

# Enhancing Wastewater Surveillance with Regression Kriging

Odey R. Mofokeng

With: Inger Fabris-Rotelli, Raeesa Docrat, Pravesh Debba, Jenny Holloway, Nontembeko Dudent-Tlhone, Jabulani Jele, Lisa Schaefer (Née Burke), Wouter le Roux, David Rose, Rene Stander and Nada Abdelatif

School of Actuarial Science and Statistics, University of the Witwatersrand, Johannesburg, South Africa



## Introduction and Problem Statement

Traditional spatial methods like standard Kriging often fail in complex urban areas because they ignore environmental and demographic factors.

### Key Challenges:

- Data misalignment between health districts and WWTP drainage areas
- Standard Kriging ignores key environmental covariates
- The need for accurate predictions to support public health decisions

**Our Solution:** A **Regression Kriging with Spatial Error Model (RK-SEM)** that integrates wastewater data, COVID-19 cases, and environmental predictors for more accurate spatial predictions.

## Methodology

Our RK-SEM framework addresses spatial misalignment through a three-stage approach:

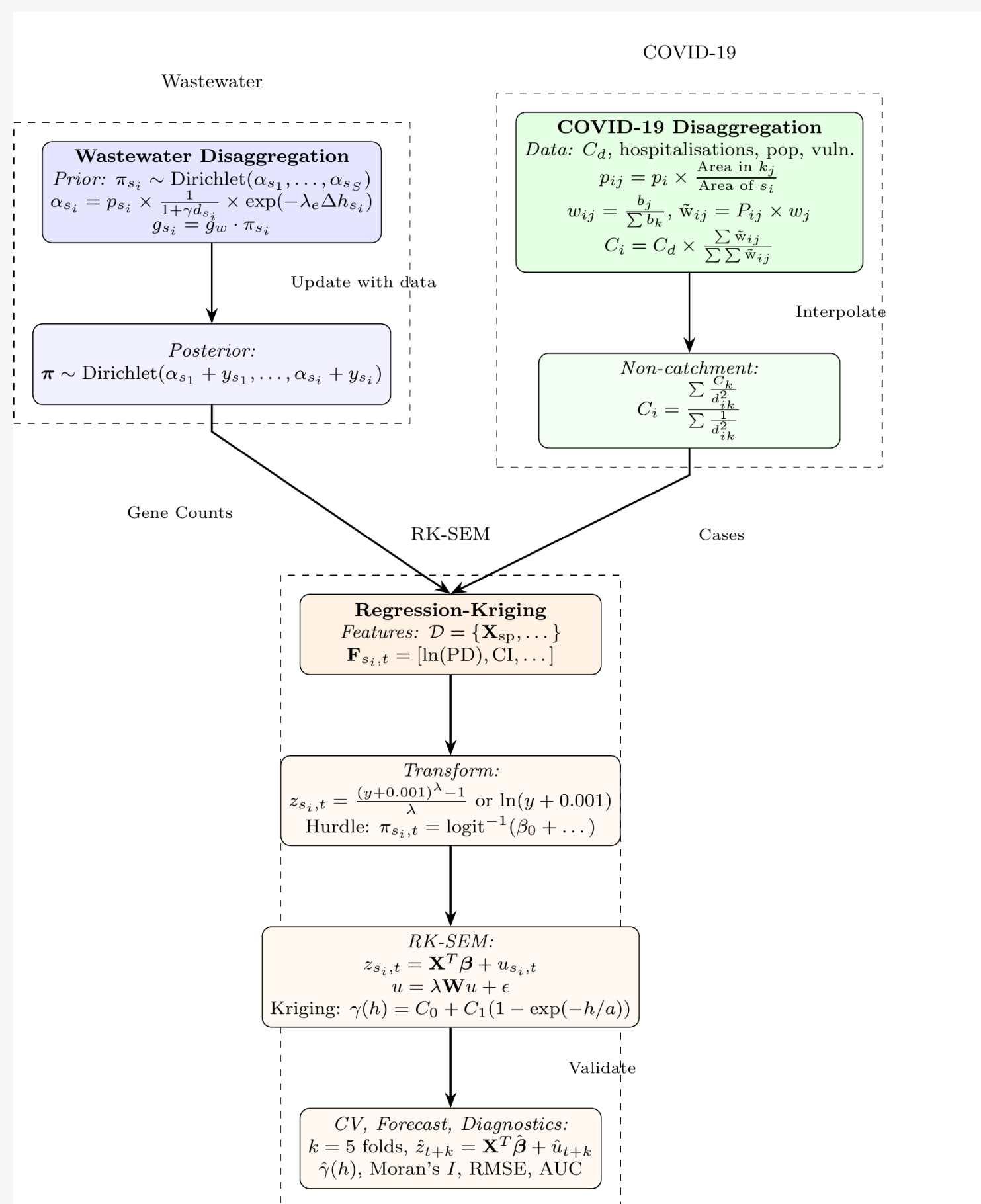


Figure Methodology flowchart showing the integrated approach to wastewater surveillance

The model captures both covariate effects and spatial dependencies in the residuals.

## Study Area and Data

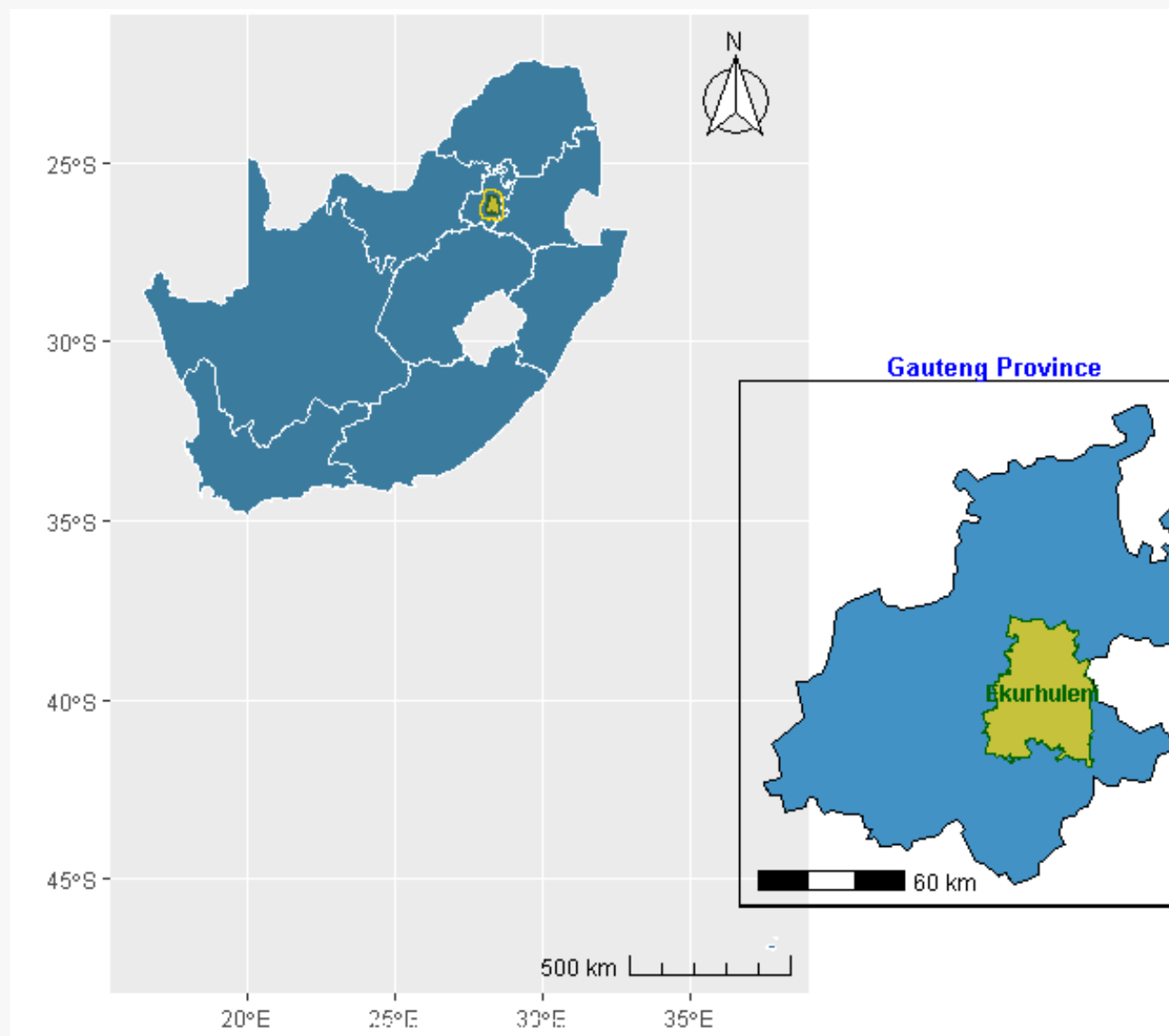


Figure Ekurhuleni Metropolitan Municipality: A complex urban environment with diverse settlement patterns and 19 wastewater treatment plants

### Why Ekurhuleni?

- Mix of formal urban centres, informal settlements, and rural farmland
- Major economic hub with mining, manufacturing, and logistics sectors
- 19 wastewater treatment plants (8 sampled for this study)
- Represents typical urban challenges in South African municipalities

### Data Sources:

- Wastewater SARS-CoV-2 gene counts from ERWAT treatment plants
- COVID-19 case data from municipality health records
- Hospital accessibility and catchment areas
- Population density and vulnerability indices

## Model Performance

Our RK-SEM framework significantly outperforms both baseline methods and sophisticated alternatives across multiple epidemiological phases.

Table Performance comparison on 2021-01-01 (transition period)

Metric	RK-SEM	Rolling Avg.	LOCF	Spatial Kriging	Overall Avg.
MAE	<b>0.0133</b>	0.1546	0.2066	0.2548	0.1847
RMSE	<b>0.0185</b>	0.2547	0.3056	0.3556	0.2865
sMAPE	<b>21.16</b>	35.01	50.07	25.09	48.01
R <sup>2</sup>	<b>0.9045</b>	0.2254	0.2037	0.5056	0.3885

### Key Findings:

- RK-SEM error metrics are 11-19 times lower than baseline methods
- Explains 40-50% more variance (R<sup>2</sup>) than best baseline
- Consistent superior performance across peak, transition, and post-COVID phases

## Spatial Prediction Accuracy

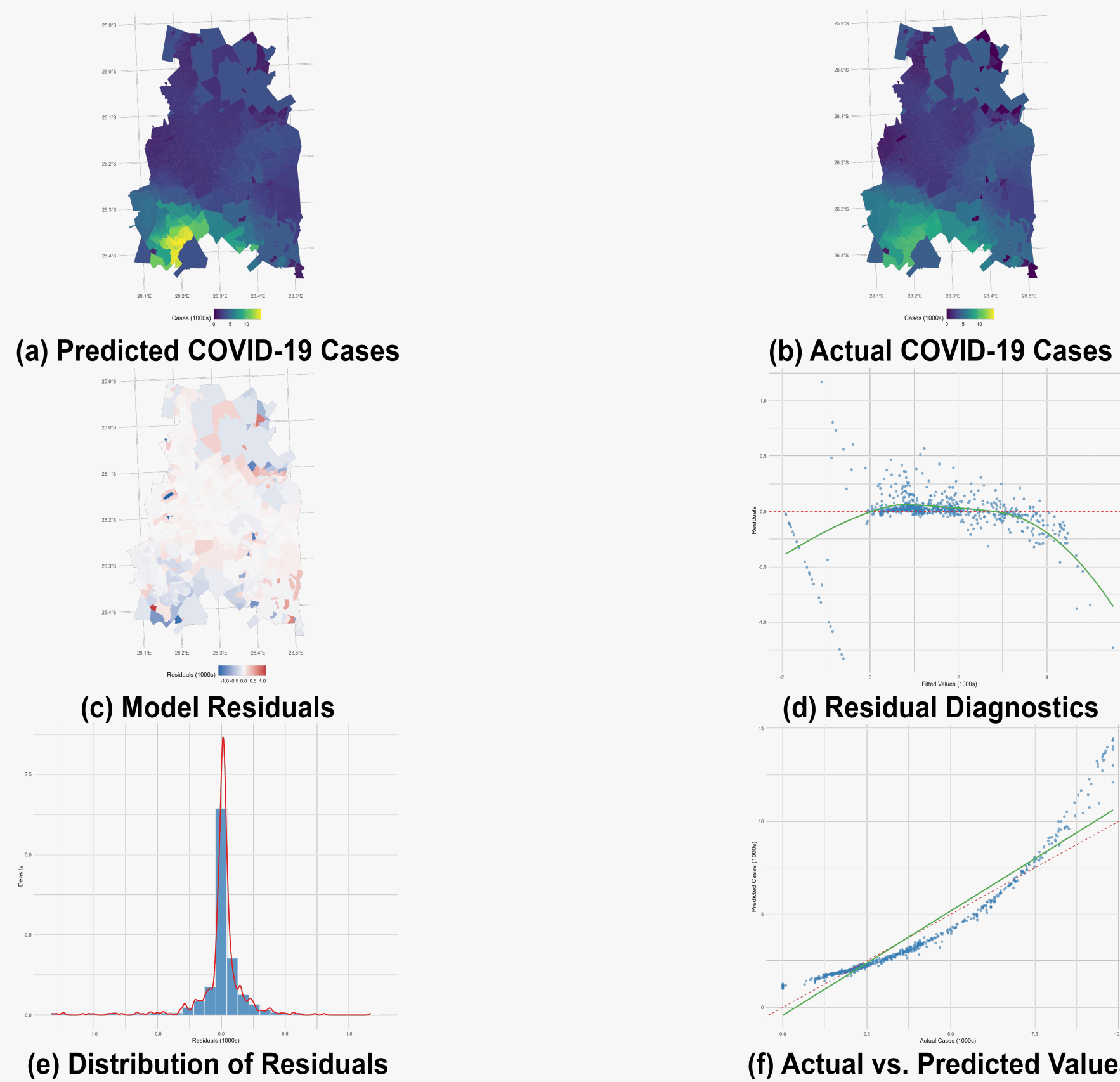


Figure RK-SEM predictions closely match actual COVID-19 case distribution, effectively capturing spatial gradients and clusters across Ekurhuleni subplaces

### Comparison with Spatial Linear Mixed Model (SLMM):

Table RK-SEM vs SLMM performance across epidemiological phases

		2021-01-01		2021-12-24		2023-01-01
Metric	SLMM	RK-SEM	SLMM	RK-SEM	SLMM	RK-SEM
MAE	0.0164	<b>0.0133</b>	7.87	<b>4.68</b>	0.686	<b>0.576</b>
R <sup>2</sup>	0.860	<b>0.904</b>	0.449	<b>0.690</b>	0.740	<b>0.849</b>

The performance gap is largest during complex peak periods, where RK-SEM's MAE is 40% lower and R<sup>2</sup> is 24% higher than SLMM.

## Public Health Impact: Outbreak Detection

Table Outbreak detection capability (Sensitivity = ability to detect real outbreaks)

		2021-01-01		2021-12-24		2023-01-01
Metric	SLMM	RK-SEM	SLMM	RK-SEM	SLMM	RK-SEM
Sensitivity	0.825	<b>0.836</b>	0.158	<b>0.842</b>	0.751	<b>0.842</b>
Specificity	1.000	<b>1.000</b>	0.863	<b>0.855</b>	1.000	<b>1.000</b>
F1 Score	0.911	<b>0.911</b>	0.205	<b>0.749</b>	0.752	<b>0.914</b>

**Critical Finding:** RK-SEM's outbreak detection capability remains robust during challenging peak periods, while SLMM's sensitivity collapses to 0.16, missing 84% of real outbreaks.

## Conclusions and Impact

- RK-SEM framework** integrates wastewater data, covariates, and spatial structure
- Outperforms baselines and SLMM**, especially during complex periods
- Robust outbreak detection** with high sensitivity for early warnings
- Strong spatial autocorrelation** ( $\lambda \approx 0.95$ ) shows disease clustering
- Key drivers:** Case acceleration and healthcare access influence spread
- Enables proactive interventions** in South African urban settings