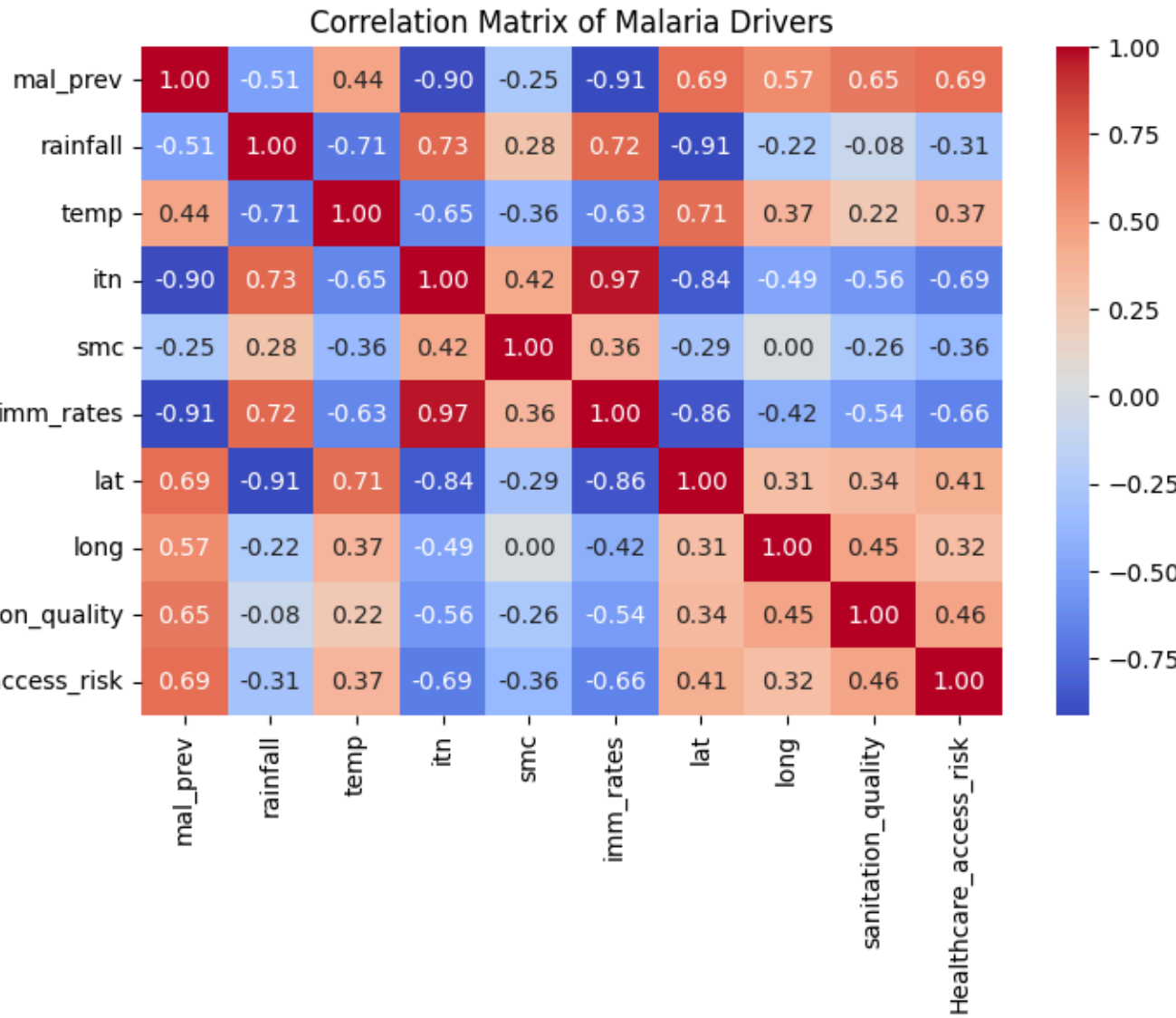
- **ITN (-0.90):** The strong negative correlation remains consistent, reinforcing the critical role of insecticide-treated nets in reducing malaria prevalence.
- **Immunization Rates (-0.91):** Again, this highlights the importance of high immunization rates in areas with lower malaria prevalence, possibly reflecting both direct (malaria-targeted vaccines) and indirect (overall health improvement) impacts.
- **Healthcare Access Risk (0.69):** The positive correlation remains moderate to strong, suggesting that areas with limited healthcare access are at higher risk of malaria prevalence due to delayed treatment and reduced preventive measures.
- **Latitude (0.69) and Longitude (0.57):** These relationships suggest malaria prevalence is influenced by geography, with areas closer to the equator (lower latitude) and specific longitudinal bands experiencing higher prevalence.

### Environmental Factors

- **Rainfall (-0.51):** A moderate negative correlation indicates that higher rainfall may disrupt mosquito breeding sites or dilute larval habitats. This relationship could be highly context-specific.
- **Temperature (0.44):** A moderate positive correlation reflects the favorable temperature ranges for mosquito breeding and parasite development.

### Unexpected Trends

- **Sanitation Quality (0.65):** While strong correlation is expected, a moderate positive correlation persists, which could be due to confounding factors like urbanization, where better sanitation correlates with higher population density, increasing malaria transmission risk.
- **SMC (-0.25)** shows a weak negative correlation, indicating its effectiveness is context-dependent. Its impact may be diluted due to: application only in high-risk seasonal areas, overlap with other preventive measures like ITNs and immunization or Incomplete capture of temporal variations in malaria prevalence, as SMC targets specific times of the year.



Correlation Matrix of Malaria Drivers: Highlighting the relationships between malaria prevalence (mal\_prev) and various factors, including environmental, healthcare, and preventive measures, to identify key influences on malaria transmission and control

# State-Level Predictive Insights for Malaria Control Modelling



Leveraging machine learning, we derived state-specific predictions to inform and optimize intervention strategies across Nigeria.

The scatter plot compares the actual malaria prevalence (on the x-axis) with the predicted malaria prevalence (on the y-axis) based on a model. The dashed red line represents the ideal alignment, where predictions match the actual values perfectly.

### Key Observations:

1.Strong Positive Correlation:

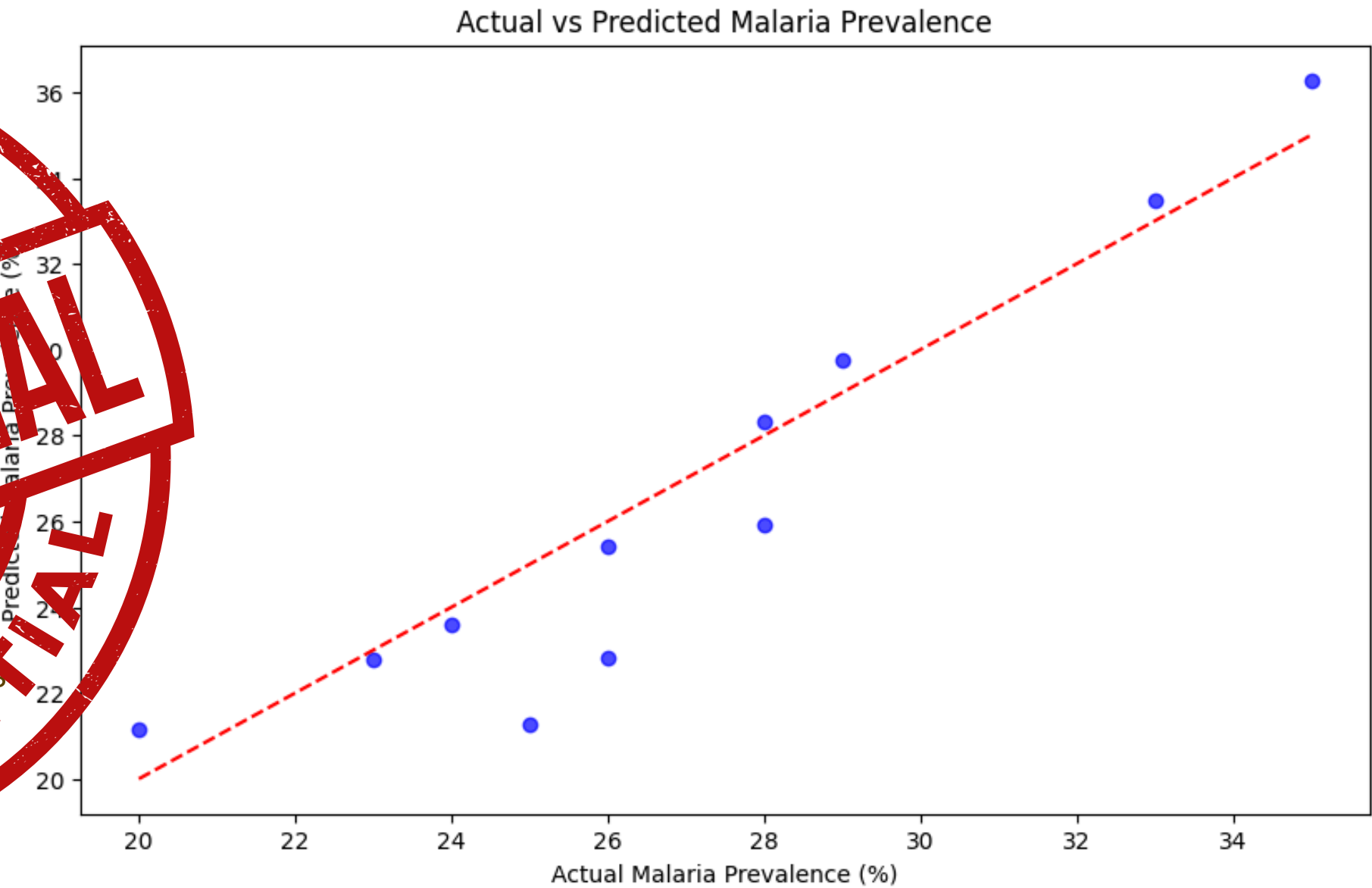
- The data points are closely aligned with the red line, indicating that the model's predictions are generally accurate.
- This reflects a high degree of agreement between the actual and predicted values.

2.Deviations:

- A few points fall slightly above or below the red line, suggesting minor prediction errors.
- These deviations could highlight areas where the model's performance might be improved (e.g., adding more features or refining existing ones).

3.Implications for Malaria Control:

- Accurate predictions allow for targeted interventions, resource optimization, and better planning of malaria control efforts in high-burden areas.



Scatter plot of actual vs predicted malaria prevalence showing strong predictive accuracy

The model's **high R<sup>2</sup> score (84.4%)** and **low MSE (2.63)** validate its utility for actionable predictions. The model explains **~85%** of the variance in malaria prevalence, providing reliable state-level predictions. These insights guide resource allocation and intervention strategies, ensuring impactful malaria control efforts tailored to state-level needs.



# State-Level Predictive Insights for Malaria Control Modelling



While a correlation matrix provides initial insights into how variables relate to malaria prevalence, running a **machine learning model** can quantify the importance of each factor to uncover deeper, more actionable patterns,

## ITN (Insecticide-Treated Nets):

- The most critical predictor (~40% importance) emphasizes its dominant role in reducing malaria prevalence. Its strong relationship with malaria dynamics aligns with expectations.

## Immunization Rates:

- With ~30% importance, immunization rates are a key driver in lowering malaria prevalence. This highlights their consistent contribution to prevention efforts.

## Healthcare Access Risk:

- Ranked third (~15% importance), limited healthcare access significantly influences malaria prevalence, especially in areas with poor infrastructure.

## Rainfall and Temperature:

- Moderate contributors (~5–10% importance each), these environmental factors shape malaria risks, reflecting their indirect but vital roles.

## Sanitation Quality:

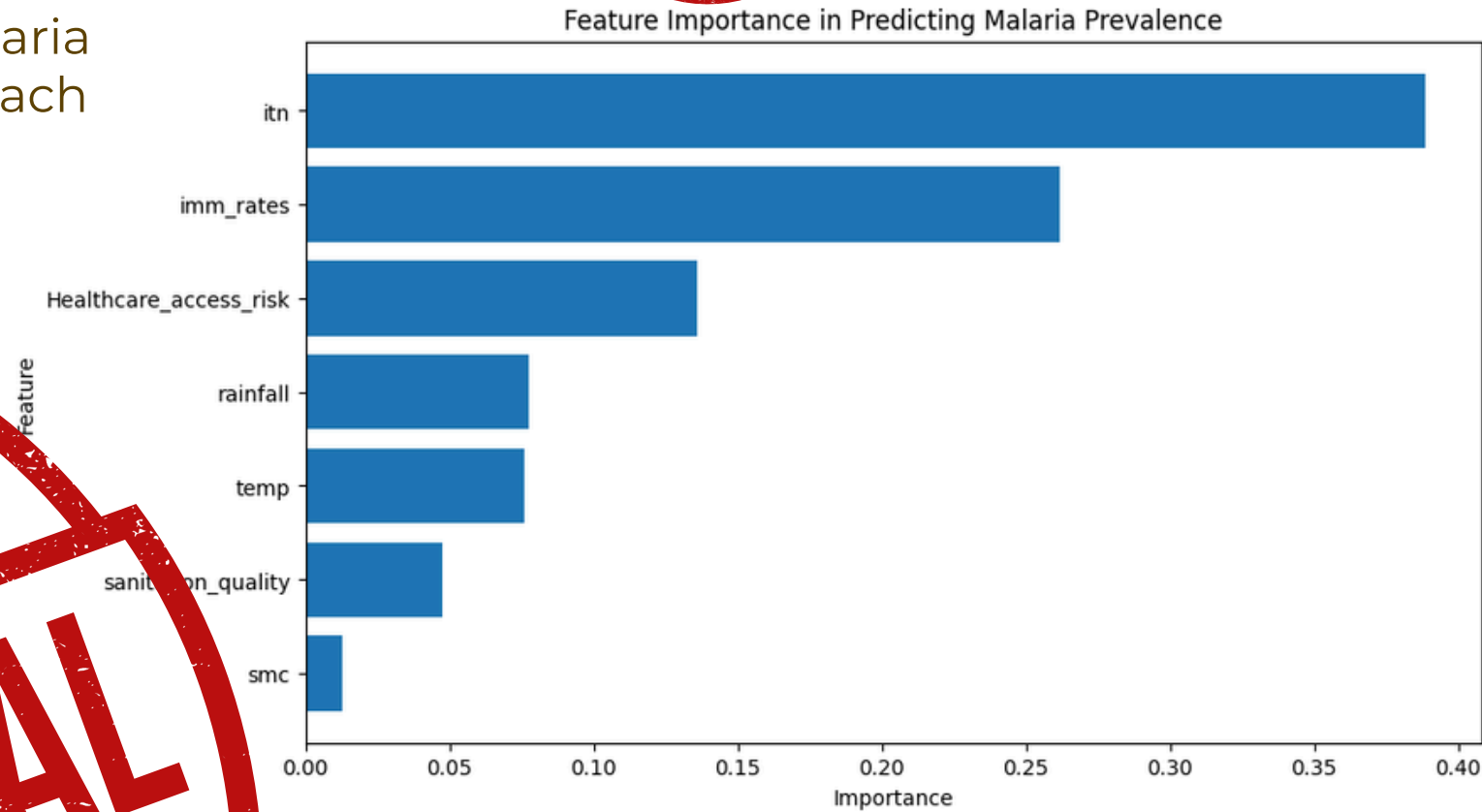
- While contributing less (~5%), sanitation quality may indirectly affect malaria prevalence, potentially through urbanization and population density.

## SMC (Seasonal Malaria Chemoprevention):

- The least important feature (~2%), suggesting its impact may be more localized or dependent on specific conditions.

## Takeaways

- ITN and immunization is confirmed as primary drivers of malaria control, while Environmental factors (rainfall, temperature) and healthcare access are significant but secondary influences.
- SMC's low importance suggests context-specific effectiveness, such as benefits not be evident across all regions in the dataset due to targeted applications or overlap with other measures (ITN/Immunizations) as well as seasonal peaks that is not factored into the analysis.



Feature importance analysis measures the influence of significant factors on malaria prevalence in Nigeria. Despite differences in methodology, it closely aligns with the correlation matrix, highlighting the primary and secondary drivers of malaria prevalence, thus validating the findings.

# Targeting High-Burden States for Maximum Impact



## Identifying Priority States:

- The top 5–10 states with the highest malaria burden were identified using:
  - Prevalence Data: Malaria prevalence rates derived from surveys and predictive models.
  - Contributing Factors: Analysis of key drivers such as ITN coverage, SMC implementation, healthcare access, rainfall, and sanitation quality.
- Priority states include regions with both high prevalence rates and seasonal spikes.

## Top High-Burden States:

- Based on analysis, the following states are identified as the top 5-10 high burden states:
  - Northern States: Borno, Kano, Katsina, Zamfara, Sokoto.
  - Southern/Other Regions: Cross River, Enugu, Akwa Ibom, Plateau, Benue

## Key Factors Contributing to High Burden:

- Northern States: Persistent prevalence due to limited healthcare access, low ITN/SMC coverage, and socio-economic challenges.
- Southern States: Seasonal spikes during the wet season, exacerbated by heavy rainfall and poor drainage.

## Recommended High Level Actions:

### Focus on Targeted Interventions:

- Deploy ITNs, SMC, and healthcare support systems in these states for maximum impact.

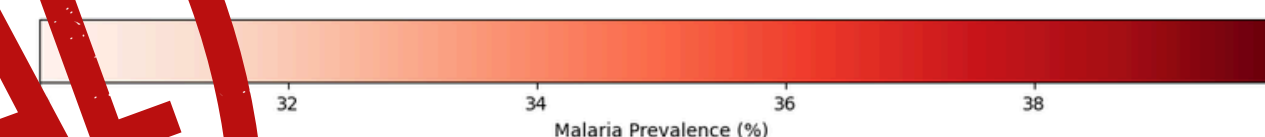
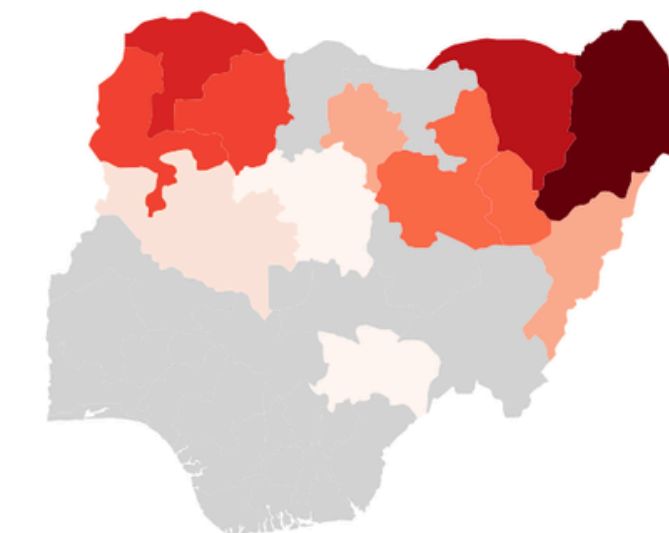
### Season-Specific Planning:

- Scale interventions ahead of the wet season for states with large seasonal spikes like Cross River, Enugu, and Plateau.

### Sustainable Solutions:

- Strengthen healthcare systems and integrate malaria control into routine health services.

Malaria data for top states above 30% Malaria Prevalence



### High Severity (Above 36% Prevalence)

- States: Borno, Yobe, Sokoto, Kebbi, Zamfara
- Key Drivers: Flooding, poor healthcare infrastructure, low ITN usage, conflict zones (high concentration of IDP camps).

### Moderate Severity (32%–36% Prevalence)

- States: Bauchi, Katsina, Gombe, Kano, Adamawa, Niger
- Key Drivers: Seasonal rainfall, sparse vegetation, high mosquito density, limited ITNs and SMC coverage.

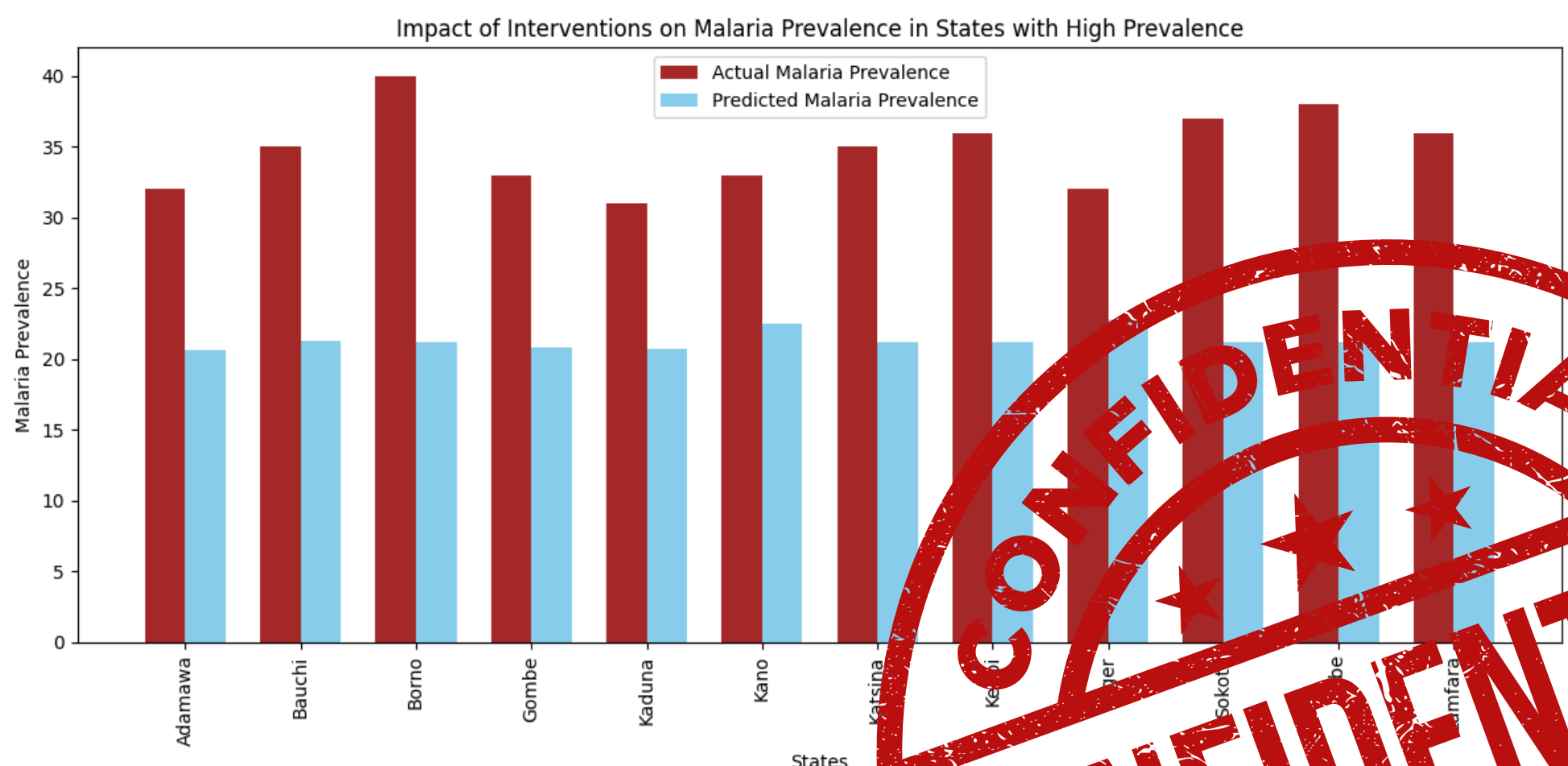
### Lower Severity (30%–32% Prevalence)

- States: Kaduna, Benue, Plateau
- Key Drivers: Migration patterns (IDP Camps), seasonal rainfall, challenging terrain, inadequate preventive measures.



# High Burden State ML Simulations for Malaria Control

## Impact of Increased Interventions on Malaria Prevalence



### Overall Effectiveness:

- **The interventions**
  - 20% increase in ITN coverage
  - 20% increase in immunization rates
  - 10% improvement in healthcare access—significantly reduce malaria prevalence across all high-burden states.

### Magnitude of Reduction:

Predicted malaria prevalence (blue bars) consistently shows a substantial drop compared to actual prevalence (brown bars), reflecting the combined strength of the interventions.

### State-Level Insights:

- Borno and Katsina: These states exhibit the largest reductions, indicating that their high baseline prevalence benefits the most from scaling up interventions.
- Sokoto, Kebbi, and Zamfara: Although starting with high prevalence, these states also demonstrate notable reductions, suggesting improvements in interventions could close gaps in prevention and treatment.

### Role of Interventions:

- **ITN and Immunization Rates:** The dominant predictors in the feature importance analysis are likely driving the sharp reductions.
- **Healthcare Access:** The 10% improvement reduces barriers to treatment and prevention, particularly impactful in remote or underserved areas.

### Remaining Gap:

Despite the improvements, the predicted prevalence is still relatively high, indicating the need for additional localized interventions or addressing other factors (e.g., environmental or socio-economic).

### Conclusion

The simulation highlights that scaling up ITNs, immunization, and healthcare access can substantially reduce malaria prevalence, demonstrating the effectiveness of integrated interventions in high-burden regions. However, to fully address residual prevalence, especially in the most affected states, there is a critical need for targeted information gathering. Incorporating region-specific factors and contextual peculiarities into machine learning models will enable more precise predictions and tailored intervention strategies, ensuring that resources are deployed where they are most needed.