

Spatiotemporal hotspots of neonatal and child mortality in Nyeri County, Kenya, 2018–2025

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Abstract

Background

Understanding the spatial and temporal distribution of under-five mortality is critical for targeting public health interventions. County-level estimates may mask important local variations and fail to identify persistent mortality hotspots. This study examined whether under-five mortality in Nyeri County, Kenya, was spatially clustered, whether hotspot patterns differed by age group, and how mortality trends varied between hotspot and non-hotspot wards.

Methods

We conducted a retrospective ecological spatio-temporal analysis using annual ward-level mortality data for children aged 0–59 months in Nyeri County from 2018 to 2025. Mortality data from the Kenya Health Information System were categorized into neonates (0–28 days), infants (1–11 months), and children (12–59 months). Ward-level death counts were linked to population denominators and geographic data. A retrospective space-time Poisson scan statistic in SaTScan identified significant mortality clusters using 999 Monte Carlo replications. Annual mortality maps were generated, and mortality trends were compared between hotspot and non-hotspot wards.

Results

Under-five mortality was concentrated in a few wards rather than evenly distributed across the county. The primary cluster included Ruring'u, Kiganjo/Mathari, and Rware wards, with 747 observed deaths versus 199.8 expected deaths ($RR = 5.82$; $p < 0.001$). Additional clusters were identified in Magutu, Iriaini, and Karatina Town wards ($RR = 3.33$; $p < 0.001$) and in Iria-ini ward alone ($RR = 2.05$; $p = 0.008$). Significant clustering occurred across all age groups, with the strongest effect among neonates, where the primary cluster recorded 692 observed versus 142 expected deaths ($RR = 9.29$; $p < 0.001$). Annual under-five mortality increased from 229 deaths in 2018 to 289 in 2021 before declining to 118 in 2025. Hotspot wards consistently experienced higher mortality rates than non-hotspot wards.

Conclusions

Under-five mortality in Nyeri County was spatially concentrated and temporally dynamic, with persistent hotspots across age groups. These areas should be prioritized for mortality audits, strengthened surveillance systems, and targeted interventions to improve neonatal, infant, and child health outcomes.

Introduction

Understanding where and when mortality is concentrated is essential for effective public health planning. Although county-level or national summaries are useful for describing the overall burden of mortality, they can conceal important inequalities across smaller geographic units and over time. The World Health Organization has emphasized that health inequality monitoring should examine differences across policy-relevant population subgroups and residence. Spatial epidemiologic methods provide an important means of identifying localized excess risk that may remain hidden in aggregated reporting ¹. The spatial scan statistic, in particular, has become a widely used method for detecting geographic clustering while accounting for the underlying population at risk ².

In Kenya, subnational inequalities in mortality-related outcomes have been well documented. National progress in child survival has occurred alongside persistent geographic disparities, with substantial variation in under-five mortality between counties and over time ³. These findings suggest that mortality burden is unlikely to be uniformly distributed within counties

and that geographically resolved analyses are needed to identify areas with persistently elevated risk. At the same time, much of the operational and research attention in Kenya has concentrated on neonatal mortality and newborn care, while relatively less geographically resolved evidence is available on infant and child mortality beyond the first 28 days of life, particularly within counties. This gap matters because the determinants and service-delivery bottlenecks affecting deaths after the neonatal period may differ from those driving neonatal deaths, even when they occur within the same county health system^{4–6}. Nyeri County, as one of Kenya's devolved county units, therefore represents an appropriate setting for analysis because local planning and resource allocation increasingly depend on subcounty and lower-level evidence generated within decentralized health systems^{7,8}.

Routine health information systems provide an important opportunity for this kind of surveillance. In Kenya, DHIS2 serves as the primary platform for routine health indicator reporting and supports planning, monitoring, and decision-making across multiple levels of the health system⁹. At the same time, routine data systems face recognized challenges, including inconsistent reporting tools, variable analytical capacity, incomplete reporting, and concerns about data quality, all of which underscore the need for careful interpretation of mortality patterns derived from routine data^{9,10}. Despite these limitations, routinely collected mortality and population data remain useful for identifying places where the combined burden of neonatal, infant, and child deaths is repeatedly elevated and where more detailed clinical, audit, and qualitative investigation should be focused.

Against this background, the present study was designed to examine the spatial and temporal distribution of mortality in Nyeri County using annual ward-level aggregated data from 2018 to 2025. Specifically, the study sought to determine whether deaths were spatially concentrated, whether hotspots persisted across years, and whether mortality trends differed between hotspot and non-hotspot wards. By combining routine mortality data with ward-level spatial analysis, the study aimed to generate evidence that could support more geographically targeted mortality surveillance, deeper inquiry into infant and child mortality beyond the neonatal period, and more locally responsive public health action.

Methods

Study design and setting

We conducted a retrospective ecological spatio-temporal analysis of mortality in Nyeri County, Kenya, using annual ward-level aggregated data for the period 2018 to 2025. The unit of analysis was the ward-year. Nyeri County has an estimated under-five population of approximately 73,000 children, accounting for about 10–11% of the county population. Although child health indicators in the county are generally more favorable than national averages, morbidity among children under five remains dominated by largely preventable conditions. The main causes of illness include acute respiratory infections, particularly pneumonia, diarrhoeal diseases, malaria, and nutrition-related conditions. While malaria transmission is lower than in more endemic regions of Kenya, it remains an important contributor to childhood morbidity. These patterns are consistent with the broader epidemiology of child health in Kenya and highlight the continued need to strengthen immunization, integrated management of childhood illnesses, nutrition services, and water, sanitation, and hygiene interventions to reduce preventable morbidity and mortality.

The analytical dataset linked annual deaths and population denominators to ward identifiers, ward names, ward centroid coordinates, and constituency designation, thereby enabling both descriptive spatial analysis and formal space-time cluster detection.

Data sources and study variables

Mortality data for children under five were abstracted from the Kenya Health Information System (KHIS), the national implementation of DHIS2. These data were disaggregated by age into three age groups: neonates (0–28 days), infants (1–

11 months), and children (12–59 months). Deaths were assigned to wards based on the reporting facilities, while denominators were obtained from KHIS for the population estimated to be < 5 years old and verified by the health records information officers. KHIS compiles routine health service data reported through the national health information platform. For the present analysis, the working dataset was structured as annual ward-level counts of deaths and corresponding ward population denominators, together with administrative identifiers and geographic coordinates. Although deaths are reported through routine service platforms, the final analytic file used in this study was aggregated to the ward-year level for spatio-temporal analysis.

The primary outcome was the annual number of deaths recorded in each ward. The corresponding denominator was the annual ward population available for the same year. Because ward-level age-specific population denominators were not available, age-specific analyses should be interpreted as exploratory. For descriptive age-stratified comparisons, the total under-five population was apportioned across age groups using the observed distribution of deaths. The combined under-five analysis was therefore treated as the primary analysis, while age-specific findings were used to examine whether spatial patterns were broadly consistent across neonatal, infant, and older-child deaths. For descriptive analyses, we calculated annual mortality rates per 1,000 population as:

$$\text{Mortality rate per 1,000} = \frac{\text{deaths}}{\text{population}} \times 1000$$

Additional variables used for spatial display and linkage included ward name, constituency, longitude, and latitude. Ward boundary shapefiles were used to map annual mortality patterns and statistically detected clusters.

Data preparation and spatial linkage

Data management and spatial analysis were conducted in R using the packages `readr`, `dplyr`, `sf`, `rsatscan`, and `ggplot2`. The mortality file was imported into R and core variables were recast to appropriate formats, including ward identifier as character, year as integer, and deaths, population, longitude, and latitude as numeric. The ward-level dataset was then sorted by year and ward identifier to support creation of SaTScan input files and descriptive summaries.

Ward centroid coordinates were used to generate the geographic input required for cluster detection. A ward polygon shapefile was used for spatial visualization of annual mortality patterns and cluster membership. To support the space-time scan, three SaTScan input files were generated from the ward-year dataset: (1) a case file containing ward identifier, deaths, and year; (2) a population file containing ward identifier, year, and population; and (3) a geographic coordinates file containing ward identifier, latitude, and longitude. These files were written in SaTScan-readable format using `rsatscan`.

Space-time cluster detection

Space-time cluster detection was conducted using the Kulldorff scan statistic implemented in SaTScan through the R package `rsatscan`. We specified a retrospective space-time Poisson model, appropriate for count data where the expected number of events varies with the underlying population at risk. Under this framework, the observed number of deaths in each ward-year was assumed to follow a Poisson distribution conditional on the ward-year population denominator. Statistical significance was assessed using 999 Monte Carlo replications. Detected clusters were summarized using the log likelihood ratio (LLR), relative risk (RR), and associated p-values, with $p < 0.05$ used to define statistical significance.

The scan was configured as a retrospective space-time Poisson analysis (`AnalysisType = 3`; `ModelType = 0`) with annual time precision and yearly aggregation units. The study period extended from 1 January 2018 to 31 December 2025. Geographic coordinates were specified as latitude/longitude (`CoordinatesType = 1`). To avoid clusters that were too large to be programmatically useful, the maximum spatial cluster size was set to 20% of the estimated population at risk, and the

maximum temporal cluster size was set to 7 years. These specifications were chosen to identify geographically meaningful and operationally interpretable space-time clusters rather than overly broad high-risk windows.

Descriptive spatial and temporal analyses

In addition to formal cluster detection, we conducted descriptive analyses to characterize the spatial and temporal distribution of mortality across Nyeri County. Annual ward-level maps of deaths and mortality rates per 1,000 population < 5 years old were generated for each year from 2018 to 2025. These maps were examined for spatial persistence, temporal intensification, and concordance with the statistically detected space-time clusters. The annual maps were used to assess whether excess mortality remained localized, whether its intensity changed over time, and whether hotspot wards remained consistently distinguishable from the rest of the county.

We also generated county-level annual summary statistics, including total deaths, total population, annual mortality rate per 1,000 population of < 5 years old, and the minimum and maximum ward-specific death counts observed in each year. These summary measures were used to describe overall temporal changes in mortality burden across the study period.

Classification of hotspot and non-hotspot wards

For post-scan comparisons, wards identified as members of statistically significant space-time clusters were classified as hotspot wards, while all remaining wards were classified as non-hotspot wards. Cluster membership was extracted from the SaTScan geographic output and linked back to the ward shapefile using ward identifiers. Because candidate scan windows may overlap, some wards may appear in more than one reported cluster. For descriptive mapping, each ward was assigned uniquely using a significance-first precedence rule, such that statistically significant clusters took priority over non-significant candidate clusters. Hotspot ward labels were generated from point-on-surface coordinates and overlaid on the cluster map for interpretability. This hotspot classification was then used to compare temporal mortality patterns between hotspot and non-hotspot wards.

Excess mortality and hotspot detection

Excess mortality was assessed using the log-likelihood ratio (LLR) under a Poisson-based hotspot detection framework and was defined as a ward or time period recording more deaths than would be expected given its population size and the overall mortality pattern in the study area. For each candidate spatial or spatio-temporal cluster, the observed number of deaths within the cluster was compared with the expected number under the null hypothesis that mortality risk was constant across all wards and time periods. The alternative hypothesis was that mortality risk was higher inside the candidate hotspot than outside it. The strength of evidence for excess mortality was quantified using the LLR, calculated as

$$LLR = O \log \left(\frac{O}{E} \right) + (C - O) \log \left(\frac{C - O}{C - E} \right)$$

where:

- O = observed deaths inside the candidate hotspot
- E = expected deaths inside the candidate hotspot
- C = total deaths in the whole study area

LLR values remain small when observed deaths are close to expected levels, but increase as the excess of observed over expected deaths becomes larger. Thus, a high LLR indicates stronger evidence that the concentration of deaths in a given ward or period is unlikely to be due to random variation alone and is more consistent with a true mortality hotspot. In

interpreting identified hotspots, we considered both the magnitude of excess mortality, reflected by the difference between observed and expected deaths, and the statistical strength of the hotspot signal, reflected by the LLR.

Results

Overall under-five hotspot detection

Figure 1 shows statistically significant space-time mortality clusters in Nyeri County, with each coloured area representing a ward assigned to a significant cluster. Grey wards were not assigned to a significant cluster. Three main clusters are shown. Cluster 1, is concentrated around central Nyeri and includes Kiganjo/Mathari, Rware, and Ruring'u. This appears to be the central hotspot cluster and is geographically compact around the Nyeri town area. Cluster 2, is located in the eastern part of the county and includes Magutu, Iriaini, and Karatina Town. This cluster covers a larger contiguous area extending along the eastern side of the county. The third cluster, (3) is located in the southern part of the county and is mainly represented by Iria-ini. This suggests a more localized hotspot area compared with the larger eastern and central clusters (Fig. 1).

Age-specific mortality hotspot analysis

Figure 2 presents age-specific space-time mortality clusters in Nyeri County for three groups: neonates aged 0–28 days, infants aged 1–11 months, and children aged 12–59 months. Across all three age groups, clustering was not evenly distributed across the county but was concentrated in a limited number of wards. For neonatal deaths, three statistically significant clusters were identified. The main cluster was located around Kiganjo/Mathari, and Rware, with additional clusters in the Karatina/Iria-ini wards. For infants aged 1–11 months and children aged 12–59 months, the cluster pattern was broadly similar, with recurrent clustering around the central Nyeri town wards, but an additional 3 clusters were detected at Ruring'u near Nyeri Town and Iria-ini, Magutu near Karatina Town. The repetition of these spatial patterns across age groups suggests that excess mortality was concentrated in persistent geographic hotspots rather than being randomly or diffusely distributed (Fig. 2).

Caption. Ward-level space-time clusters of mortality in Nyeri County identified using a retrospective space-time Poisson scan. Colored wards indicate detected significant hotspot clusters, while grey wards represent areas not included in a significant cluster.

The space-time scan identified statistically significant mortality clusters across all age groups, with the strongest clustering observed among neonates. For neonates, the primary cluster included two wards and recorded 692 observed deaths compared with 142 expected deaths, corresponding to a relative risk of 9.29 ($p < 0.001$). Among infants aged 1–11 months and children aged 12–59 months, the primary clusters each included three wards, with 736 observed deaths compared with approximately 191 expected deaths and a relative risk of 6.14 ($p < 0.001$). Secondary significant clusters were also identified in each age group, with relative risks ranging from 2.05 to 3.33. One additional candidate cluster in both the infant and child analyses was not statistically significant and should not be interpreted as a confirmed hotspot. Overall, the findings indicate that excess mortality was concentrated in a small number of ward clusters, rather than being evenly distributed across the county. In the combined analysis for all decedents < 5 years, the strongest cluster had 747 observed against 199 expected deaths and a relative risk of 5.82 ($p < 0.001$), (Table 1).

Table 1. Summary of space-time mortality clusters identified in Nyeri County

Clusters	No. wards	Observed deaths	Expected deaths	Relative risk	LLR	P-value	Wards in cluster
Neonates (0-28 days)							
1	2	692	142	9.29	704.34	<0.001	1119, 1214
2	1	215	78	3.1	88.96	<0.001	1136
3	1	47	18.7	2.57	15.38	<0.001	1029
Infants (1-11 months)							
1	3	736	191.2	6.14	564.49	<0.001	1069, 1119, 1214
2	3	252	84.7	3.33	116.77	<0.001	1027, 1046, 1136
3	1	48	23.7	2.05	9.72	0.010	1029
4	1	6	1.6	3.66	3.42	0.965	1027
Children (12-59 months)							
1	3	736	191.1	6.14	564.93	<0.001	1069, 1119, 1214
2	3	252	84.7	3.33	116.74	<0.001	1027, 1046, 1136
3	1	48	23.7	2.05	9.73	0.009	1029
4	1	6	1.6	3.67	3.44	0.949	1027
All children <5 years							
1	3	747	199.8	5.82	565.09	<0.001	1069, 1119, 1214
2	3	269	88.6	3.41	116.75	<0.001	1027, 1046, 1136
3	1	52	24.8	2.13	9.72	0.002	1029
4	1	8	1.7	4.66	3.41	0.254	1027

Abbreviations: LLR, log likelihood ratio. **Ward names:** 1119 KIGANJO/MATHARI; 1136 KARATINA TOWN; 1029 IRIA-INI; 1069 RURING'U; 1027 MAGUTU; 1214 RWARE; 1046 IRIAINI

***NOTE:** All reported candidate clusters are shown. Because SaTScan may return overlapping candidate clusters, some wards may appear in more than one cluster. The overlap columns summarize this pattern. For mapping, each ward was assigned to a single display cluster using a significance-first precedence rule.

Caption: Retrospective space-time Poisson scan done independently for three age groups. Significant clusters are interpreted as areas and periods with elevated mortality relative to expectation.

Across the combined under-five analysis, seven of the 30 wards were included in statistically significant clusters, indicating that excess mortality was concentrated in less than one-quarter of wards.

Overall spatial distribution of annual deaths

The annual ward-level maps of deaths showed marked spatial heterogeneity across Nyeri County, with the highest death counts repeatedly concentrated in wards overlapping the statistically significant hotspot clusters, especially Rware, Kiganjo/Mathari, Ruring'u, Karatina Town, Iriaini, Magutu, and Iria-ini. Mortality was not uniformly distributed across the county; instead, hotspot patterns recurred across successive annual panels, indicating repeated concentration of deaths in a limited number of wards. Across the study period, total annual deaths increased from 229 in 2018 to 250 in 2019,

remained relatively high at 236 in 2020, and peaked at 289 in 2021. Thereafter, deaths declined to 196 in 2022, 181 in 2023, 153 in 2024, and 118 in 2025. These patterns indicate that the greatest mortality burden occurred around 2020 to 2021, after which the overall burden declined, although spatial concentration persisted.

The annual death map collage suggests that mortality burden in Nyeri was both spatially concentrated and temporally dynamic. Rather than showing diffuse elevation across the county, across years, the distribution of deaths remained clustered in a relatively small number of hotspot wards, with the most pronounced burden occurring around the countywide peak. Although total deaths declined in later years, the spatial alignment of hotspot wards was persistent, suggesting continued relative excess in these areas even as the overall burden fell (Figure 3).

Spatial distribution of annual mortality rates

The annual ward-level mortality rate maps showed a similar pattern after standardizing for ward population size. Mortality rates remained highest in wards corresponding to the significant hotspots identified by the scan analysis, notably Rware, Kiganjo/Mathari, Ruring'u, Karatina Town, Iriaini, Magutu, and Iria-ini. Across the study period, the mortality rate was 2.92 per 1,000 population under 5 years in 2018, 2.80 in 2019, 2.72 in 2020, and peaked at 3.71 in 2021. Thereafter, the rate declined to 2.38 in 2022, 2.12 in 2023, 1.75 in 2024, and 1.33 in 2025. The use of a common scale across annual panels strengthened comparability and showed that the contrast between hotspot and non-hotspot wards was greatest around the 2020 to 2021 peak, before narrowing in subsequent years.

These rate maps reinforce the findings from the annual death maps while demonstrating that the hotspot pattern was not simply a reflection of larger ward populations. Instead, the standardized rates indicate that hotspot wards experienced a disproportionate mortality burden relative to their population size, particularly during the years in which countywide mortality was highest. Although the magnitude of excess declined in later years, hotspot wards remained distinguishable from the rest of the county (Figure 4).

Hotspot vs non-hotspot temporal trends

Across all three age groups, hotspot wards consistently had higher mortality rates than non-hotspot wards throughout the period. The difference was most pronounced among infants aged 1-11 months, where hotspot rates were markedly elevated, peaking around 2021 before declining steadily through 2025. Children aged 12-59 months also showed substantially higher rates in hotspot wards, with a visible peak around 2021, followed by a gradual decline. For neonates, the hotspot wards still had higher mortality rates than non-hotspot wards, but the absolute rates were much lower than those observed for infants and older children in this figure. Neonatal mortality rates in hotspot wards remained relatively stable over time, with only modest year-to-year variation. Non-hotspot wards had consistently low mortality rates across all three age groups, with only a little fluctuation over time. This indicates that the excess mortality burden was concentrated in hotspot wards rather than being evenly distributed across the county.

Overall, the figure suggests that hotspot wards experienced persistently elevated mortality across all age groups, with the largest excess burden among infants aged 1-11 months and children aged 12-59 months. The downward trend in the infant and older-child panels after 2021 may indicate a reduction in mortality intensity over time, although hotspot rates remained higher than non-hotspot rates by 2025 (Figure 5). Overall, a similar pattern is exhibited by the combined dataset for the three age groups (Supplementary Figure 3).

Discussion

This ward-level spatio-temporal analysis showed that under-five mortality in Nyeri County was geographically concentrated, temporally recurrent, and consistently higher in a small number of hotspot wards than in the rest of the county. The main hotspot pattern was centred around the Ruring'u–Kiganjo/Mathari–Rware cluster, with additional significant clustering

around Magutu–Iriaini–Karatina Town and the single-ward Iria-ini cluster. These findings indicate that mortality was not diffusely distributed across the county, but was concentrated in specific wards that remained repeatedly prominent across annual maps and hotspot-versus-non-hotspot trend comparisons. The divergence between hotspot and non-hotspot wards was clearest around 2020–2021, when countywide mortality also peaked, suggesting that underlying local vulnerabilities may have been amplified during a period of broader health-system stress. These findings are consistent with previous evidence from Kenya, which shows that under-five mortality varies substantially across time and place, and that subnational analyses can reveal inequalities that are hidden in aggregate estimates ^{3,6,11}.

The observed hotspot pattern should be interpreted as a surveillance signal rather than definitive evidence of causal mechanisms. The analysis identifies where and when reported mortality was concentrated, but it does not by itself explain why deaths were concentrated in these wards. Several non-mutually exclusive mechanisms may account for the findings: concentration of severe referred cases in higher-volume facilities, gaps in the quality and continuity of intrapartum and newborn care, weaknesses in sick-infant and sick-child management beyond the neonatal period, facility-level health-system bottlenecks, and household or contextual vulnerabilities that delay timely care seeking and follow-up. This interpretation is consistent with the broader literature showing that child survival is shaped by interacting clinical, health-system, household, and environmental determinants rather than by service coverage alone ^{4,6,12}.

One plausible explanation is that some hotspots partly reflect the geography of referral and reporting rather than residential risk alone. Wards containing or surrounding higher-volume referral facilities may record excess deaths because critically ill neonates, infants, and children are referred there from wider catchment areas. In Nyeri County, this may be relevant for wards linked to referral settings such as Nyeri County Referral Hospital and Karatina Sub-County Hospital, where preterm and low-birth-weight newborns, severely ill infants, and children with complications are more likely to be managed. However, referral concentration alone is unlikely to fully explain the pattern, because the excess mortality was spatially focused and recurrent over time. Rather, the hotspots may represent locations where severe case-mix, referral delays, stabilization capacity, and early inpatient management intersect. Kenyan hospital-based studies have shown that neonatal mortality varies substantially across facilities and is disproportionately concentrated among small and sick newborns, supporting the interpretation that quality of inpatient care and facility readiness matter in addition to case mix ^{13,14}.

A second explanation, particularly for the neonatal component of the burden, is that the identified hotspots may reflect gaps in the content, timeliness, and effectiveness of intrapartum care, immediate newborn care, stabilization, referral, and early inpatient management rather than lack of service contact alone. This interpretation is consistent with the broader “Nyeri paradox”: maternal service coverage appears relatively strong, with 99% of births delivered by a skilled provider and 82% of women receiving four or more antenatal care visits, compared with national estimates of 89% and 66%, respectively, while mortality remains elevated in the identified hotspots ¹⁵. Similar access–outcome mismatches have been documented more broadly, with evidence suggesting that increased facility delivery alone does not necessarily translate into lower neonatal mortality where quality of care is weak ^{16,17}. Kenyan evidence also supports a quality-of-care explanation: only 32.7% of mothers in the 2022 KDHS reported that their newborns received all components of quality newborn care after childbirth ¹⁸, while hospital-based studies have documented substantial early neonatal mortality and gaps in effective inpatient care for small and sick newborns ^{10,13,14}. These findings suggest that conventional coverage indicators may be insufficient to detect deficiencies in intrapartum monitoring, neonatal resuscitation, immediate postnatal care, stabilization before referral, and early inpatient management.

The hotspot pattern, however, should not be interpreted as a neonatal problem alone. Because the analysis examined deaths among children under five years, the observed clusters also captured mortality among post-neonatal infants and children aged 12–59 months, whose risk pathways extend beyond labour, delivery, and immediate newborn care. The persistence of excess mortality across age groups suggests that some hotspot wards may face broader weaknesses across the maternal, newborn, infant, and child health continuum. National and regional evidence shows that under-five mortality is also associated with inadequate antenatal and postnatal continuity, socioeconomic disadvantage, suboptimal

breastfeeding and care-seeking, environmental exposures, previous child loss, and weaknesses in the recognition and management of common childhood illnesses ^{4,12,19}. In practical terms, the excess mortality observed in hotspot wards may reflect a mixed burden of neonatal complications, severe infections, pneumonia, diarrhoeal disease, malnutrition, delayed referral, and poor follow-up among infants and young children. Therefore, hotspot investigations should not focus exclusively on maternity and newborn units, but should also examine outpatient triage, emergency care, pediatric inpatient management, nutrition services, immunization status, post-discharge follow-up, and community recognition of danger signs.

A third explanation is facility-level health-system fragility, including workforce limitations, documentation gaps, inadequate commodities and equipment, weak referral functionality, and inconsistent use of routine data for action. Evidence from Nyeri and Nakuru counties suggests that primary healthcare workers in Nyeri reported lower competence in maternal and newborn care than their counterparts in Nakuru, which may translate into delayed recognition of danger signs, incomplete stabilization, weaker triage, and inconsistent follow-up ²⁰. Kenyan studies have also shown that poor inpatient documentation and gaps in routine neonatal data quality undermine monitoring and quality improvement, while uneven DHIS2 data use may limit the ability of managers to identify and respond to service-delivery problems in real time ^{9,10}. Similarly, studies on sick young infants in Kenyan primary healthcare settings have highlighted family- and provider-level concerns about quality of care, referral, and service readiness ¹⁹. In this sense, the hotspot wards may be functioning as spatial markers of underlying service-delivery bottlenecks rather than simply identifying areas with higher background mortality risk.

Household and contextual determinants may also be reinforcing mortality risk within hotspot settings, especially for infant and older-child deaths. National analyses of the 2022 KDHS identified socioeconomic, demographic, and environmental factors associated with under-five mortality in Kenya, including inadequate care continuity and household-level vulnerabilities ⁴. Broader East African evidence has similarly highlighted breastfeeding practices, maternal age, previous child loss, and care-seeking patterns as important determinants of child survival ¹². These patterns imply that Nyeri's mortality hotspots may reflect the intersection of relatively good service coverage with unresolved maternal, household, and contextual vulnerabilities. The presence of both larger multi-ward clusters and more localized single-ward clusters further suggests that different combinations of maternal, child, household, and health-system risks may be operating across wards, rather than a single uniform pathway explaining mortality throughout the county.

The temporal peak in mortality around 2021 may represent a period when broader health-system stress amplified pre-existing local vulnerabilities. Although this ecological analysis cannot attribute the increase to COVID-19 or any other specific shock, the timing is consistent with possible disruption in service utilization, referral, staffing, and follow-up during the pandemic period. Evidence from Kenya, Uganda, Zambia, and other low- and middle-income settings suggests that the COVID-19 pandemic and associated policy responses disrupted reproductive, maternal, newborn, child, and adolescent health services and, in some contexts, contributed to increased neonatal and child mortality ^{21–24}. It is therefore plausible that the 2020–2021 intensification observed in Nyeri reflects a combination of delayed care seeking, referral bottlenecks, staffing pressures, interrupted service utilization, and weaker follow-up for sick infants and children. However, the persistence of excess mortality in hotspot wards after the countywide decline suggests that these areas were not affected solely by transient pandemic-related pressures. Rather, underlying structural vulnerabilities, including referral dependence, uneven quality of care, and facility-readiness constraints, likely remained in place even after overall mortality began to decline. This interpretation is consistent with earlier spatio-temporal analyses from Kenya showing that under-five mortality varies across time and place because of persistent local determinants rather than short-lived fluctuations alone ²⁵.

These findings have important implications for action at the count. First, the identified hotspot wards should be prioritized for facility-based mortality audits, MPDSR review, and qualitative inquiry because the spatial analysis has narrowed the geography of excess mortality to a small number of statistically robust clusters. Second, follow-up investigations should distinguish deaths driven mainly by severity at presentation from deaths that may have been preventable through earlier

recognition, faster referral, better stabilization, stronger inpatient care, and improved post-discharge follow-up. Third, audit teams should examine timing and place of death, residence versus reporting facility, referral source and delays, gestational age and birth weight for neonatal deaths, cause-of-death patterns, availability of oxygen, antibiotics, neonatal resuscitation equipment, incubators, phototherapy, blood products, essential pediatric commodities, staffing patterns, weekend and night coverage, documentation quality, discharge planning, and post-discharge follow-up. This approach would link ward-level surveillance signals to concrete clinical and health-system improvement opportunities. Evidence from Kenya and multi-country newborn-care studies supports the importance of improving both quality of care and health-system readiness for small and sick newborns and young infants ^{13,14,19,26,27}.

This study has several strengths. First, it used an eight-year ward-level dataset, allowing examination of both spatial concentration and temporal persistence. Second, the analysis combined formal space-time scan statistics with descriptive annual maps and hotspot-versus-non-hotspot trend comparisons, strengthening interpretation through triangulation. Third, the age-stratified analyses provided additional insight into whether hotspot patterns were confined to neonates or extended to infants and older children. Finally, the outputs are operationally meaningful because wards are relevant units for county-level planning, supervision, mortality audit prioritization, and targeted quality-improvement action.

The findings should also be interpreted in light of several limitations. First, the study used aggregated ward-year data, which limits inference to ecological patterns and does not allow conclusions to be drawn about individual-level risk factors for mortality. Second, the analysis depended on routine KHIS/DHIS2 data, which may be affected by under-reporting, delayed reporting, inconsistent facility documentation, and variation in reporting completeness across wards and years. Deaths occurring outside the health system may also be less completely captured, potentially leading to underestimation of mortality in some areas. Third, age-specific population denominators were not available at the ward level. The total estimated under-five population was therefore apportioned across neonatal, infant, and child age groups using the observed distribution of deaths. This assumption may affect the precision of age-specific mortality rates and relative risks, particularly where death counts are small or unevenly distributed. The combined under-five analysis should therefore be regarded as the primary analysis, while age-specific findings should be interpreted as exploratory. Fourth, ward centroid coordinates were used for cluster detection, meaning that spatial analyses represent ward-level patterns rather than the exact locations of deaths. This may reduce spatial precision, especially in geographically large or heterogeneous wards. Fifth, the analysis could not fully distinguish whether deaths were assigned by place of residence, facility location, or reporting unit. If deaths were recorded according to the reporting facility, wards containing referral hospitals may appear as hotspots because they receive severe cases from broader catchment areas. Conversely, community-reported deaths may more closely reflect mortality occurring within the reporting ward. The findings should therefore be interpreted as identifying priority reporting, service-delivery, or catchment locations for further investigation, rather than definitive residential risk areas. Finally, SaTScan results are sensitive to analytic choices, including maximum spatial and temporal cluster sizes, population denominators, and the aggregation of data by year. Although these parameters were selected to produce operationally meaningful clusters, alternative specifications could identify different hotspot boundaries.

In conclusion, under-five mortality in Nyeri County was spatially concentrated, temporally recurrent, and programmatically meaningful. The identified hotspots should be interpreted as priority surveillance signals rather than definitive evidence of causal pathways. The excess burden likely reflects an interaction between severe referred case-mix, uneven quality of intrapartum and newborn care, gaps in infant and child case management beyond the neonatal period, facility-level bottlenecks, and broader household and contextual vulnerabilities. The next step is to link these ward-level findings to facility-based mortality audits, MPDSR records, referral pathway review, and qualitative inquiry in hotspot catchments. Such work would help distinguish deaths driven mainly by severity at presentation from those that may be preventable through earlier referral, better stabilization, stronger inpatient care, improved post-discharge follow-up, and more responsive community-facility linkages.

Conclusion

Under-five mortality in Nyeri County was not evenly distributed but was concentrated in a small number of wards that experienced persistent excess mortality over time. Significant spatiotemporal clustering was observed across neonatal, infant, and child age groups, with the strongest hotspot signals occurring among neonates. Although overall mortality declined after 2021, hotspot wards consistently recorded higher mortality rates than non-hotspot wards throughout the study period. These findings demonstrate the value of routine health information systems and spatial epidemiological approaches in identifying localized areas of elevated mortality risk that may be overlooked by county-level estimates. Prioritizing hotspot wards for enhanced surveillance, mortality audits, and targeted health system strengthening initiatives could support more equitable and effective strategies to improve neonatal and child survival in Nyeri County. Further investigations are needed to better understand the contextual, service-delivery, and referral-related factors contributing to the observed mortality patterns.

Abbreviations

COVID-19

Coronavirus Disease 2019

DHIS2

District Health Information Software 2

KDHS

Kenya Demographic and Health Survey

KHIS

Kenya Health Information System

LLR

Log Likelihood Ratio

MPDSR

Maternal and Perinatal Death Surveillance and Response

NACOSTI

National Commission for Science, Technology and Innovation

RR

Relative Risk

SaTScan

Spatial and Temporal Scan Statistics software

Declarations

Ethical considerations

This study was based on an ecological analysis of aggregated ward-level mortality data and did not involve direct contact with human participants or the use of individual-level identifiers in the analytic dataset. Spatial outputs were displayed at the ward level rather than at the household or individual level, thereby reducing the risk of personal identification. The use of aggregated counts and geo-referenced cluster-level information was therefore consistent with the confidentiality principles described in the broader study framework. The study was approved by Amref Ethical Review Committee, approval number P2090-2026, and National Commission for Science, Technology and Innovation (NACOSTI), Application number 189195.

Consent for publication

Not Applicable

Availability of data and materials

All the data set used for this manuscript is available upon request

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

AG, YO, NM, MN, HB, GG, AK, MK, AGi, and JK conceptualized the research proposal. YO, PM, BO, and EK contributed to protocol development and writing. PM, YO, BO, EK, AG, MK, and AK trained research assistants and supervised the data collection process. AW, LO, PM, BO, and YO were responsible for data management and analysis. AW drafted the manuscript. GG, MN, AG, YO, EM, PM, BO, NM, AGi, and JK critically reviewed the manuscript for important intellectual content. All authors read and approved the final manuscript.

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Figures

Nyeri mortality space-time clusters

Significant clusters; primary cluster assignment per ward

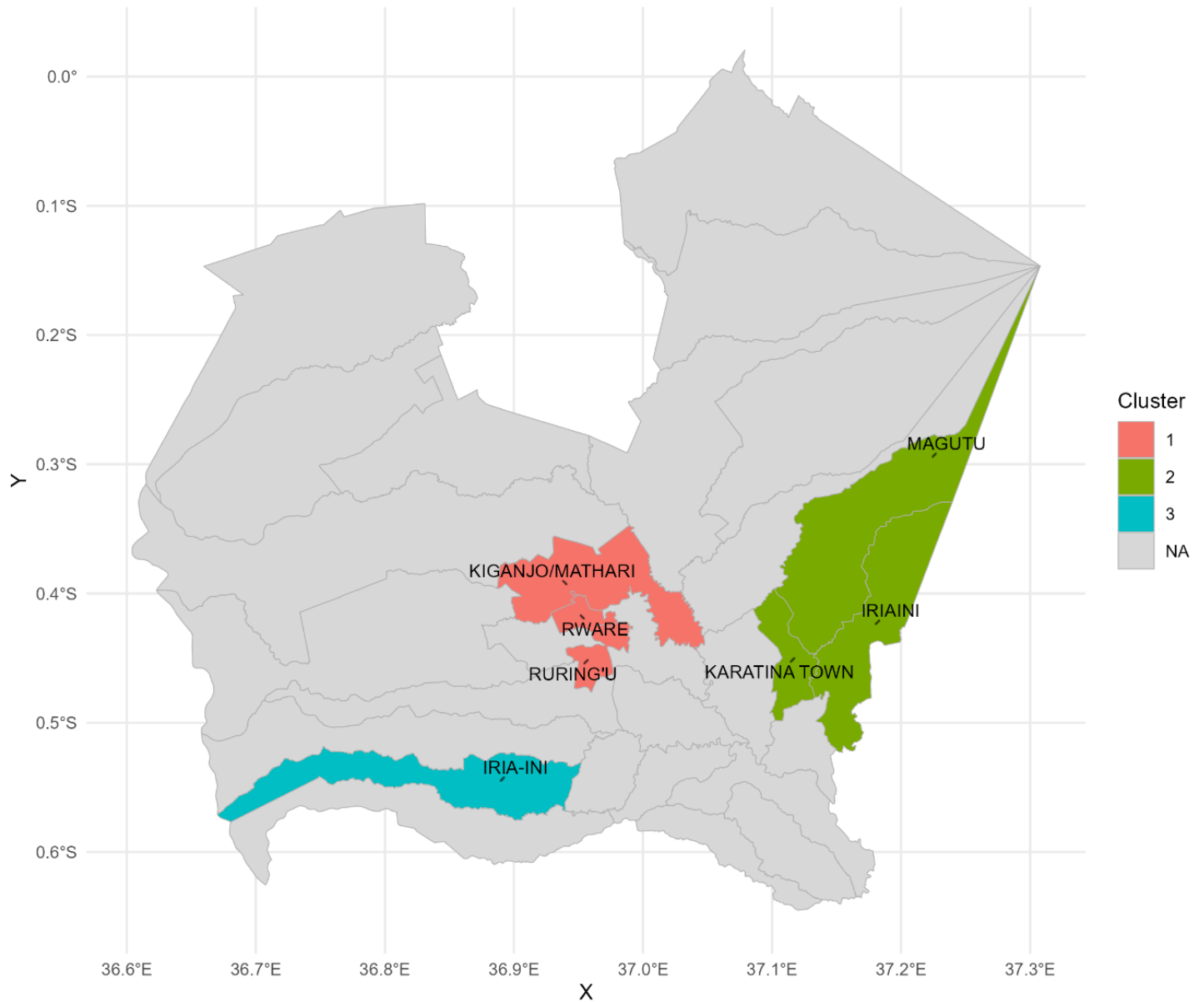


Figure 1

Ward-level space-time clusters of mortality for < 5-year-old children in Nyeri County, 2018-2025

Age-specific space-time mortality clusters in Nyeri County

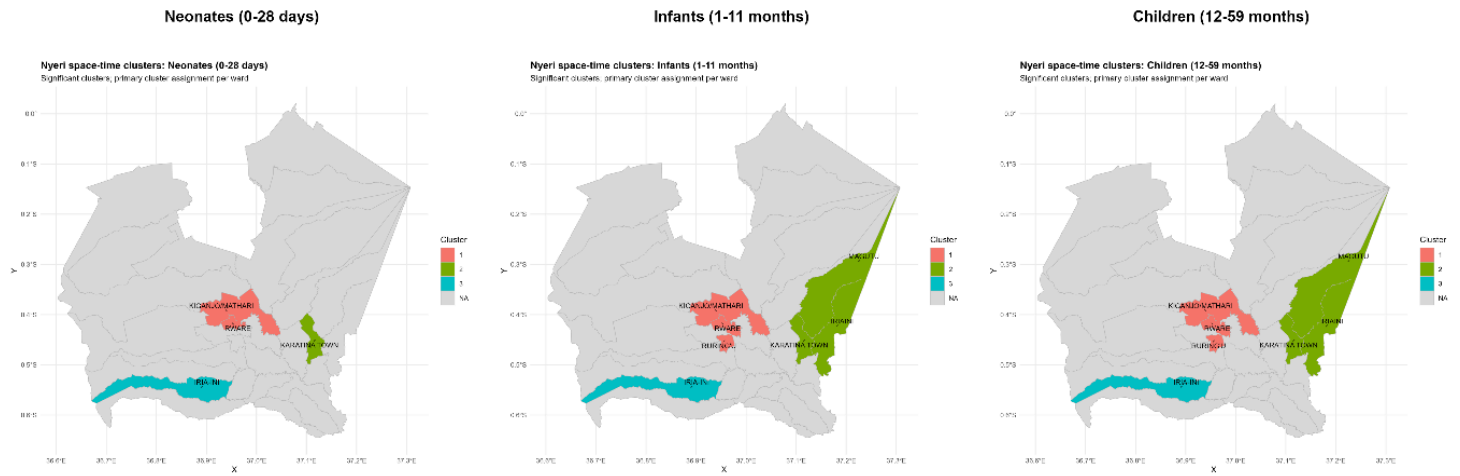


Figure 2

Ward-level space-time clusters of mortality by age in Nyeri County, 2018-2025

Caption. Ward-level space-time clusters of mortality in Nyeri County identified using a retrospective space-time Poisson scan. Colored wards indicate detected significant hotspot clusters, while grey wards represent areas not included in a significant cluster.

Annual ward-level deaths in Nyeri County

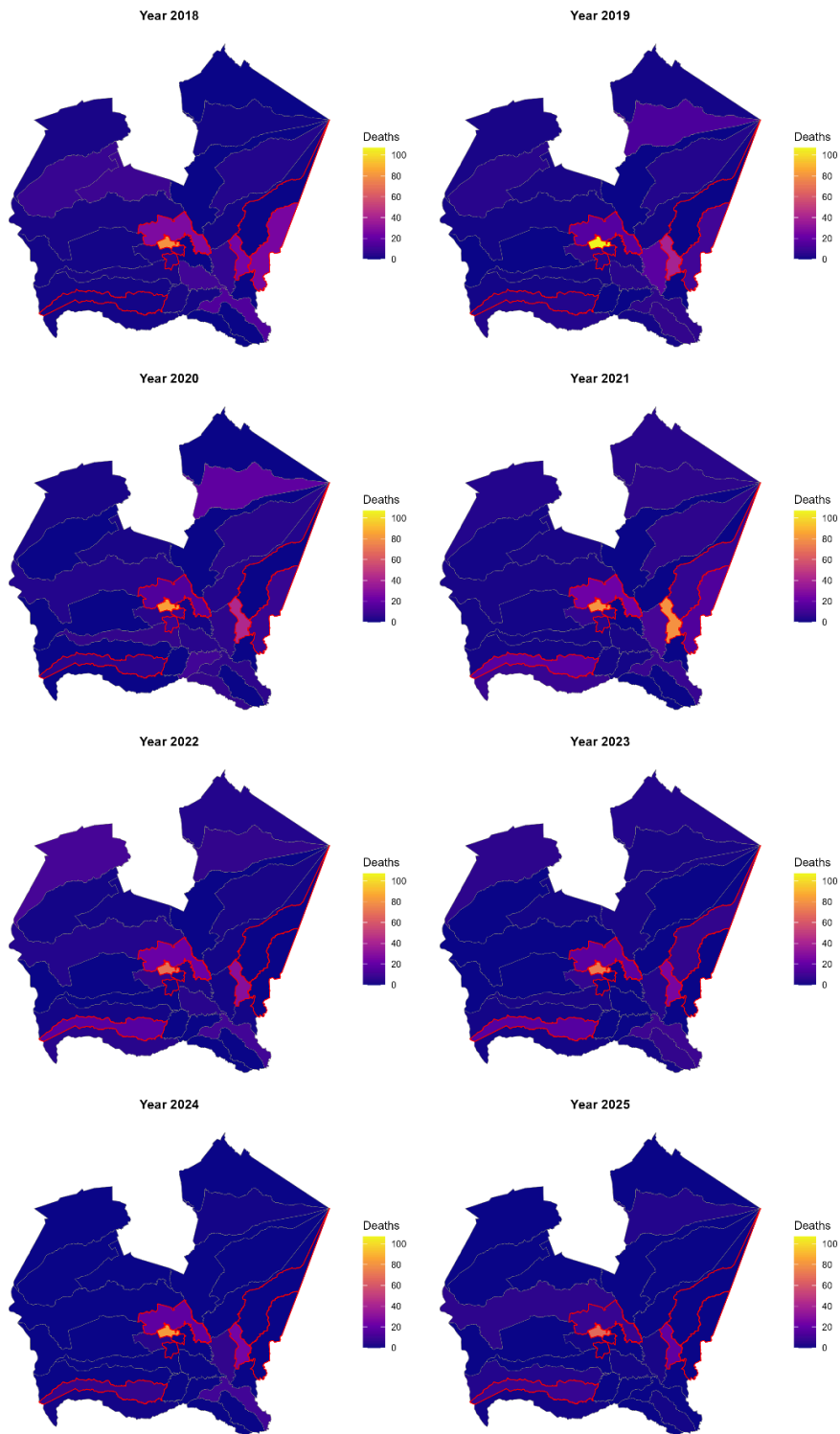


Figure 3

Annual ward-level deaths for decedents <5 years in Nyeri County, 2018-25

Caption. Annual ward-level deaths in Nyeri County, 2018 to 2025. The maps show persistent spatial concentration of deaths in central wards, with the highest burden observed during 2021.

Annual ward-level mortality rate in Nyeri County

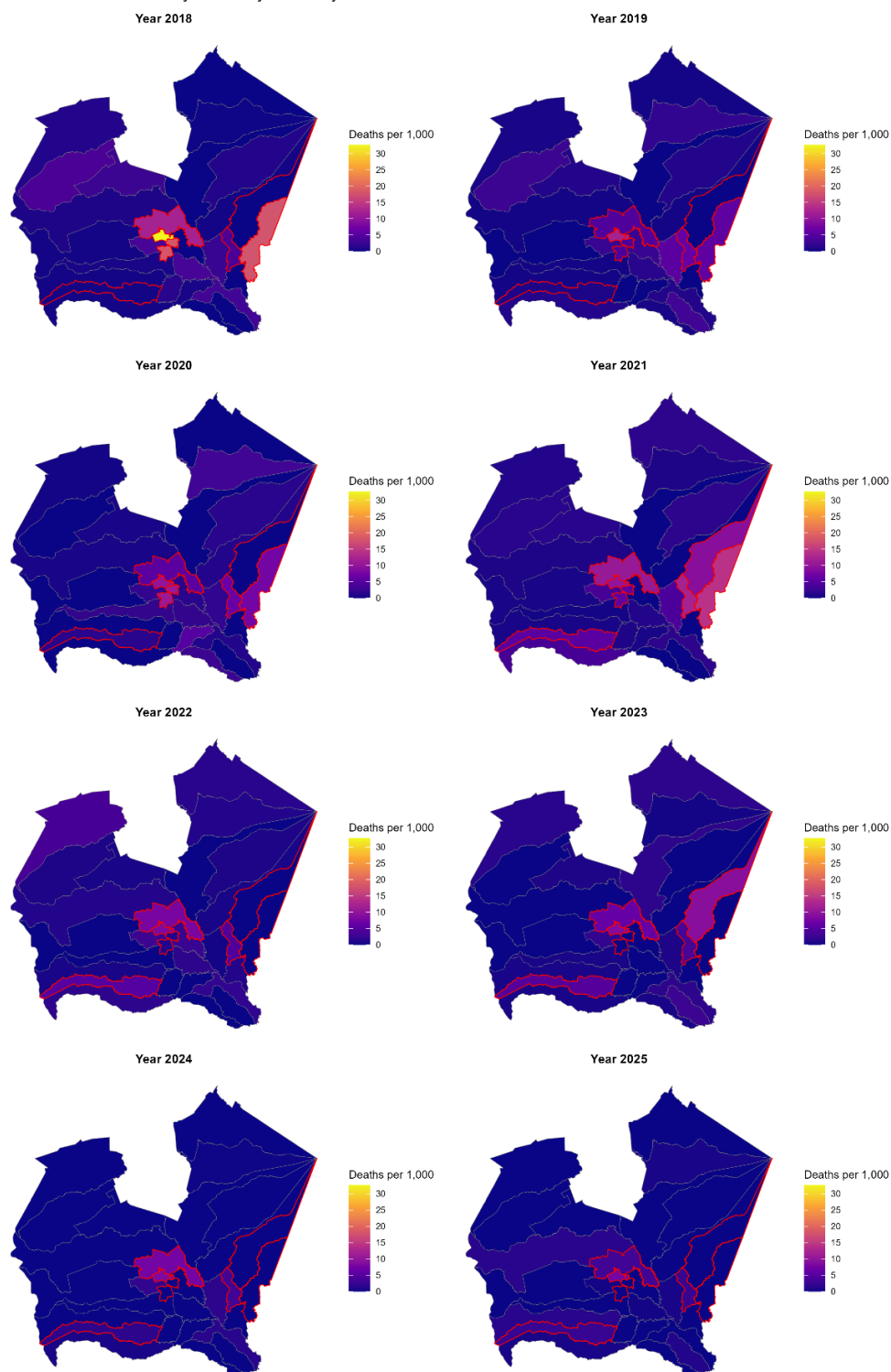


Figure 4

Annual ward-level mortality rates per 1,000 population for decedents <5 years in Nyeri County, 2018-25

Caption. Annual ward-level mortality rates per 1,000 population in Nyeri County, 2018 to 2025. The maps show persistent spatial heterogeneity in mortality, with the highest rates concentrated in central wards and peaking during 2021 to 2023.

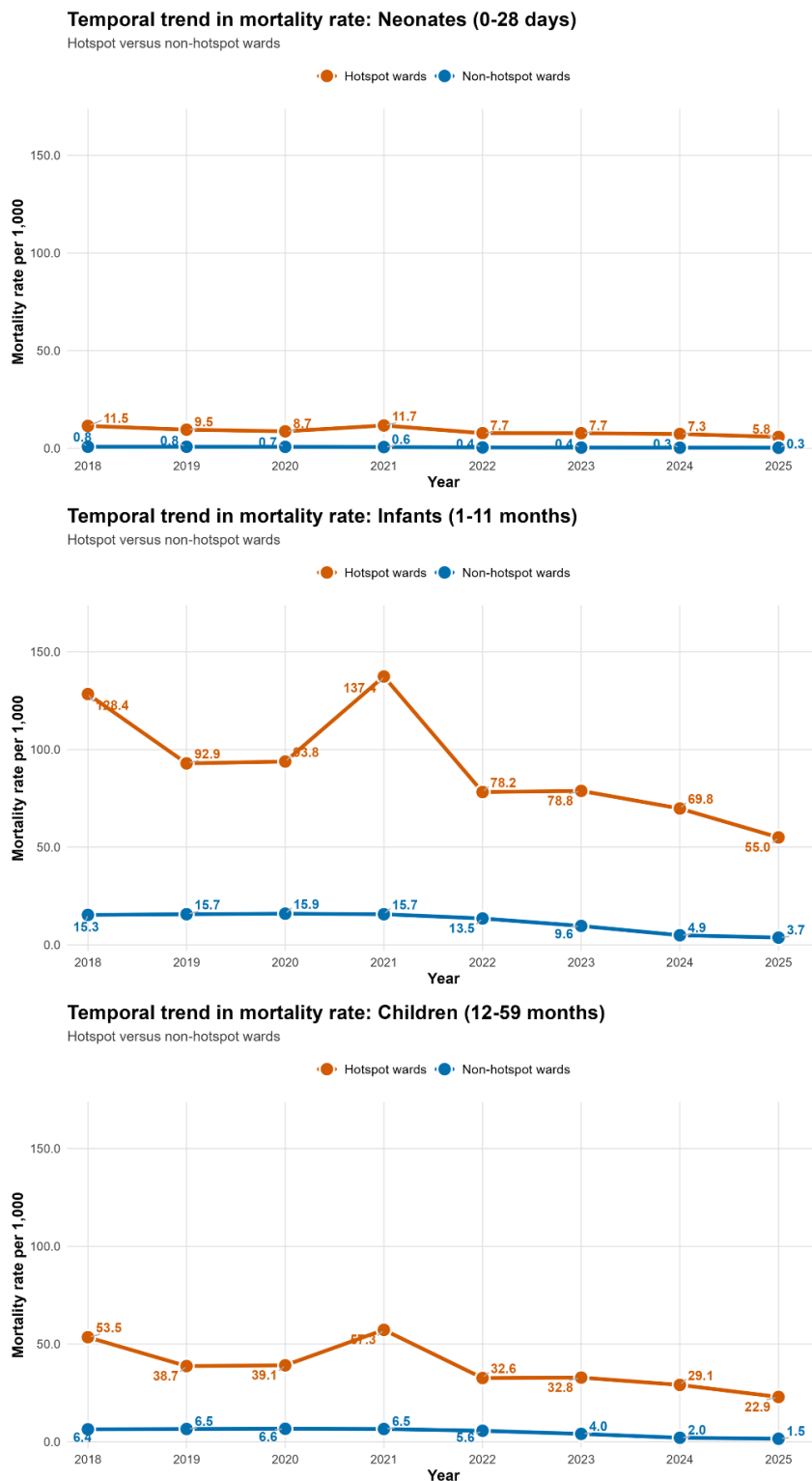


Figure 5

Temporal trend in mortality rates by age in hotspot and non-hotspot wards in Nyeri County, 2018 to 2025

Caption: The figure compares age-specific mortality-rate trends in hotspot and non-hotspot wards from 2018 to 2025. The same y-axis scale is used across the three panels, allowing the direct comparison of rates between neonates, infants, and children aged 12-59 months.