Small Area Estimation of Under-5 Mortality in Zambia

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I would additionally like to express my deepest gratitude to the Central Statistical Office of Zambia and researchers at the University of Zambia for graciously granting me access to and assisting me in acquiring the census data used in this analysis.

Dedication

To my husband and parents, for the continued support, encouragement, and love.

1 Introduction

Under-5 mortality, the probability of death before age 5 ($_5q_0$), is an important overall indicator of child health. National estimates of levels and trends in under-5 mortality in Zambia are included in multiple series[1,2], but estimates at finer levels of detail, such as the district level, are not available. National estimates fail to provide information on disparities within Zambia and are of limited utility for planning purposes as they provide no indication of where efforts or resources are most needed. Consequently, district-level estimates of under-5 mortality are desirable both for illustrating in-country differentials in child health and for providing useful information to inform policy and strategy.

Since there is no vital registration system to record deaths in Zambia, the only data available for estimating under-5 mortality are from censuses and surveys. This presents at least two challenges. First, particularly with regards to the survey data, there are the problems posed by small numbers. In any given district the sample size from an individual survey is relatively small, leading to a high degree of variation in any estimates derived from this data. Second, the type of data available for estimating mortality varies from source to source. Several surveys conducted in Zambia contain complete birth histories–where a mother is asked for dates of birth and, when applicable, age at death for each of her children–which allow for direct estimation of under-5 mortality. Zambia also has several censuses and these contain only summary birth histories–where a mother is asked how many children she has given birth to and how many of these children have died, but no information about individual children is collected–which require demographic models to be utilized in order to estimate under-5 mortality. It is not obvious if one of these types of data is preferable or if both are equally useful for estimating mortality when the number of women interviewed is relatively small.

Studies of under-5 mortality or other measures of child mortality have been conducted at a sub-national level in several other countries that have data limitations similar to those found in Zambia. Some of these studies[3–5] simply produce estimates from a single source, applying the same direct or indirect demographic methods to data at the district level as would be applied at the national level. These studies utilize census data and assume that the sample size is sufficient to avoid issues related to small numbers. Other studies[6–10] utilize survey data and attempt to address the issue of small numbers by employing small area models which explicitly account for the variability inherent in estimates from small samples by borrowing strength across geographic units. In both cases, these studies tend to use only a single census or survey and, with one exception[5], provide no information about trends over time.

The ultimate aim of this study is to combine multiple sources of information about under-5 mortality to produce estimates of levels and trends in under-5 mortality for the 72 districts in Zambia from 1980 to 2010.

To this end, there are three goals:

1. To determine how useful estimates of under-5 mortality derived using various birth history analysis methods are at increasingly small sample sizes and use this information to inform the decision about what data should be included in the final analysis and how this data should be analyzed.

2. To incorporate the available data that is deemed useful into a small-area model to estimate levels and trends in under-5 mortality for each district from 1980 to 2010.

3. To assess the level of uncertainty in the final estimates that is due to both sampling and model uncertainty in each stage.

This article is organized into three sections. The first section describes the methods used to assess the usefulness of various birth history methods in the context of small sample sizes and the results of this part of the analysis. In the second section, five small area models for estimating under-5 mortality are described along with methods for incorporating uncertainty from all stages into the final estimates. Finally, the third section presents estimated levels and trends in under-5 mortality for Zambia's 72 districts.

2 Birth History Performance

The purpose of this portion of the study is to determine how useful estimates of under-5 mortality derived using various birth history methods are at sample sizes similar to those observed in the data sources available at the district level in Zambia. The results of this analysis are used to determine which data and methods can be used to produce estimates which are sufficiently reflective of true under-5 mortality so as to be included in the final analysis.

2.1 Data

All Demographic and Health surveys (DHS)[11] publicly available as of May 2012 which contain birth histories for all women, regardless of marital status, were used, for a total of 152 surveys in 62 countries. Table A.1 in the appendix provides a full listing of all DHS included in this part of the analysis.

2.2 Methods

2.2.1 Birth history methods

Summary birth history method Analysis of summary birth history data utilizes models and methods described in Rajaratnam, et al.[12,1]. The combined version of the maternal age cohort and maternal age period methods are used to generate annual estimates for the 25 years proceeding a census or survey. The time since first birth cohort and period methods are not used as not all of the available data sources in Zambia include information about time since first birth.

Standard complete birth history method When analyzing complete birth history data, records of children from all surveys in a district are combined[13]. The record for each child is then expanded such that there is a record of each month that a child lived and is observed under age 5 years: this will be less than the full 60 months if the child dies before age 5 or if the mother is surveyed before the child reaches age 5. For each child-month of life we indicate whether the child was alive or dead at the end of the month and then assign the child-month to the appropriate time period and age group. Time periods are non-overlapping and equally sized and are assigned starting at the time of the most recent survey and moving back in time. The ages considered are 0 months, 1-11 months, 12-23 months, 24-35 months, 36-47 months, and 48-59 months; these age groupings are designed such that mortality is expected to be reasonably constant across the age range. From these data we calculate the monthly probability of survival in each time period for each age group by calculating the proportion of child months in a given time period and age group that end with the child alive. These monthly probabilities of survival are converted to the probability of surviving the entire age interval under consideration by raising them to a power equal to the number of months in the age interval. Under-5 mortality is then calculating by subtracting from one the product of all of the age-specific survival probabilities. This process generates a single estimate of under-5 mortality for each time period which is then assigned to the midpoint of the period. Different length periods can be used with longer periods providing more pooling of information across time but also producing less frequent estimates.

Moving window complete birth history method As an alternative to the above, the same procedures are carried out except that instead of having non-overlapping time periods and generating one estimate per period, an estimate is generated for each year incorporating all data from a window around that year. This 'moving window' variant uses each observed child-month multiple times and allows for pooling of information across time. Two different versions of this variant are used. In the first, all data that are within the window are treating equally, while in the second, data are weighted using triangle weights such that child-months that are closer to the year which is being predicted for are weighted more heavily than those that are further away. Different length windows can be used, with wider windows providing more pooling of information across time.

2.2.2 Validation methods

Birth history data from DHS are used to assess the performance of the summary birth history methods and the three variants on the complete birth history methods described above at various sample sizes. For each country with DHS data, 'true' under-5 mortality is calculated for the total sample by applying the standard method described above with 2-year periods. Five-hundred samples each of sizes 10, 50, 100, 500, and 1000 women are drawn from each survey without replacement for a total of 2500 samples. Estimates of under-5 mortality are derived for each of the resulting 2500 samples using the summary birth history method and each of the complete birth history methods described above. For the complete birth history methods various period lengths are also tested: for the standard method 1, 2, and 5 year periods are tested; for the moving window methods 5 and 10 year periods are tested for both versions and 20 year periods are tested for the triangle weights variant. The estimates (${}_5\hat{q}_0$) for each of the 2500 samples from each method are matched to the true under-5 mortality (${}_5q_0$) by country and year and then the error, relative error, absolute error, and absolute relative error are calculated as shown below for each sample, method, country, and year.

$$\text{Error} = {}_5\hat{q}_0 - {}_5q_0$$

$$\text{Relative Error} = \frac{{}_5\hat{q}_0 - {}_5q_0}{{}_5q_0}$$

$$\text{Absolute Error} = |{}_5\hat{q}_0 - {}_5q_0|$$

$$\text{Absolute Relative Error} = \left|\frac{{}_5\hat{q}_0 - {}_5q_0}{{}_5q_0}\right|$$

The mean of each of these metrics is then calculated for every sample size and method. The mean error and mean relative error are intended to indicate whether or not estimates from a given method are biased: since over- and under-estimates cancel in these metrics, if methods are unbiased–that is, if over-estimates and under-estimates of the same magnitude are equally likely–the mean error and the mean relative error should be approximately zero. The mean absolute error and mean absolute relative error are intended to capture the extent to which estimates of under-5 mortality can differ from true under-5 mortality; these metrics measure the magnitude of the error, regardless of the direction.

In addition to this overall analysis, stratified analyses are also carried out. The mean of each of the error metrics are calculated for each method and sample size at five different levels of true mortality–<50, 50-100, 100-150, 150-200, >200 deaths per 1,000 births–and for periods 0-1, 2-3, 4-5, ..., and 24-25 years prior to the survey. These stratified analyses are meant to test if the methods perform consistently well at different levels of mortality and for different lengths of time prior to a survey.

2.3 Results

2.3.1 Overall performance

The left panel of figure 2.1* shows the overall mean relative error for each of the birth history methods. Most of the methods are biased to some degree at all sample sizes, but the degree of bias is relatively small when the sample size is at least 100. Below sample size 100, all methods display some degree of downward bias. This is particularly pronounced for the standard complete birth history methods and the moving window complete birth history methods with smaller windows.

The right panel of figure 2.1 gives the overall mean absolute relative error for each method. For all methods, the magnitude of the error increases noticeably as the sample size decreases. At the smallest sample sizes, even the best performing methods are essentially unusable, with no method performing on average better than 62% error at sample size 10 and 34% error at sample size 50. At larger sample sizes, the best performing methods–in this case the summary birth history method and the moving window complete birth history methods with the longest windows–still have relatively high levels of error, around 26-29% at size 100 and 16-19% at sample size 500, but these levels of error may be considered acceptable when there are no alternative sources of data. In contrast, the other methods still perform unacceptably even at

*SBH=summary birth history; CBH=complete birth history; MW=moving window; N=no weights; T=triangle weights; number in brackets indicates period or window length.

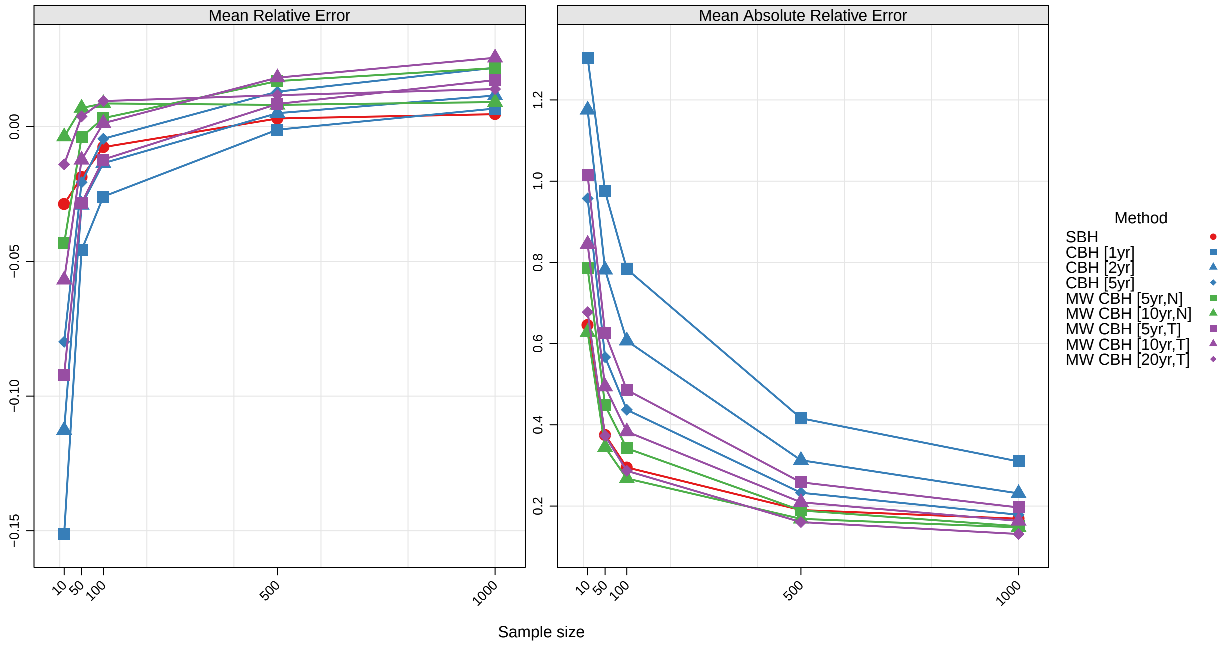

Figure 2.1: Mean relative error and mean absolute relative error for birth history analysis methods at various small samples sizes.

these relatively large sample sizes with mean errors 20-41% even at sample size 500. Figure 2.2 shows the mean error and mean absolute error results which are similar to what is described here for the relative error metrics.

2.3.2 Stratified by true mortality

Figures A.1-A.4 in the appendix depict the results of the birth history analysis stratified by true mortality level. As shown in figures A.1 and A.2, which give the mean relative error and the mean error, the direction and degree of bias varies by level of true mortality for all methods. There is a distinct tendency to over-predict when true mortality is low and to under-predict when true mortality is high. This tendency is especially evident in the summary birth history methods but is also prominent in the moving window complete birth history methods when longer windows are employed. For these methods, the problem is only slightly alleviated as the sample size increases: both the mean error and the mean relative error are essentially constant above sample size 100.

The magnitude of the error also varies by the level of mortality for all methods. In relative terms (see figure A.3), performance is always poorer when true mortality is lower. This is true for all methods, but the differential is greater in some–notably the standard complete birth history method–than in others and, broadly speaking, increases in magnitude as the sample size decreases. In non-relative terms (see figure

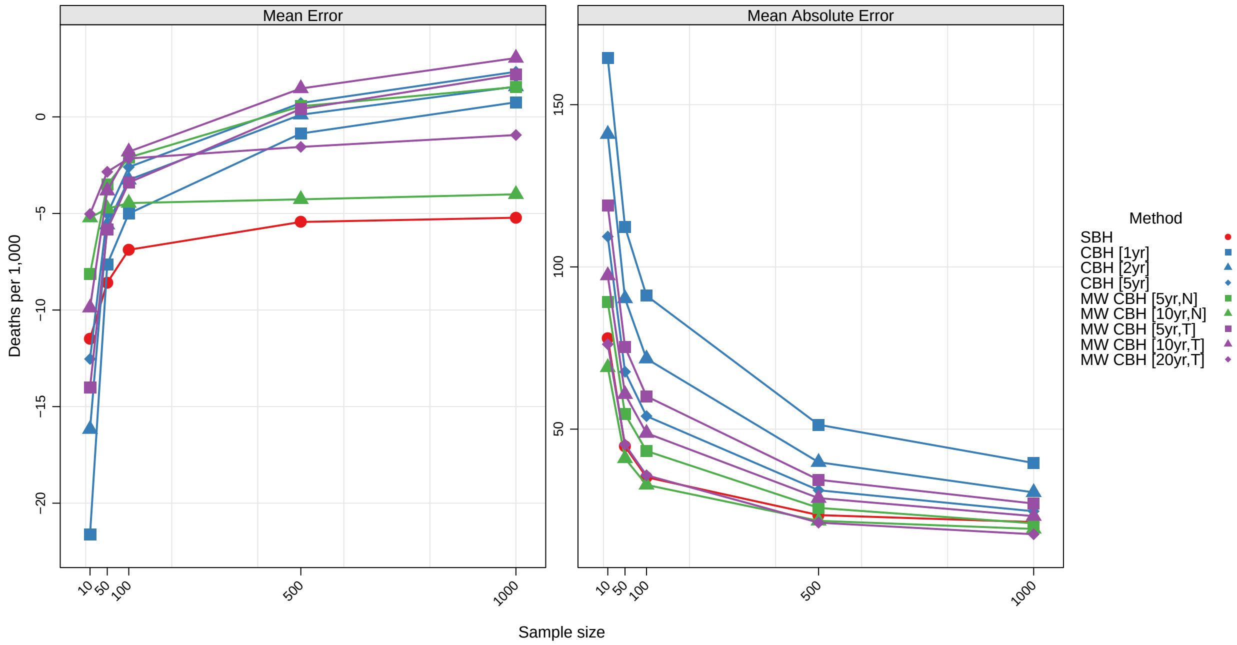

Figure 2.2: Mean error and mean absolute error for birth history analysis methods at various small samples sizes.

A.4), the magnitude of the error is greatest when true mortality is higher. As with the relative measure, the differential in performance between low and high mortality situations is greatest for the standard complete birth history method and the moving window birth history method with shorter windows.

2.3.3 Stratified by time prior to survey

Figures A.5-A.8 in the appendix present the results of the birth history analysis stratified by time prior to survey. A clear pattern of differences in the direction and magnitude of bias in various time periods prior to the survey is evident in figures A.5 and A.6 for the summary birth history method. Mortality is over-predicted in the most recent periods and under-predicted in the more distant past. Unsurprisingly, this trend is also evident, though to a lesser degree, in the moving window complete birth history methods with larger windows: the greater pooling of information over time in these methods is, to an extent, biasing the estimates in the most recent and most distant periods where the level of mortality tends to be the most extreme (since mortality generally declines with time). In both cases the extent of differential bias is generally unaffected by the sample size. In contrast, there is no evidence of differential bias in the standard complete birth history methods.

As observed in the analysis stratified by level of mortality, the magnitude of the error differs with the time prior to survey for all methods. In relative terms (see figure A.7) the magnitude of the error is always highest in more recent time periods while in non-relative terms (see figure A.8) the opposite is observed. This pattern is observed at all sample sizes, with relatively little mitigation of the differential bias as the sample size increases.

2.3.4 Methods selected

The ideal birth history analysis method would give estimates that are unbiased (low mean error and mean relative error) and that are accurate (low mean absolute error and mean absolute relative error). Further, they should perform consistently across different levels of true mortality and different times prior to survey–this criterion is particularly important if the goal is to assess trends in mortality. Based on the results presented above each of the available methods fails to some degree on at least one of these criteria. The standard complete birth history methods and the moving window complete birth history methods with shorter windows perform consistently across different levels of mortality and different times prior to survey but are highly prone to error, even at relatively large sample sizes, and tend to be biased at the smallest sample sizes. The summary birth history methods and moving window complete birth history methods with longer windows are more accurate, especially at smaller sample sizes, and less prone to bias. Their performance is dependent, however, on both the level of mortality and the time prior to the survey.

The choice of best method is not obvious given that each method is flawed. Ultimately, the moving window complete birth history method with a ten year window and no weights is selected. Although there is some degree of differential bias in this method at different levels of mortality and different times prior to survey, overall the performance of this method in terms of bias and magnitude of error is far superior to the methods which don't suffer from differential bias. In cases where this method cannot be employed (i.e. when complete birth histories were not collected) the summary birth history method, which performs similarly overall but is slightly more prone to differential performance at different times prior to survey in particular, is used.

3 Small Area Model

3.1 Data

Zambia conducts decennial population censuses. The 1990[14], 2000[15], and 2010[16] population censuses are included in this analysis. Summary birth histories and information about the age of mothers were collected in each census but complete birth histories were not. A number of districts in Zambia split in the late 1990s increasing the total number of districts from 57 to 72. There are not sufficient data available to allow assignment of individuals recorded in the 1990 census in districts that split to the appropriate current district, so these data are duplicated and assigned to all inheriting districts. Additionally, one district in the 1990 census (covering two present-day districts) is missing from the dataset available for this analysis.

Table 3.1 gives the total sample of women for each census along with the distribution of district-level sample sizes. Because the censuses did not collect complete birth histories, only summary birth history

Table 3.1: Total sample size and distribution of district-level sample sizes for each census.

	Minimum	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile	Maximum	Total
1990 Census	3,692	15,869	28,838	36,232	204,557	2,257,867
2000 Census	3,799	14,899	23,212	35,511	277,404	2,189,309
2010 Census	5,253	20,690	28,742	47,176	477,915	3,002,791

methods can be used to estimate under-5 mortality. As shown in table 3.1, even in the smallest districts, birth histories were collected from thousands of women.

Three demographic and health surveys (DHS), conducted in 1992[17], 1996-97[18], and 2007[19], were utilized in this study. The earlier two DHS include district identifiers for each household. The 2007 DHS did not collect this information but did collect latitude and longitude for each cluster allowing each cluster to be assigned a district based on these coordinates. A fourth Zambian DHS, conducted in 2001-02, was not included in this analysis because it lacks both district identifiers and coordinates and it is not possible to identify districts in this survey. For the earliest two DHS, observations in districts that split are duplicated and assigned to all inheriting districts as was done with data from the 1990 census.

Table 3.2 gives the total sample of women for each DHS and the distribution of district-level sample sizes. Not surprisingly, the sample sizes available at the district level from the DHS are considerably smaller than for the censuses. DHS contain both summary and complete birth history data. Based on the results of the preceding section, estimates of under-5 mortality are generated from these surveys using the moving window complete birth history method with a ten year window.

Table 3.2: Total sample size and distribution of district-level sample sizes for each DHS.

	Minimum	25^{th} Percentile	50^{th} Percentile	75^{th} Percentile	Maximum	Total
1992 DHS	24	70	99	168	962	7,060
1996-97 DHS	20	71	132	205	876	8,021
2007 DHS	12	46	76	118	483	7,146

3.2 Methods

3.2.1 Models

Five small area models are tested for use in synthesizing the estimates of under-5 mortality from the data and methods selected as described in the previous section. In each model, logit-transformed under-5 mortality (denoted ${}_5q_0$) in district j at time t is assumed to be normally distributed around mean μ_{jt}.

$$logit({}_5q_{0jt}) \sim Normal(\mu_{jt}, \sigma^2)$$

A logit-transformation is used to restrict predictions to be between 0 and 1.

In model 1, mortality is assumed to change linearly (in logit-space) with time:

$$\mu_{jt} = \beta^0 + \beta^1 \cdot t + u_j^0 + u_j^1 \cdot t + v_j^0 + v_j^1 \cdot t$$

β^0 and β^1 are fixed effects and represent the global mean level of under-5 mortality and rate of change in under-5 mortality with time, respectively. Two sets of district random effects are included which allow both the mean level of mortality (the intercept) and the rate at which mortality changes with time to be district specific. The random effects denoted u_j^0 and u_j^1 are intended to capture spatially-structured variation in the mean and slope among districts. Each of these random effects utilizes an intrinsic conditional autoregressive (ICAR) prior[20–22]:

$$u_j | u_{k,k \in ne(j)} \sim Normal(\overline{u_k}, \frac{\sigma_u^2}{m_k})$$

In the above equation, $k \in ne(j)$ denotes the set of districts which share a boarder with district j, m_k is the number of districts in k, and $\overline{u_k}$ is the mean of u for districts in k. Thus, for a given district, the mean of this prior is given by the mean of the same random effect for all neighboring districts and the variance is given by a common parameter divided by the number of neighbors. This suggests that mortality in any given district is similar to that of its neighbors and also that the more neighbors a district has, the more information there is about mortality in that district. The random effects denoted v_j^0 and v_j^1 are intended to capture variation among districts that is not spatially-structured. These two random effects utilize independently and identically distributed (IID) priors:

$$v_j \sim_{iid} Normal(0, \sigma_v^2)$$

Model 2 assumes that mortality may not change linearly with time and instead of using a linear time trend, models time with a series of dummies on 5-year (and one 6-year) periods:

$$\mu_{jt} = \boldsymbol{\beta} \cdot \boldsymbol{I_t} + \boldsymbol{u_j} \cdot \boldsymbol{I_t} + \boldsymbol{v_j} \cdot \boldsymbol{I_t}$$

In the equation above, $\boldsymbol{I_t}$ is a column vector of length 6; for any given observation, one element of $\boldsymbol{I_t}$ is 1, indicating which time period–1980-84, 1985-89, ..., 2005-2010–the observation belongs to. $\boldsymbol{\beta}$, $\boldsymbol{u_j}$, and $\boldsymbol{v_j}$ are each row vectors with 6 elements corresponding to the effects for each of the six time periods. The elements of $\boldsymbol{\beta}$ are fixed effects respresenting the time period specific global means while $\boldsymbol{u_j}$ and $\boldsymbol{v_j}$ are random effects that allow for district-level variation in the level of mortality in each time period. Each element of $\boldsymbol{v_j}$ has an IID prior and each element of $\boldsymbol{u_j}$ has an ICAR prior, analogous to those described in model 1, allowing for both unstructured and spatially-structured variation among the districts at each time period.

Model 2 is more flexible than model 1 in that it does not restrict the time-trend to be linear, however the final predictions are constant over each 5-year period and discontinuous at the edges of each period which is not ideal. Further, the results from this model could be sensitive to the length of the periods and placement of the boundaries. Models 3-5 use natural cubic splines[23] to allow for a more flexible time trend than model 1 while ensuring that the final estimates are continuous. A spline is a piece-wise function where polynomials of a given degree are fit over defined ranges defined by 'knots'. Constraints are placed on the function such that the overall function is continuous and smooth at each of the knots where the polynomials for adjacent periods meet. A natural spline additionally imposes the constraint that the function be linear beyond the outermost knots which helps to alleviate problems with prediction at the extremes sometimes encountered when fitting polynomials. Models 3-5 are structured similarly to model 2 but with $\boldsymbol{I_t}$ replaced by a vector giving the bases of the natural cubic spline. These three models differ only in the number and placement of knots for the spline. Model 3 has internal knots at two year intervals starting in 1982 and ending in 2008, model 4 has internal knots at 5 year intervals starting in 1985 and ending in 2005; and model 5 has internal knots at 10 year intervals, in 1990 and in 2000. All three models have boundary knots at 1980 and 2010.

In some districts the level of mortality described in estimates derived from the censuses is markedly different from the level of mortality described in the DHS. It is likely, in these cases, that the census estimates more closely reflect the true mortality level since the DHS estimates may be biased if the clusters selected are not truly representative of the district. Consequently we add an additional term, ψ_j, to each of the models above to allow for this bias:

$$logit({}_5q_{0jt}^{observed}) \sim Normal(\mu_{jt} + \psi_j, \sigma^2)$$

This bias term is modeled as:

$$\psi_j = \gamma \cdot I_{DHS} + w_j \cdot I_{DHS}$$

Where I_{DHS} is an indicator for whether or not an observation is derived from DHS data, γ is a fixed effect that gives the global bias in the DHS compared to the census and w_j is random effect with an IID prior that allows for district-specific estimates of the bias in the DHS compared to the census. This bias term is excluded when obtaining predictions from the fit models.

All models are fit in the INLA[24] package in R.14.1[25]. Default hyperpriors–loggamma(1,0.00005) distributions–were used for the precision (inverse variance) of the random effects. Model selection is determined, in part, based on the deviance information criterion (DIC)[26], a metric that favors models which more adequately explain the data used to fit them while penalizing models for complexity. Models with a lower DIC are preferred.

3.2.2 Uncertainty propagation

There are several sources of uncertainty that should be accounted for in the final estimates of under-5 mortality: there is uncertainty in the observed under-5 mortality estimates used to fit the models, both from sampling variation (in the case of surveys) and from the use of indirect demographic methods (where summary birth history methods are utilized), and there is also uncertainty in the small area models. In order to account for this uncertainty in the final estimates, simulation is used to propagate uncertainty from each step into subsequent stages[27].

Uncertainty in complete birth history estimates that is due to sampling error is accounted for with bootstrapping[28,29]. Bootstrapping allows for estimation of uncertainty in the under-5 mortality estimates that takes into account the complex survey design of the DHS. Further, using bootstrapping in this portion of the analysis allows us to avoid parametric approximations which may not hold in small samples.

In order to produce a single bootstrapped sample for a district, the following procedure is used:

1. For each survey, the clusters are sampled with replacement until the original number of clusters are obtained;

2. For each sampled cluster, the households in that cluster are sampled with replacement until the original number of households are obtained;

3. For each sampled household, all children of all women in that household are included in the bootstrapped sample.

This procedure is repeated 500 times for each district and a series of under-5 mortality estimates is produced from each sample using the moving window complete birth history method with a ten year window for a total of 500 series.

Uncertainty in summary birth history estimates is due both to sampling error in the inputs to summary birth history models (i.e. the mean number of children ever born and the mean proportion children died) as well as model error. For summary birth history estimates derived from census data, sampling error is not an issue since the inputs to the summary birth history model are calculated for the whole population rather than estimated from a sample. Consequently, for this analysis only model error needs to be taken into account. For this component of the analysis bootstrapping is prohibitively expensive computationally and alternative simulation procedures are employed instead. King et al.[30] describe methods for assessing uncertainty in model predictions by simulating from model parameter estimates and the associated variance-covariance matrix using a normal approximation. These methods are used here to simulate 500 predicted series from the maternal age cohort method and the maternal age period method, each of which are then combined as usual into an overall combined series.

The 500 series of complete birth history estimates and the 500 series of summary birth history estimates jointly form 500 complete datasets. The small area model is then fit on each of the 500 datasets. For each model fit, 100 draws from the posterior distribution of each fitted value are simulated for a total of 50,000 draws for each fitted value. The final best estimate for a given district and year is the mean of these 50,000 draws while the upper and lower uncertainty intervals are calculated as the 2.5^{th} and 97.5^{th} percentiles of these draws. Because this procedure is computationally intensive, it is only carried out for the best model selected from the five described in the previous section.

3.3 Results

3.3.1 Models

Figures 3.3-3.6 show the mean estimates from each of the five models for four districts. In districts like Chadiza (figure 3.3) where the data are relatively consistent across sources and there is a roughly linear decline, the estimates from the various models are similar. In contrast, in districts like Ndola (figure 3.4)

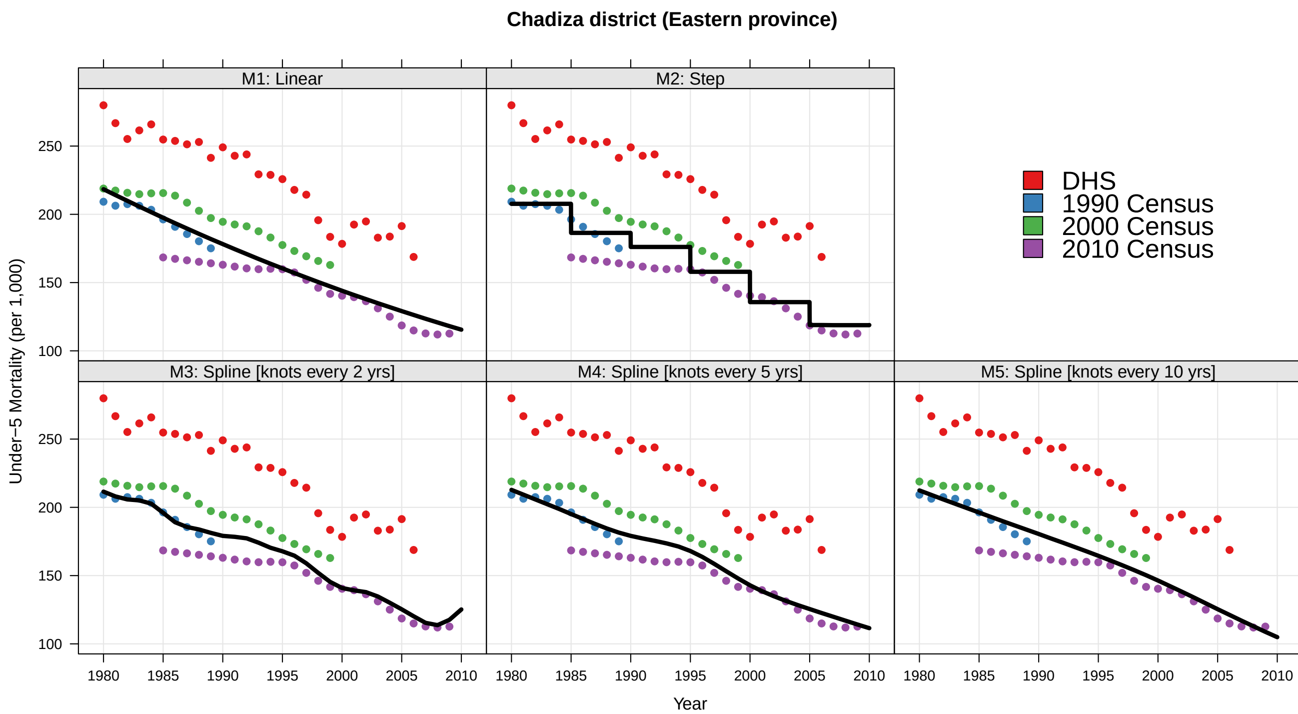

Figure 3.3: Data from all sources and estimates from all models, Chadiza district (Eastern province).

where the data are still relatively consistent but the time trend is distinctly non-linear, models 2-5 give markedly different predictions than model 1, much more closely mimicking the trend observed in the data. All five models diverge somewhat in districts like Chavuma (figure 3.5) where the data are less consistent and consequently the trend is less obvious. In this case, the spline models with more knots, particularly model 3, give less smooth predictions as they attempt to closely fit all of the data.

The model predictions shown for these four districts are representative of what is observed in all 72 districts. In general, model 1 is unsatisfactory; there are frequently distinct non-linear trends that are confirmed by multiple data sources which this model is unable to replicate. Model 2, while better able to accommodate non-linearity, is unsatisfying due to the disjoint nature of its predictions. Model 3, the spline with the most knots of the models tested, is also the model that follows the data most closely. Both model 3 and model 2, however, have trouble in districts where the data are less consistent. Because these models provide relatively little smoothing compared to the other three models, the predictions in these districts fluctuate more rapidly than is expected. Both model 4 and model 5 strike a balance between flexibility in capturing the time-trend while imposing sufficient smoothing to guarantee reasonable predictions.

It is interesting to look at the posterior predictions of each random effect for the 72 districts. For the random effects that are part of estimating the time-trend–those given by the u_j and v_j terms–the most

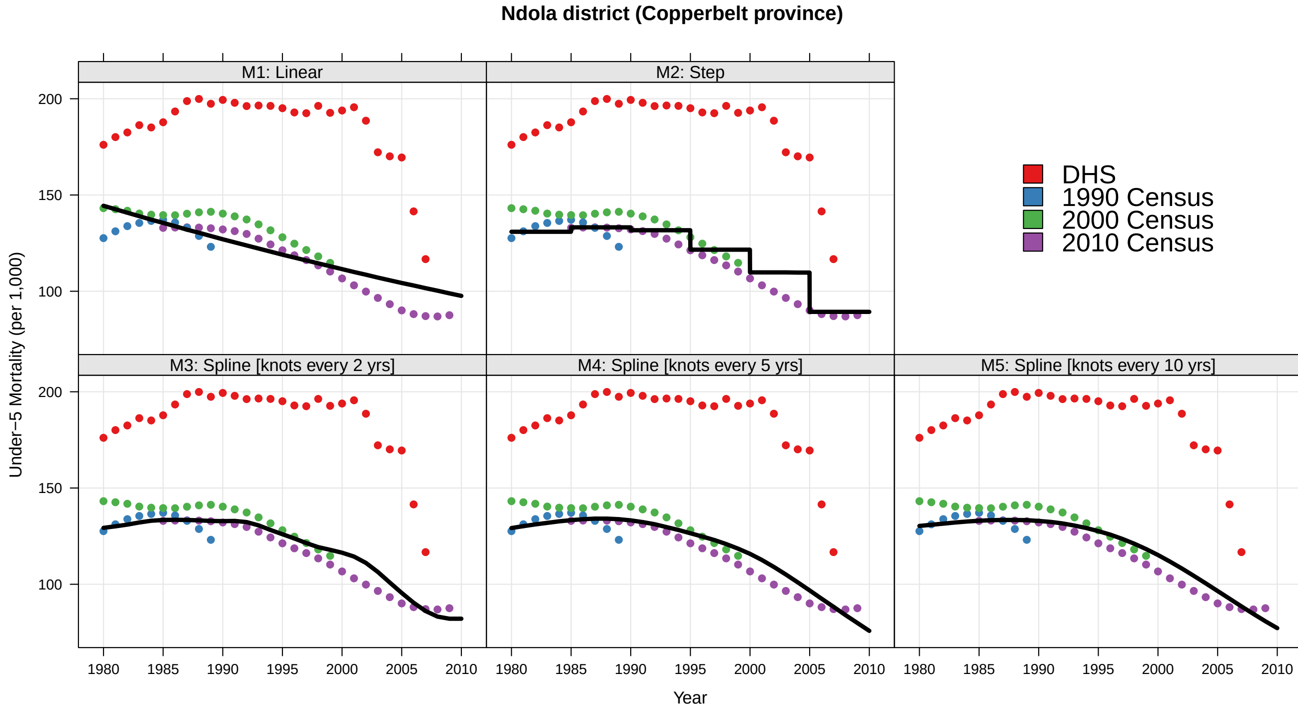

Figure 3.4: Data from all sources and estimates from all models, Ndola district (Copperbelt province).

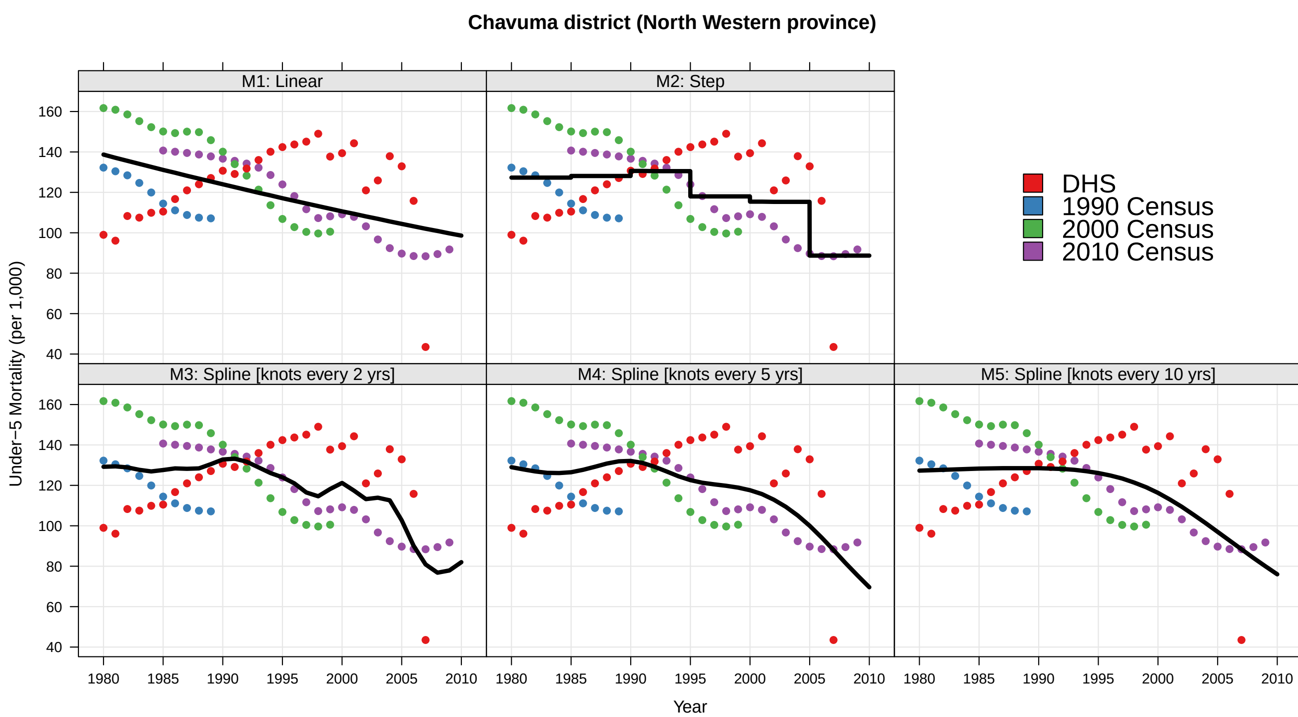

Figure 3.5: Data from all sources and estimates from all models, Chavuma district (North Western province).

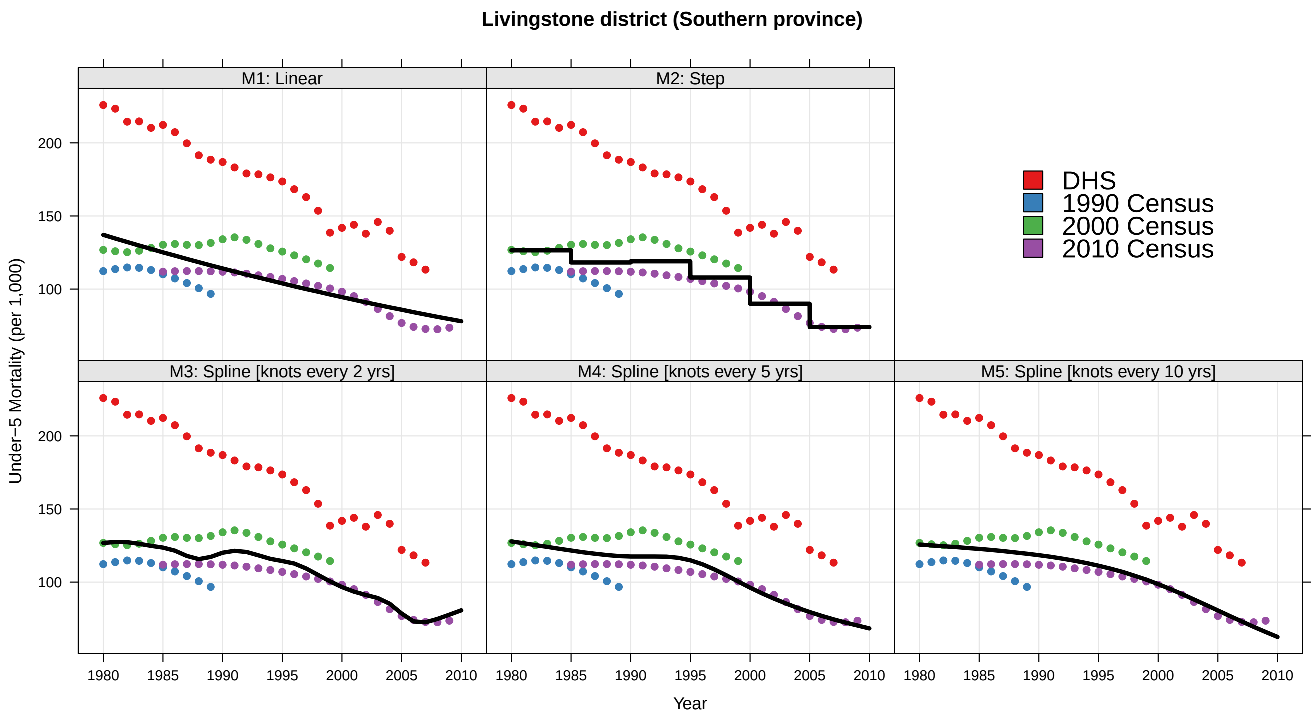

Figure 3.6: Data from all sources and estimates from all models, Livingstone district (Southern province).

interesting comparison is between the unstructured (IID) random effects and the spatially-structured (ICAR) random effects. Figure 3.7 shows the posterior estimates of each of the 12 random effects included in model 2 for all 72 districts (ordered by district number). In each time period (arranged by column) the magnitude of the spatially-structured random effects (top row) dwarfs that of the unstructured random effects (bottom row). This suggests that a considerable proportion of the observed variation in under-5 mortality in each period is explained by factors that vary relatively smoothly in space. Table 3.3 gives the standard deviation of the posterior random effect estimates for each set of random effects in each model. In general, this table shows that the other models exhibit similar patterns whereby most of the variation between districts is captured by the spatially-structured random effects (i.e. the standard deviation of the posterior value of these effects is larger) There are some exceptions to this trend, however, and in each of the spline models (models 3-5) there is at least one spline basis where there is more variation in the corresponding unstructured random effect than in the corresponding structured random effect.

As is evident in figures 3.3, 3.4, and 3.6, in some districts the estimates of under-5 mortality derived from the DHS are noticeably lower or higher than those derived from the census. The global intercept for the included DHS bias term, γ, is consistently positive across all five models (0.15 [0.10-0.19] in model 5 and very similar in the other four models). This suggests that estimates from the DHS are generally higher than

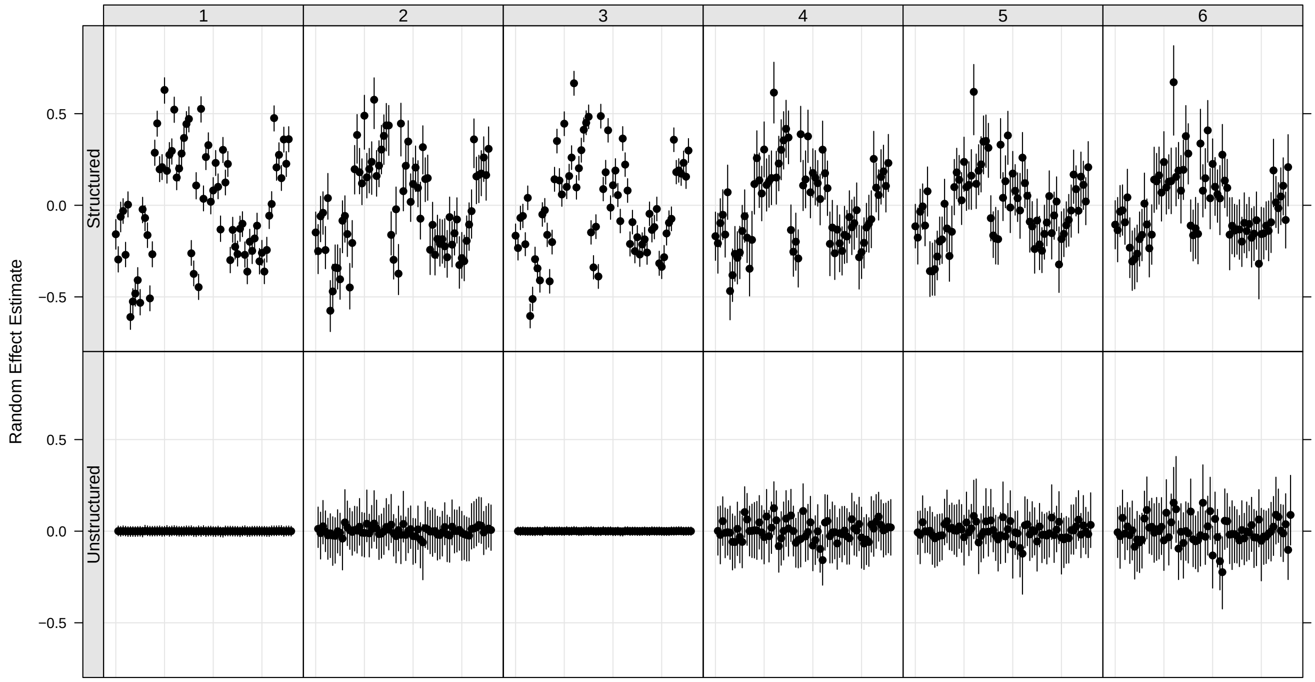

Figure 3.7: Estimated random effects on time periods in Model 2.

estimates from the censuses. The posterior values of the random effect for this component of the model, w_j, however, show considerable variation amongst districts, as shown in figure 3.8 which gives the posterior estimates of the random effect for each district (ordered by district number). 45 of the districts have random effects that are significantly different from zero in all five models, with Chililabombwe, Luwingu, and Gwembe having the greatest sized effects overall.

Table 3.4 gives the deviance information criterion for each of the five models and also provides the rank of the models on this metric. The best performing model by this metric is model 5, the spline model with knots at 10 year intervals. Model 4, the spline model with knots at 5 year intervals is second, but the third spline model, model 3, which has knots at 2 year intervals is fourth behind model 2 with categorical time periods. Unsurprisingly, model 1 performs worst on this metric.

Model 5 is selected as the best model given its superior performance on the DIC, which balances model complexity against ability to fit the data closely, and the desirable properties of its predictions described above.

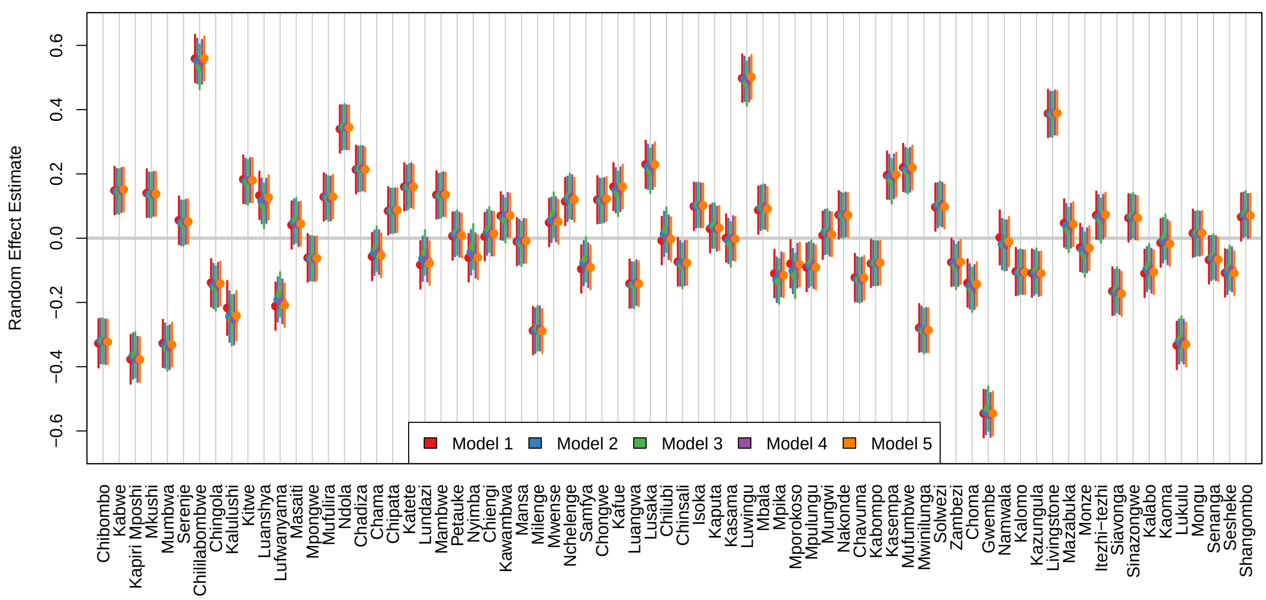

Figure 3.8: Estimated DHS random effect size.

3.3.2 Uncertainty propagation

Estimates from model 5 with uncertainty intervals generated as described in section 3.2.2 are show for all districts in figures A.9-A.80 in the appendix. In absolute terms, the width of the uncertainty intervals (upper bound - lower bound) range from a low of 14 per 1,000 to a high of 96 per 1,000 across all district-years. This corresponds to estimates where the uncertainty is plus or minus 6% to 41% percent of the mean estimate. The mean uncertainty interval is 30 per 1,000 wide while the mean relative uncertainty is plus or minus 11% percent.

The degree of uncertainty in the estimates varies across time. Figure 3.9 shows a plot of the width of the uncertainty interval for each district in each year and also shows the range over which estimates are available from each of the data sources utilized. Uncertainty is greater in time periods with less data, for example before 1985, where there are no estimates from the 2010 census and after 2000 when there are no estimates from the 2000 census. Unsurprisingly, the greatest uncertainty is observed in 2010, the only year where there is no data available at all.

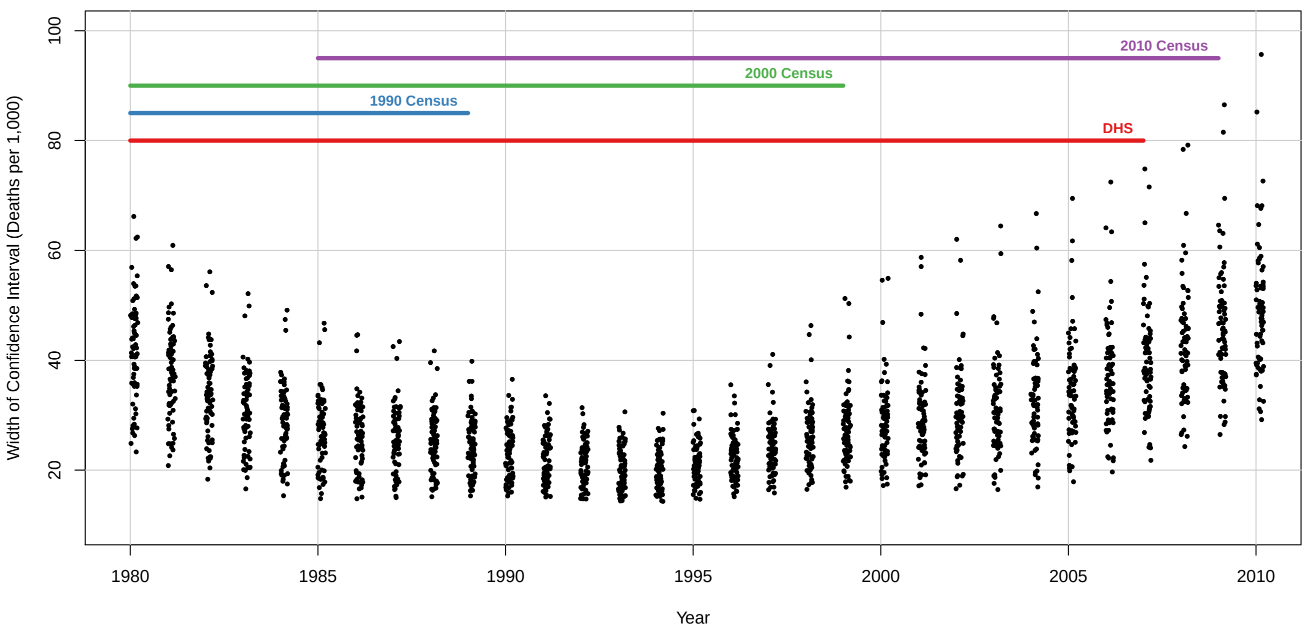

Figure 3.9: Width of uncertainty interval (upper bound - lower bound) by year (jittered).

Table 3.3: Standard deviation of the posterior random effect estimates for all models.

	Effect	Unstructured Effect	Structured Effect
Model 1	Intercept	<0.001	0.255
	Slope	0.004	0.004
Model 2	Period 1	<0.001	0.304
	Period 2	0.021	0.266
	Period 3	<0.001	0.269
	Period 4	0.052	0.226
	Period 5	0.039	0.197
	Period 6	0.068	0.189
Model 3	Basis 1	<0.001	0.227
	Basis 2	0.142	0.218
	Basis 3	<0.001	0.259
	Basis 4	0.106	0.225
	Basis 5	<0.001	0.267
	Basis 6	0.062	0.228
	Basis 7	<0.001	0.267
	Basis 8	<0.001	0.238
	Basis 9	<0.001	0.265
	Basis 10	<0.001	0.213
	Basis 11	0.102	0.165
	Basis 12	<0.001	0.197
	Basis 13	0.227	0.106
	Basis 14	<0.001	0.109
	Basis 15	0.124	0.553
	Basis 16	<0.001	<0.001
Model 4	Basis 1	<0.001	0.217
	Basis 2	<0.001	0.285
	Basis 3	0.063	0.229
	Basis 4	0.068	0.214
	Basis 5	0.172	<0.001
	Basis 6	0.001	0.608
	Basis 7	<0.001	0.048
Model 5	Basis 1	<0.001	0.231
	Basis 2	0.077	0.085
	Basis 3	0.076	0.540
	Basis 4	0.118	0.015

Table 3.4: Deviance information criterion for all models.

Model	DIC	Rank
Model 1: Linear	-6881	5
Model 2: Binned	-7796	3
Model 3: Spline [2yrs]	-7659	4
Model 4: Spline [5yrs]	-8376	2
Model 5: Spline [10yrs]	-8415	1

4 Mortality Estimates

Figures A.9-A.80 in the appendix show the under-5 mortality estimates with uncertainty for each district. These plots show both the point estimates from each data source (the circles) as well as the simulated series from each data source (the lines) that were used in generating the uncertainty intervals. Table 4.5 gives the under-5 mortality estimate for each district in 1980, 1990, 2000, and 2010 as well as the percent decline over each decade in this period. Additionally, table 4.5 gives the percent decline from 1990 to 2010; this is shown given the special relevance of percent declines from 1990 for tracking progress on Millennium Development Goal 4 (MDG4)[31] which calls for a 2/3 decline in the level of under-5 mortality from the 1990 level by 2015.

Both the figures and the table show mortality declining over the period 1980-2010 in nearly every district. The rates of decline, however, have not been constant over this entire period. In the 1980s there were 19 districts for which the rate of decline is actually negative (i.e. mortality increases) though in all of these the confidence intervals for the rate of decline are wide and cross 0. In contrast, there are no districts where the estimated rate of decline from 1990-2000 or 2000-2010 is negative, though many have confidence intervals that cross 0. Further, the number of districts with positive declines that are statistically significant increases with each subsequent decade, from 18 in the period 1980-1990, to 49 in the period 1990-2000, to 69 in the period 2000-2010. Over the period 1990-2010, only one district–Chililabombwe–does not have a statistically significant positive decline.

Although the period for achieving the MDG4 is not yet over, it is interesting to see which districts are on track to achieve this goal. There are no districts where the mean estimate of the percent decline in mortality from 1990 to 2010 is 2/3, but there are three districts–Milenge, Lukulu, and Sesheke–where 2/3 is contained within the confidence interval and it is possible that these districts have already obtained MDG4. If the rate of decline is constant over the period 1990 to 2015 at the level needed to obtain MDG4, a 58.5% reduction is expected by 2010. There is one district–Sesheke–where the mean estimate of the percent decline 1990-2010 is this high and 27 districts where the confidence interval includes this value. This suggests that less than half of the districts may be on track to achieve MDG4.

Figure 4.10 shows maps of the level of under-5 mortality every 5 years from 1980 to 2010. Regional patterns are apparent: although all areas improve with time, the north eastern part of the country (Luapula, Northern, and Eastern provinces in particular) and the western part of the country (Western province in particular) consistently have higher mortality than the central portion of the country.

Figure 4.11 shows the level of under-5 mortality in 1980, 1990, 2000, and 2010 for each district, grouped by province. The regional patterns seen in figure 4.10 are also apparent here: districts in Copperbelt, Lusaka, Southern and Central Provinces generally have lower mortality and districts in Luapula, Western,

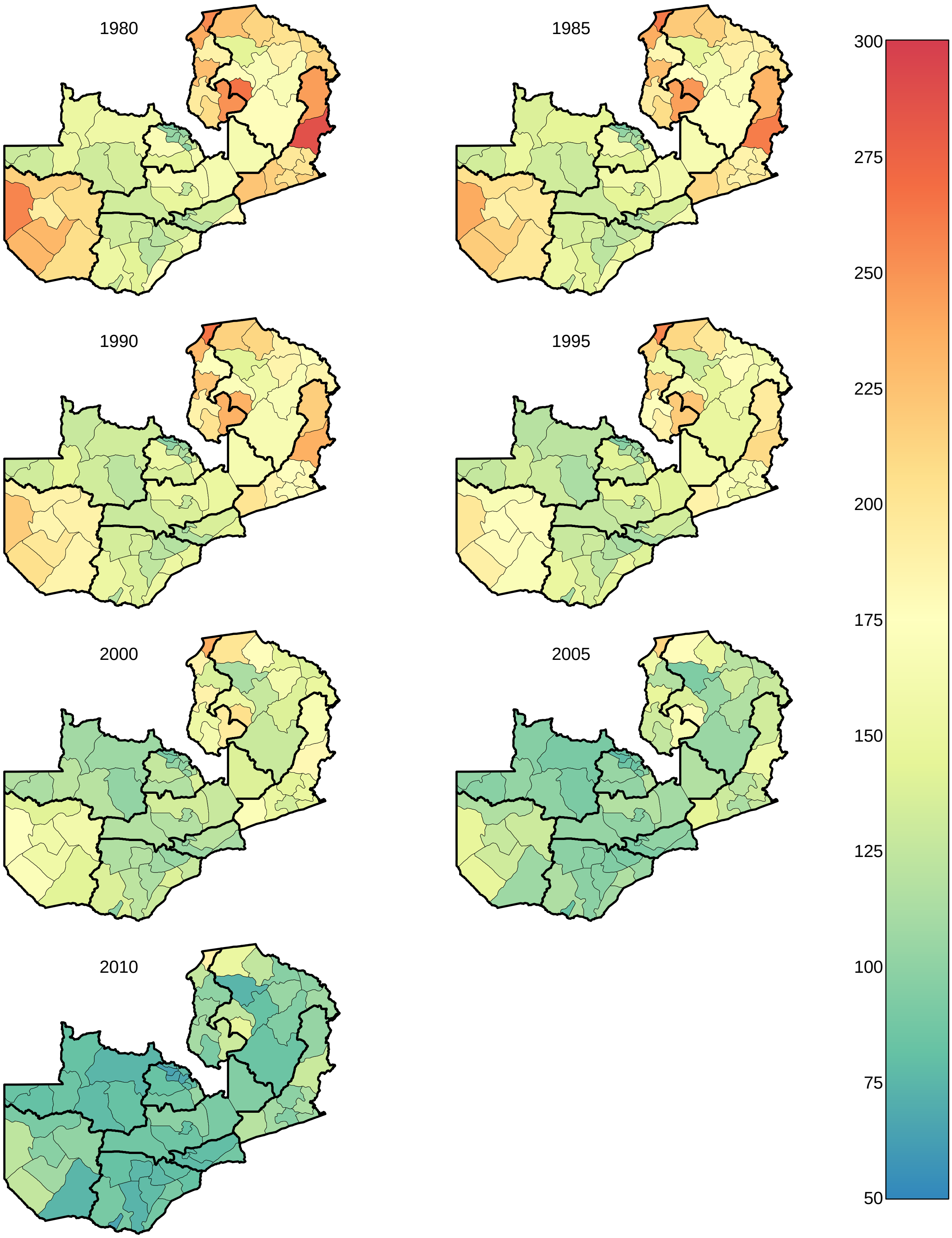

Figure 4.10: Maps of under-5 mortality estimates by year.

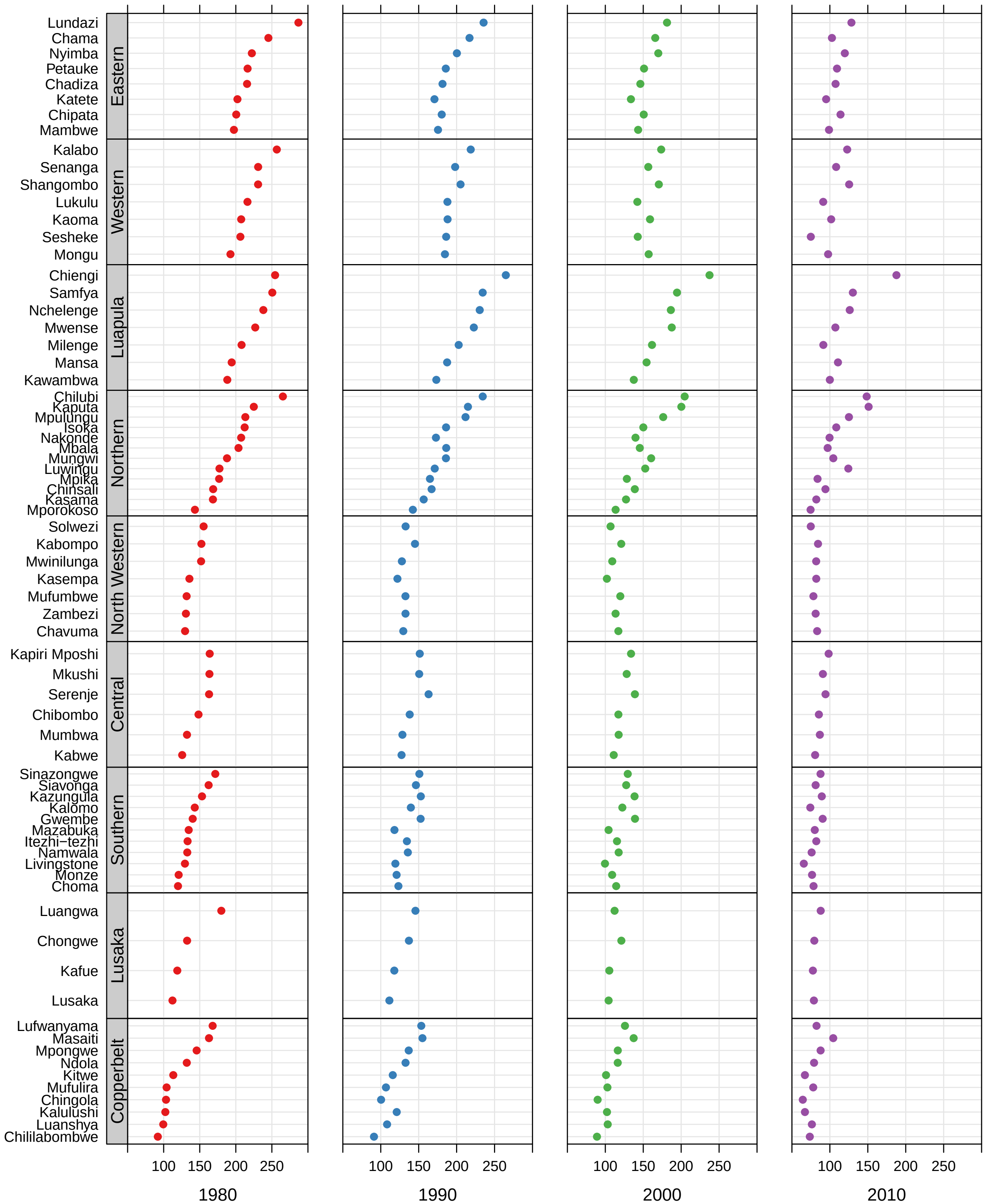

Figure 4.11: Under-5 mortality in 1980, 1990, 2000, and 2010 for each district, by province.

and Eastern Provinces generally higher mortality in all time periods. Figure 4.11 also demonstrates that in absolute terms, inequality amongst districts has decreased with time. The difference between the lowest and highest mortality districts in 1980 was 195 deaths per 1,000 but this decreased to 174 in 1990, 148 in 2000, and 123 in 2010. Similarly, the standard deviation of the under-5 mortality estimates across the districts is in every year smaller than the previous year, dropping from 46.3 in 1980 to 22.1 in 2010. The relative difference between the highest and lowest mortality districts has not always decreased with time, however. In 1980 children in the highest mortality district were 2.1 times as likely to die before age five than those in the lowest mortality district. This figure declined until 2000, when there was a 1.7 fold difference, but then began to increase again such that there is a 1.9 fold difference in 2010.

Table 4.5: Under-5 mortality estimates and percent decline by district and decade with uncertainty.

	Under-5 Mortality				Percent Decline			
	1980	1990	2000	2010	1980-1990	1990-2000	2000-2010	1990-2010
Central Province								
Chibombo	148 (122,176)	138 (128,149)	117 (105,130)	86 (66,106)	6.2 (-10.9,20.1)	15 (2.9,26.5)	27.1 (11.8,41.8)	37.9 (21.3,54.2)
Kabwe	126 (112,141)	127 (118,137)	111 (101,122)	81 (62,101)	-1.7 (-14.5,10.1)	12.7 (1.9,22.9)	27.4 (9.5,43.6)	36.7 (19.2,51.8)
Kapiri Mposhi	164 (138,190)	151 (141,163)	134 (121,148)	98 (79,119)	7.1 (-8.1,19.5)	11.4 (-0.9,22.3)	26.5 (11.4,40.5)	34.9 (19.6,48.9)
Mkushi	163 (146,182)	151 (141,161)	128 (117,140)	91 (71,112)	7.6 (-3.9,18.1)	14.8 (5.3,23.9)	29.1 (13.7,43.2)	39.6 (24.8,53.1)
Mumbwa	132 (112,154)	129 (118,139)	118 (102,132)	87 (63,112)	2.3 (-12.9,16.4)	8.3 (-7.1,23.2)	26.2 (7.4,44.1)	32.2 (9.6,53.5)
Serenje	163 (144,183)	163 (151,175)	139 (125,155)	94 (70,121)	-0.4 (-13.1,10.8)	14.6 (2,25.5)	32.2 (16,48)	42 (24,58.5)
Copperbelt Province								
Chililabombwe	92 (72,111)	91 (83,101)	89 (76,103)	74 (47,100)	-0.2 (-27.5,18.4)	1.9 (-17.6,21.5)	17.5 (-7.1,42.3)	18.6 (-15.3,51.8)
Chingola	103 (91,117)	100 (93,110)	90 (80,100)	64 (40,87)	2.4 (-10.9,14.8)	10.3 (-3,23.3)	28.5 (4.3,53.5)	35.7 (9.8,61.6)
Kalulushi	102 (86,120)	121 (112,131)	102 (94,111)	67 (53,83)	-19.3 (-46.1,2.5)	15.5 (7.1,23.4)	34.2 (18.5,48.1)	44.5 (31.2,56.1)
Kitwe	113 (101,126)	116 (108,124)	101 (92,110)	67 (53,84)	-2.5 (-14.6,8.7)	12.7 (2.8,22)	33.5 (18.1,47.3)	42 (27.4,54.7)
Luanshya	99 (85,114)	108 (101,117)	103 (92,115)	76 (58,96)	-9.5 (-26.5,4.9)	4.6 (-9.1,17)	26 (8.3,42.5)	29.4 (9.7,47.7)
Lufwanyama	168 (146,191)	153 (142,166)	126 (113,140)	82 (57,107)	8.3 (-4.5,20)	17.8 (5.9,29.1)	34.6 (17.4,53.4)	46.1 (28.5,64.4)
Masaiti	163 (138,187)	155 (144,166)	137 (122,153)	104 (83,128)	4.4 (-11.6,17.1)	11.2 (-1.1,23.5)	23.9 (8.4,38)	32.5 (16.3,47.4)
Mpongwe	146 (126,166)	137 (127,147)	116 (103,131)	88 (68,108)	5.7 (-8.4,17.9)	14.8 (2.3,26.6)	24.6 (8.8,39.1)	35.7 (20.2,50.6)
Mufulira	104 (91,117)	107 (99,115)	103 (92,115)	78 (58,102)	-3 (-16.5,9.2)	3.6 (-11.3,16.7)	24.1 (3.3,42.4)	26.7 (1.8,47.8)
Ndola	132 (118,146)	133 (124,142)	116 (106,127)	79 (61,99)	-0.7 (-12.5,10.1)	12.2 (2.5,21.3)	31.9 (15.5,46.9)	40.2 (24.2,54.8)
Eastern Province								
Chadiza	216 (194,238)	181 (169,195)	146 (133,160)	108 (83,132)	15.7 (5.4,25)	19.3 (9.6,28.5)	26.4 (9.5,42.3)	40.6 (25.8,55.1)
Chama	245 (218,274)	217 (203,232)	166 (151,182)	103 (77,130)	11.2 (0.4,20.6)	23.5 (14,32.5)	38 (22.7,52.5)	52.5 (38.5,65.6)
Chipata	201 (182,220)	180 (169,193)	151 (139,163)	114 (92,138)	9.9 (0.1,18.9)	16.4 (8.2,24.1)	24.3 (8.7,38.5)	36.7 (22.5,49.5)
Katete	202 (183,223)	171 (159,183)	134 (121,146)	95 (71,119)	15.4 (6.2,23.8)	21.6 (12.7,30.5)	28.9 (11.6,46)	44.2 (28.6,59.5)
Lundazi	287 (262,313)	236 (221,251)	181 (166,197)	128 (99,158)	17.7 (9.7,25.2)	22.9 (14.8,30.9)	29.2 (14,43.7)	45.4 (31.9,58.5)
Mambwe	197 (179,217)	175 (164,187)	143 (132,155)	99 (74,124)	10.9 (1.5,19.7)	18.3 (9.9,26.4)	31 (14.4,47.4)	43.6 (28.6,58.7)
Nyimba	222 (200,246)	200 (186,215)	170 (153,187)	120 (86,154)	9.7 (-0.1,18.8)	15.1 (3.1,25.9)	29.6 (12.1,47.1)	40.1 (21,58.5)
Petauke	216 (196,238)	186 (173,198)	151 (138,164)	109 (83,136)	14 (4.5,22.7)	18.6 (10,27.4)	27.6 (11,43.9)	41 (25.4,56.7)
Luapula Province								
Chiengi	254 (231,279)	265 (249,282)	237 (218,258)	188 (137,233)	-4.3 (-15,5.9)	10.3 (0.8,19.5)	20.9 (3.1,40.6)	29 (11,49.3)
Kawambwa	188 (167,212)	173 (161,186)	138 (121,154)	100 (74,131)	7.7 (-3.8,18.6)	20.5 (8.3,32.6)	27.3 (6.2,44.8)	42.1 (21.8,58)
Mansa	194 (175,215)	187 (175,200)	154 (141,169)	111 (89,135)	3.3 (-7.6,13.2)	17.6 (8.4,25.8)	28.3 (13.6,41.4)	40.9 (27.4,52.6)

Table 4.5 continued.

	Under-5 Mortality				Percent Decline			
	1980	1990	2000	2010	1980-1990	1990-2000	2000-2010	1990-2010
Milenge	208 (187,230)	203 (190,217)	162 (148,176)	91 (69,116)	2.3 (-8.3,12.2)	20.2 (11.5,28.7)	43.4 (28.8,56.9)	54.8 (41.7,66.8)
Mwense	227 (202,255)	223 (208,238)	188 (169,207)	107 (80,138)	1.6 (-10.6,12.5)	15.7 (4.8,26.4)	42.8 (27.8,56.3)	51.7 (36.5,65)
Nchelenge	238 (215,263)	230 (216,245)	186 (170,203)	126 (94,159)	3 (-7.1,12.5)	19 (10.4,27.6)	32.3 (16.5,48.5)	45.1 (30.3,60.2)
Samfya	251 (226,276)	234 (220,249)	195 (177,213)	130 (102,163)	6.3 (-3.5,15.1)	16.9 (7.2,26.1)	33 (18.4,46.2)	44.3 (29.8,57.1)
Lusaka Province								
Chongwe	132 (118,149)	137 (128,147)	121 (110,132)	79 (61,100)	-3.8 (-16.7,8)	11.5 (1.4,21.1)	34.4 (18.1,48.6)	41.9 (25.6,56.3)
Kafue	119 (106,133)	118 (110,126)	105 (96,115)	78 (61,97)	0.6 (-12,12.1)	10.6 (0.9,19.6)	26.2 (9,40.9)	34 (16.9,48.5)
Luangwa	180 (151,217)	146 (131,162)	112 (88,135)	88 (67,112)	18.5 (4.5,31.6)	22.5 (-0.2,44.2)	21.4 (3.5,36.4)	39.3 (19.1,56.6)
Lusaka	112 (101,124)	111 (104,119)	104 (96,113)	79 (64,96)	0.5 (-11,11.1)	6.2 (-3.1,14.7)	24.3 (7.9,38.9)	29 (13.1,43)
North Western Province								
Chavuma	130 (113,148)	130 (119,141)	117 (102,132)	83 (60,113)	-0.4 (-14.4,12.4)	9.4 (-5.6,24.6)	29 (5.6,47.4)	35.5 (9.5,55.6)
Kabompo	152 (135,172)	145 (135,155)	121 (109,134)	84 (66,104)	4.4 (-8,15.8)	16.5 (6,26.6)	30.2 (14.4,44.2)	41.8 (27.2,55.3)
Kasempa	136 (111,158)	122 (111,134)	102 (85,121)	82 (60,108)	9.5 (-7.2,22.8)	16 (-4.2,34.9)	19.5 (-0.9,38.6)	32.4 (8.2,53.3)
Mufumbwe	132 (110,158)	133 (123,142)	120 (104,134)	78 (57,101)	-1.3 (-20.3,15.8)	9.5 (-3.2,23.5)	34.6 (17.3,50.8)	40.8 (22.7,58.2)
Mwinilunga	152 (133,174)	128 (117,139)	109 (95,125)	82 (62,105)	15.5 (3.4,27.2)	14.4 (-2.8,28.5)	24.9 (7.2,41)	35.6 (14.4,53.5)
Solwezi	155 (139,174)	133 (124,142)	107 (98,117)	75 (60,91)	14.3 (3.1,24.4)	19.4 (11,27.4)	30 (15.3,43.3)	43.6 (31.1,54.8)
Zambezi	131 (114,149)	133 (123,144)	114 (101,127)	81 (56,105)	-1.7 (-16.1,10.9)	14.2 (0.8,27.2)	28.5 (10.1,49.3)	38.5 (18.4,59.4)
Northern Province								
Chilubi	265 (234,297)	234 (216,253)	205 (178,233)	149 (110,195)	11.4 (1.2,20.7)	12.5 (-4.5,27.1)	27.6 (11,42.4)	36.4 (13.4,55.1)
Chinsali	169 (148,190)	167 (156,178)	139 (126,153)	94 (75,116)	0.6 (-13.6,12.7)	16.8 (7,25.6)	32.1 (17.8,45.3)	43.5 (30.2,55.3)
Isoka	212 (190,236)	186 (173,200)	150 (134,166)	108 (80,138)	12.1 (2.3,21.1)	19.2 (8.2,30.8)	27.8 (11,44.3)	41.6 (23.9,58.7)
Kaputa	225 (193,255)	215 (198,231)	200 (177,232)	151 (118,190)	4.1 (-10.2,15.9)	6.6 (-13.6,20.4)	24.5 (9.2,38.7)	29.5 (8.4,46.8)
Kasama	168 (151,187)	157 (146,167)	127 (116,140)	82 (65,102)	6.7 (-4,16.5)	18.6 (9.3,27.6)	35.5 (21,48.4)	47.5 (34,59.2)
Luwingu	177 (156,200)	171 (159,184)	153 (137,169)	124 (92,160)	3.2 (-9.6,14.6)	10.7 (-3,22.1)	18.6 (-1.7,37.9)	27.1 (3.4,48)
Mbala	204 (184,225)	186 (173,201)	145 (131,160)	97 (71,123)	8.4 (-2.3,17.9)	21.8 (11.9,31.9)	33.3 (16.4,50.6)	47.7 (32.1,63.5)
Mpika	177 (155,201)	165 (151,178)	128 (113,144)	84 (59,112)	6.4 (-6.9,19.8)	21.9 (8.6,33.8)	34.8 (15.9,52.4)	49 (29.2,65.3)
Mporokoso	143 (123,164)	142 (132,153)	114 (99,128)	75 (51,98)	0.3 (-14.8,12.9)	20 (7.9,33.3)	34.3 (14.4,54.2)	47.5 (30.2,65.2)
Mpulungu	213 (193,235)	212 (198,227)	176 (161,193)	125 (100,153)	0.5 (-10.4,10.5)	16.6 (7,25.6)	29 (13.7,43)	40.8 (26.7,53.5)
Mungwi	188 (169,207)	186 (174,199)	160 (147,175)	105 (81,129)	0.8 (-10.2,10.8)	13.6 (3.8,23.1)	34.8 (20.3,48.1)	43.7 (29.9,57)
Nakonde	207 (186,230)	173 (161,185)	140 (126,154)	100 (77,123)	16.5 (7,25.1)	18.9 (8.7,29.3)	28.8 (13.1,43.4)	42.2 (27.3,56.8)
Southern Province								
Choma	120 (106,134)	123 (115,132)	114 (103,126)	78 (60,98)	-3.1 (-15.9,8.6)	7.1 (-3.6,18.1)	31.3 (15,46.7)	36.2 (19.1,52.2)

Table 4.5 continued.

	Under-5 Mortality				Percent Decline			
	1980	1990	2000	2010	1980-1990	1990-2000	2000-2010	1990-2010
Gwembe	140 (112,169)	153 (141,165)	139 (123,155)	91 (64,121)	-10 (-39.8,11.2)	8.7 (-3.6,20.1)	34.9 (14.7,53.6)	40.5 (19.1,59.3)
Itezhi-tezhi	133 (112,156)	134 (123,148)	115 (95,134)	82 (48,116)	-1.5 (-17.1,11.6)	13.8 (-5.1,34.1)	29.1 (5.7,55.6)	38.5 (9.2,65.9)
Kalomo	143 (126,162)	140 (130,150)	122 (111,135)	74 (53,95)	2.1 (-11.3,14.2)	12.2 (1.7,22.8)	39.4 (23.5,55.8)	46.7 (30.3,63.2)
Kazungula	153 (135,173)	153 (142,165)	139 (126,152)	89 (63,117)	-0.1 (-13.1,12)	9.2 (-2.1,20.2)	35.5 (16.3,53.8)	41.4 (21.7,60.1)
Livingstone	129 (112,148)	119 (110,130)	100 (87,113)	66 (46,85)	7.5 (-5.8,20.1)	16.3 (1.5,30.4)	34 (15.9,51.5)	44.7 (26.5,62.4)
Mazabuka	135 (119,151)	118 (110,127)	104 (94,115)	80 (62,100)	12.1 (0.8,22.4)	11.5 (1,21.6)	23.1 (4.9,39.7)	32 (14,48.4)
Monze	121 (106,137)	121 (112,130)	109 (98,120)	77 (59,96)	-0.4 (-14,11.6)	9.7 (-1.8,21.2)	29.8 (12.8,44.5)	36.6 (18.5,52)
Namwala	133 (116,151)	136 (126,145)	118 (108,128)	76 (60,93)	-2.7 (-19.4,12.6)	13.3 (4.8,21.1)	35.3 (20.2,48.8)	44 (31.2,55.4)
Siavonga	162 (138,190)	146 (134,159)	128 (112,146)	81 (61,104)	9.3 (-6.4,24)	12.6 (-4.1,26.6)	36.3 (20.5,50.4)	44.3 (26.7,59.7)
Sinazongwe	172 (147,195)	151 (139,164)	130 (115,146)	88 (59,120)	11.7 (-3,22.8)	13.9 (-0.2,26.6)	32.4 (11,53.4)	41.6 (17.9,62.5)
Western Province								
Kalabo	257 (231,285)	219 (205,233)	174 (157,191)	123 (96,150)	14.7 (5.1,23.7)	20.5 (11.2,29.8)	29.2 (14,43.7)	43.7 (30.6,57.1)
Kaoma	207 (184,232)	188 (175,201)	159 (143,179)	102 (79,129)	9.1 (-2.1,19.2)	15.4 (2,26)	36 (21.5,49.4)	45.8 (29.6,59)
Lukulu	216 (192,241)	188 (172,204)	142 (126,160)	91 (61,120)	12.9 (2,22.9)	24.1 (10.6,35.7)	35.9 (18.5,55.5)	51.2 (33.8,69.1)
Mongu	193 (172,214)	185 (172,197)	157 (143,172)	98 (77,122)	3.9 (-7.8,14.5)	14.8 (5.1,23.4)	37.8 (23.3,50.7)	47 (33.4,59)
Senanga	231 (208,255)	198 (185,212)	157 (144,171)	108 (84,134)	14.1 (4.8,23)	20.8 (12,29.2)	30.9 (15.6,45.3)	45.2 (31.2,58.4)
Sesheke	206 (182,233)	186 (173,201)	143 (126,159)	75 (51,101)	9.4 (-2.8,20.2)	23.2 (12.5,34.6)	47.5 (30.7,63.9)	59.7 (44.4,73.4)
Shangombo	231 (208,255)	205 (191,220)	171 (155,186)	125 (98,155)	10.9 (0.6,20.4)	16.8 (7,25.9)	26.5 (10.5,41.3)	38.8 (22.6,53.1)

5 Discussion

5.1 Strengths and limitations

This study has estimated levels and trends of under-5 mortality for all 72 districts in Zambia. It improves in four ways upon other studies that have estimated child mortality at a small area in countries with similar data restrictions. First, multiple data sources are utilized to generate the final estimates. Second, a formal analysis of the performance of various birth history methods at small sample sizes was undertaken allowing for the best performing methods to be selected when the data allow for multiple types of analysis. Third, uncertainty from multiple sources was taken into account when generating confidence intervals for the estimates, allowing for a more accurate quantification of the uncertainty in the final estimates. Finally, estimates are made for multiple years, allowing for study not only of the level of mortality but also trends in mortality.

This study nonetheless has several limitations, most of which are inherent in the context of estimating under-5 mortality in the absence of a functioning, high-quality vital registration system. First, although sampling and model uncertainty were both accounted for in analyzing birth history data, other potential sources of bias were not addressed. Recall and other misreporting biases are possible in both the summary birth histories of the censuses and the complete birth histories of the DHS and can compromise the quality of the estimates derived from either source. The estimates from the DHS can also be compromised if the clusters selected in a district are not representative of that district. For any given district there are generally only a handful of clusters selected and it is possible–both by chance and due to other factors (e.g. accessibility)– that the clusters selected have higher or lower mortality than the district as a whole. It is concerning that the DHS estimates of under-5 mortality tend to be higher than the census estimates (as evidenced by the coefficient on the offset term for DHS data). We have, for this analysis, chosen to trust the level of the census data since, unlike the DHS, there is no sampling involved. There is, however, the possibility that the DHS and census levels differ due to recall or misreporting bias in the census that is not present in the DHS, and this is cause for caution when interpreting these results. Migration is also potentially problematic: because of the nature of birth history analysis, all reported births and deaths are assumed to have occurred in the district where a women is interviewed though there is no guarantee that this is the case. This could bias the estimates if migrants to a district have children with higher or lower mortality than the children in the district. Migration is particularly worrisome when conducting an analysis at a sub-national level since women are more likely to move across district borders than, for example, national borders.

This study is also limited in that there is considerable uncertainty in the estimates of under-5 mortality generated as evidenced by the typically wide uncertainty intervals. Finally, this study is limited in that there is no external evaluation of the adequacy of the small area model used for estimating under-5 mortality utilizing data like that which are available in Zambia. This is unsurprising, given that in countries with data limitations akin to those experienced in Zambia accurate estimates of under-5 mortality which would allow for validation of this or similar models are not generally available.

5.2 Implications

Under-5 mortality estimates such as those generated in this study are valuable for several purposes. First, they allow for identification of districts where mortality is relatively high or where declines in mortality over the past decades have been relatively small. As discussed above, in 2010, the most recent year of estimates, children were almost twice as likely to die before reaching the age of 5 in the highest mortality district as in the lowest mortality district. Similarly, though mortality has declined in essentially all districts over the past three decades, some districts experienced declines of less than 25% while a considerable number of districts were able to achieve declines of more than 50%. It is useful for planning purposes to be able to identify districts where mortality is particularly high or where progress has been particularly slow insofar as it suggests where more attention and resources may be beneficial.

The converse of the above is also true: it is useful to identify districts where mortality is relatively low or where rapid declines in mortality have occurred. Study of these districts may suggest effective strategies for reducing under-5 mortality in all districts.

Finally, these estimates are useful for tracking progress towards goals. Though progress towards MDG4 for Zambia as a whole has been documented elsewhere[1], it is interesting to look at variation amongst districts in achieving this goal. Despite considerable uncertainty in the estimated under-5 mortality trends, it is clear that there are districts that stand a good chance of meeting MDG4 while there are also districts where achieving this goal is highly unlikely.

Overall, the estimates presented in this study paint a picture of considerable progress in reducing under-5 mortality in Zambia, but also of persisting high mortality compared to what has been achieved in the developed world and appreciable inequality within Zambia. Ideally, these estimates could be used in efforts to accelerate the decline in under-5 mortality and to tackle the issue of inequality.

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Appendices

Table A.1: DHS included in the analysis to assess performance of birth history methods at small sample sizes.

Country	Surveys
Albania	2008-09
Armenia	2000; 2005; 2010
Azerbaijan	2006
Benin	1996; 2001; 2006
Bolivia	1989; 1993-94; 1998; 2003-04; 2008
Botswana	1988
Brazil	1986; 1996
Burkina Faso	1992-93; 1998-99; 2003
Burundi	1987
Cambodia	2000; 2005-06; 2010-11
Cameroon	1991; 1998; 2004
Central African Republic	1994-95
Chad	1996-97; 2004
Colombia	1986; 1990; 1995; 2000; 2004-05
Comoros	1996
Congo	2005
Congo, the Democratic Republic of the	2007
Cote d'Ivoire	1994; 1998-99
Dominican Republic	1986; 1991; 1996; 2002; 2007
Ecuador	1987
Eritrea	1995-96; 2002
Ethiopia	2000; 2005; 2010-11
Gabon	2000-01
Ghana	1988; 1993-94; 1998-99; 2003; 2008
Guatemala	1987; 1995; 1998-99
Guinea	1999; 2005
Guyana	2009
Haiti	1994-95; 2000; 2005-06
Honduras	2005-06
Kazakhstan	1995; 1999
Kenya	1988-89; 1993; 1998; 2003; 2008-09
Kyrgyzstan	1997
Lesotho	2004-05; 2009-10
Liberia	1986; 2006-07
Madagascar	1992; 1997; 2003-04; 2008-09
Malawi	1992; 2000; 2004-05; 2010
Mali	1987; 1995-96; 2001; 2006
Mauritania	2000-01
Moldova	2005
Mozambique	1997; 2003
Namibia	1992; 2000; 2006-07
Nicaragua	1997-98; 2001
Niger	1992; 1998; 2006
Nigeria	1990; 2003; 2008
Paraguay	1990

Table A.1 continued.

Country	Surveys
Peru	1986; 1991-92; 1996; 2000; 2004-08
Philippines	1998; 2003; 2008
Rwanda	1992; 2000; 2005; 2007-08; 2010-11
Sao Tome and Principe	2008-09
Senegal	1986; 1992-93; 1997; 2005; 2010-11
Sierra Leone	2008
South Africa	1998
Swaziland	2006-07
Tanzania, United Republic of	1991-92; 1996; 1999; 2004-05; 2009-10
Timor-Leste	2009-10
Togo	1988; 1998
Trinidad and Tobago	1987
Uganda	1988-89; 1995; 2000-01; 2006
Ukraine	2007
Uzbekistan	1996
Zambia	1992; 1996-97; 2001-02; 2007
Zimbabwe	1988-89; 1994; 1999; 2005-06; 2010-11

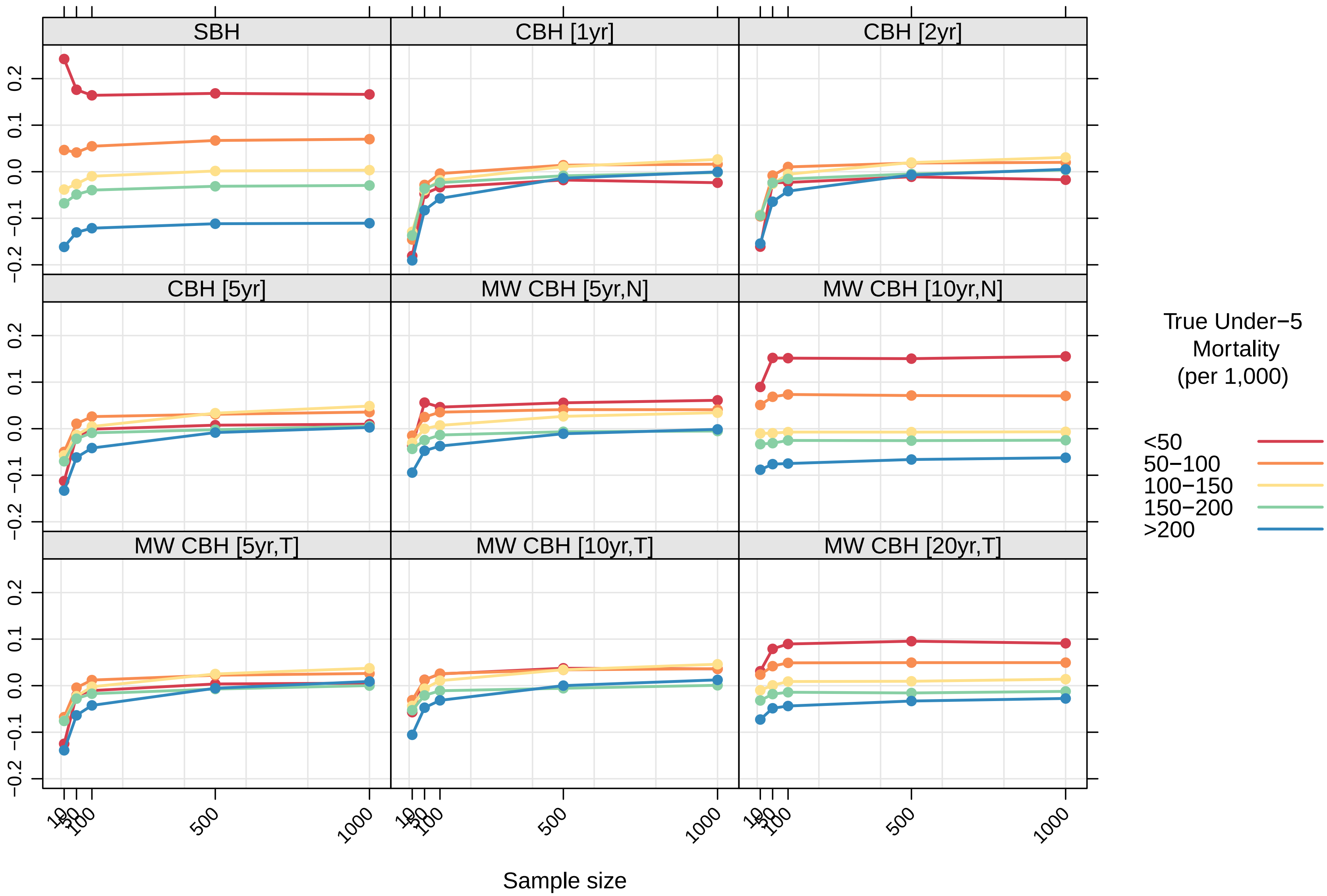

Figure A.1: Mean relative error for birth history analysis methods at various small samples sizes, stratified by true mortality level.

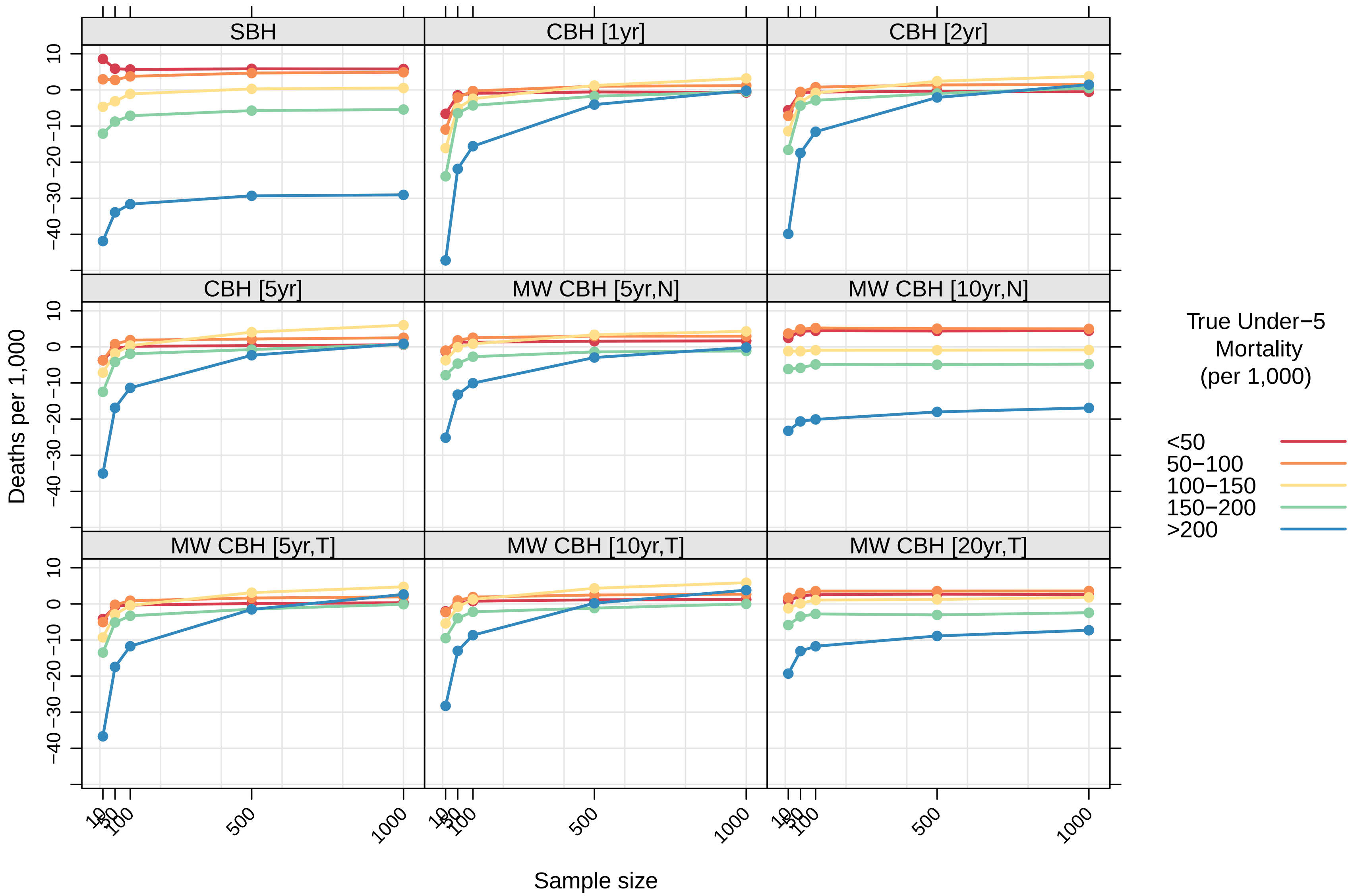

Figure A.2: Mean error for birth history analysis methods at various small samples sizes, stratified by true mortality level.

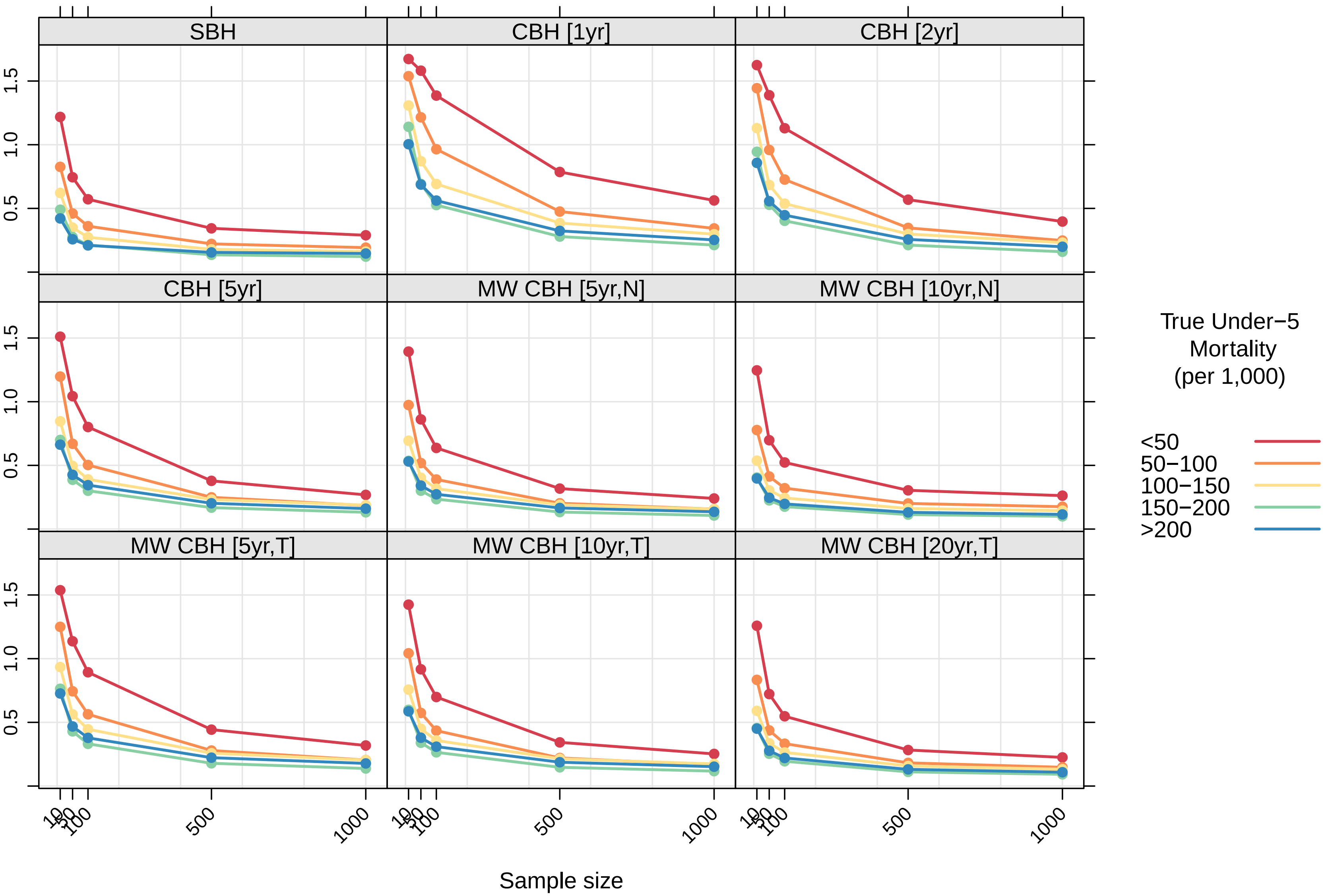

Figure A.3: Mean absolute relative error for birth history analysis methods at various small samples sizes, stratified by true mortality level.

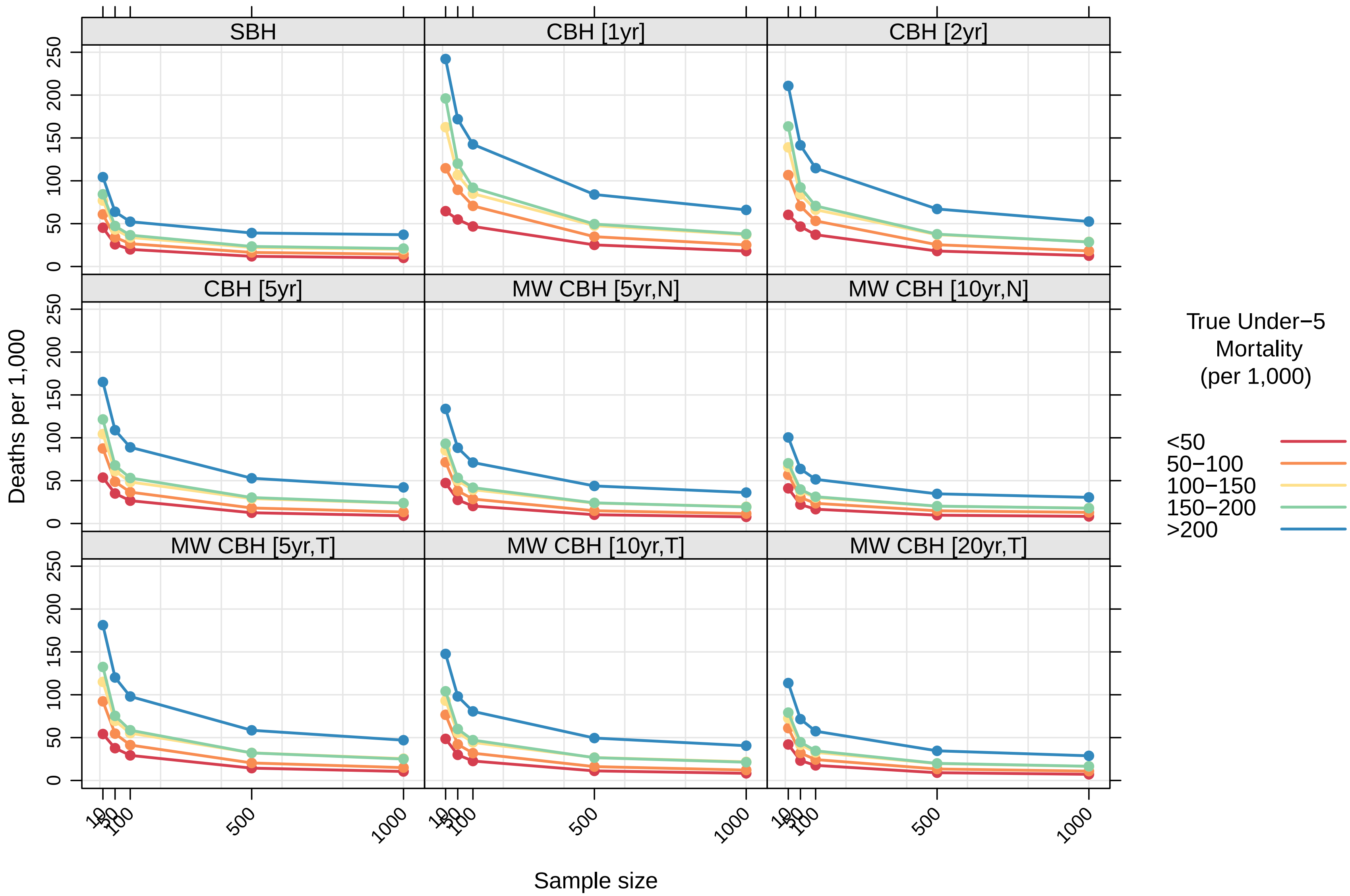

Figure A.4: Mean absolute error for birth history analysis methods at various small samples sizes, stratified by true mortality level.

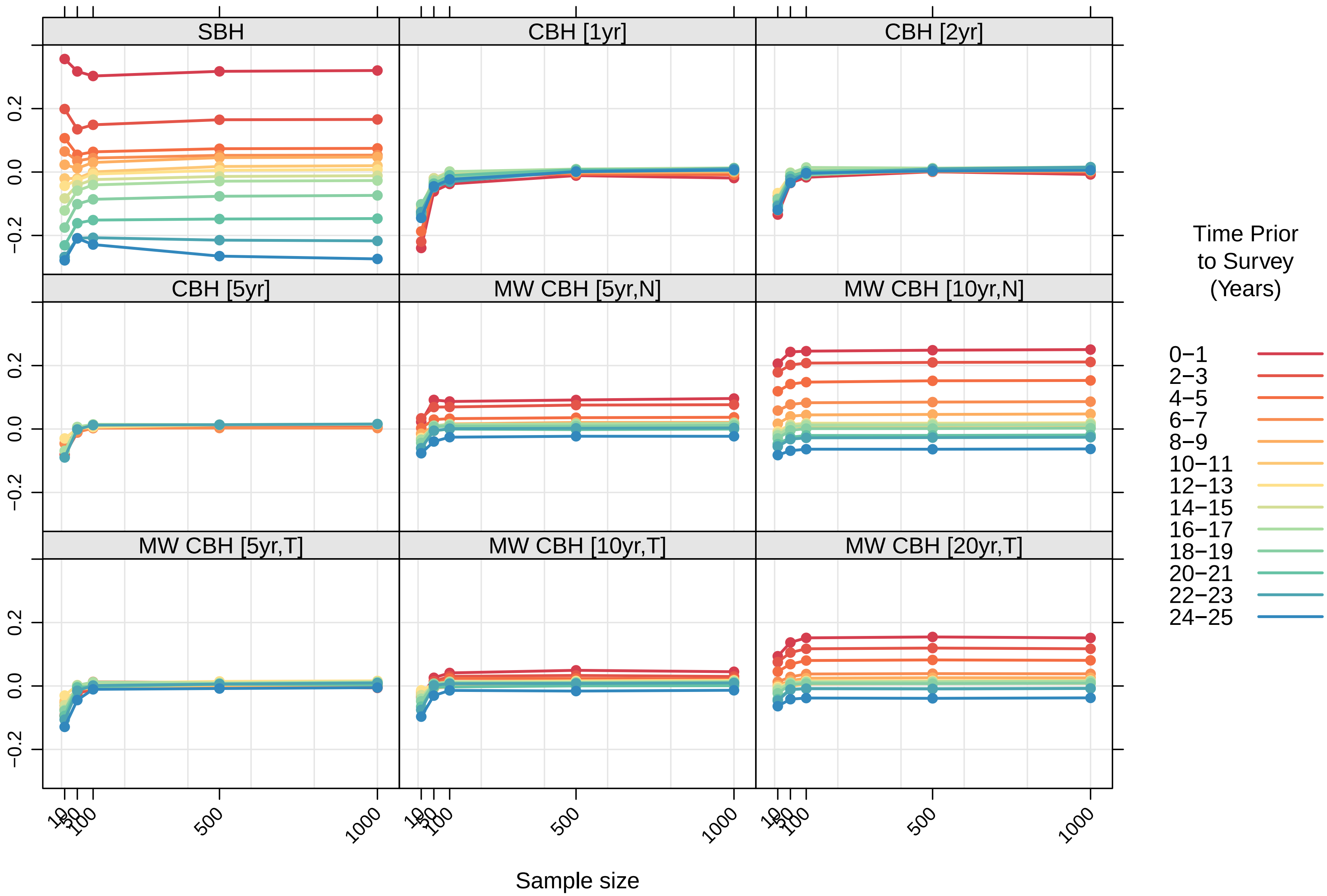

Figure A.5: Mean relative error for birth history analysis methods at various small samples sizes, stratified by time prior to survey.

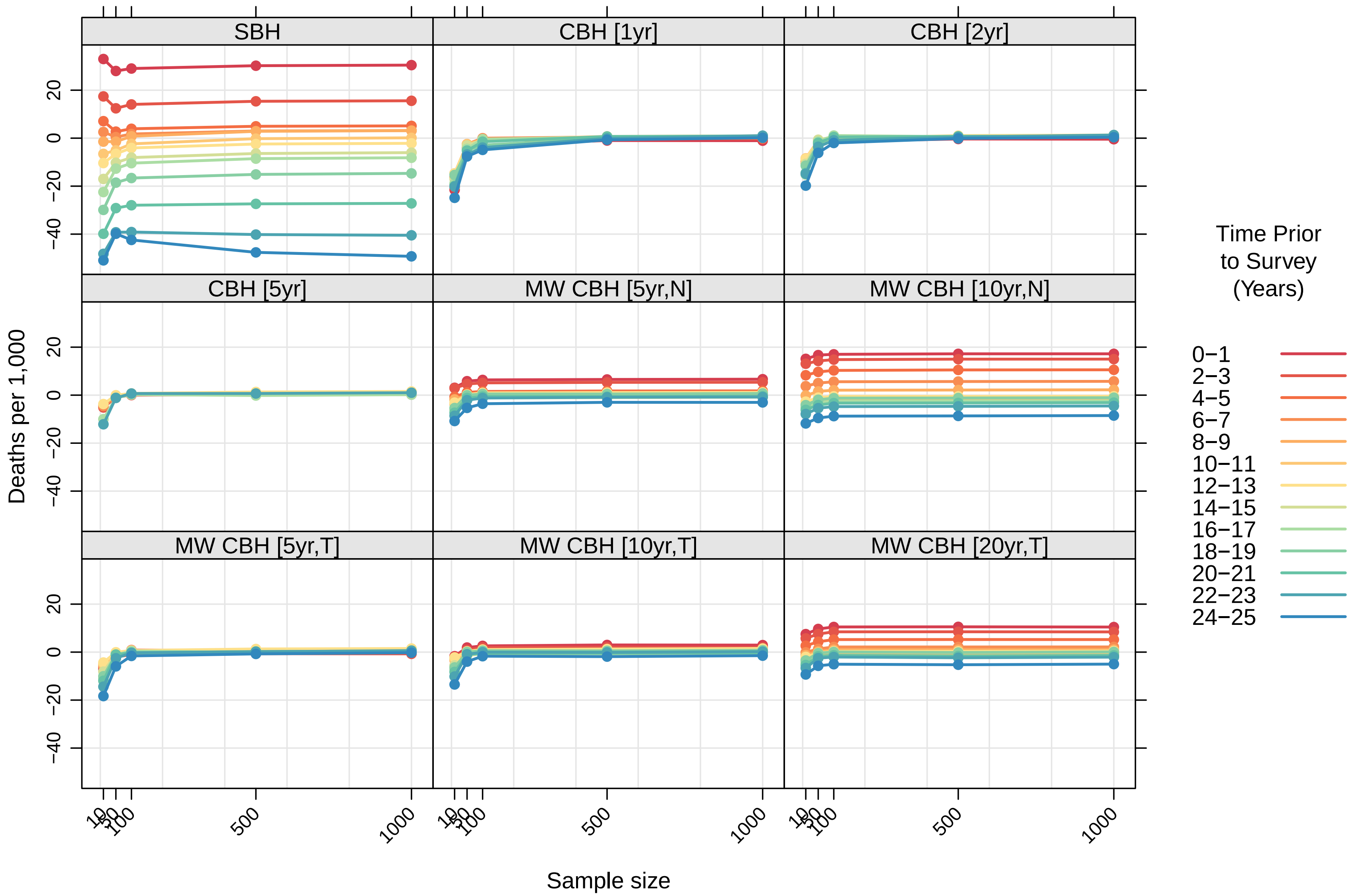

Figure A.6: Mean error for birth history analysis methods at various small samples sizes, stratified by time prior to survey.

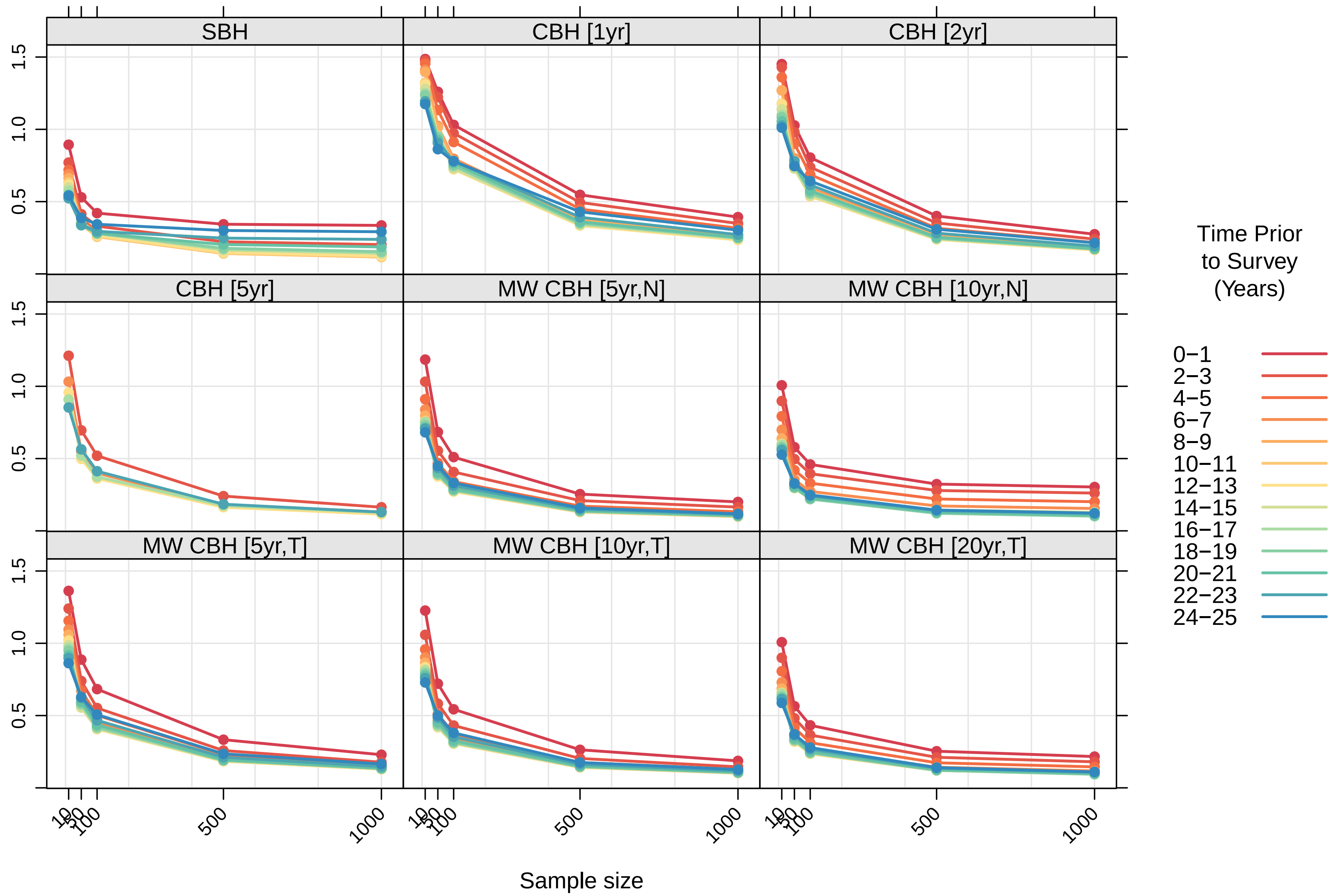

Figure A.7: Mean absolute relative error for birth history analysis methods at various small samples sizes, stratified by time prior to survey.

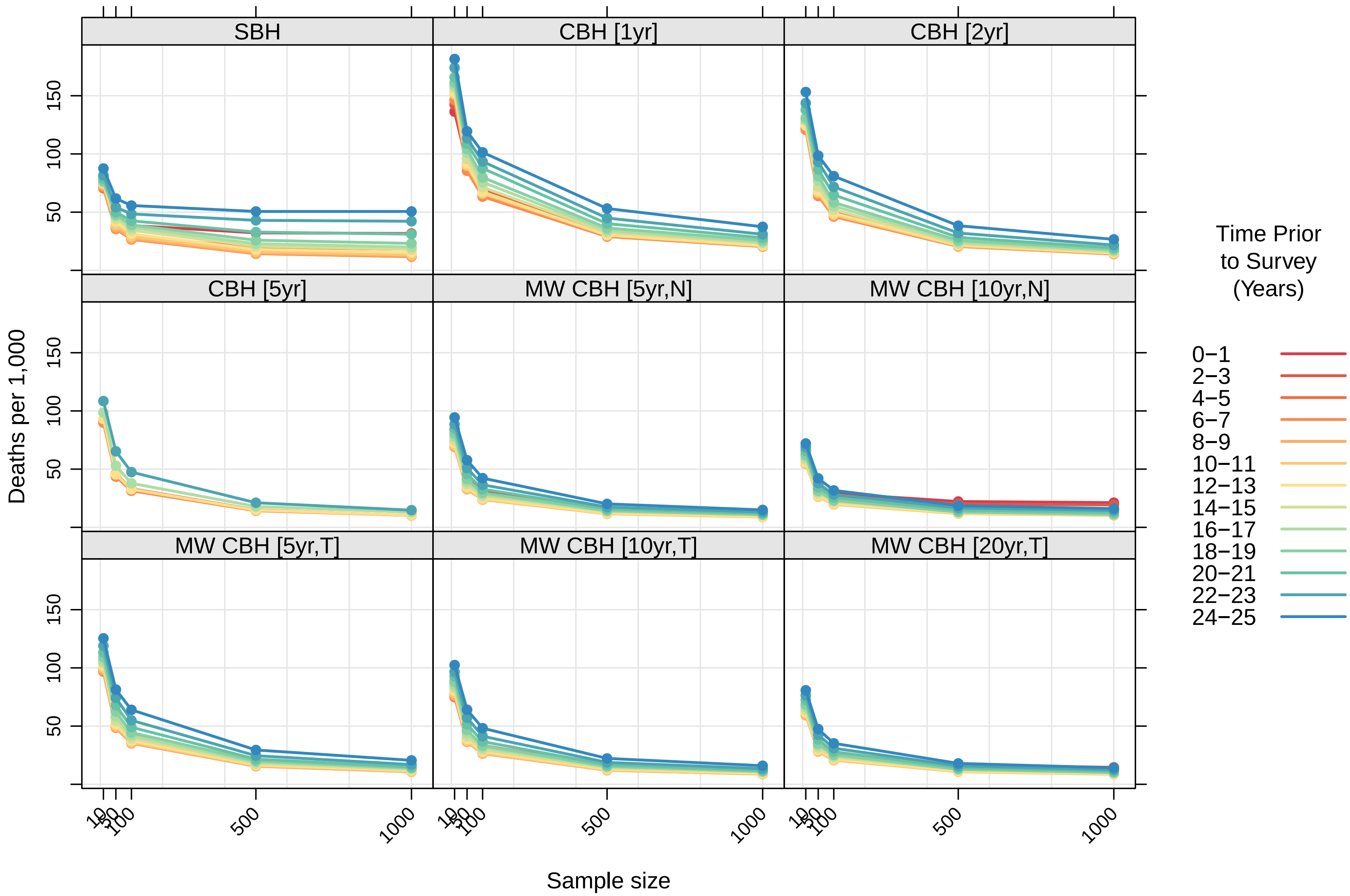

Figure A.8: Mean absolute error for birth history analysis methods at various small samples sizes, stratified by time prior to survey.

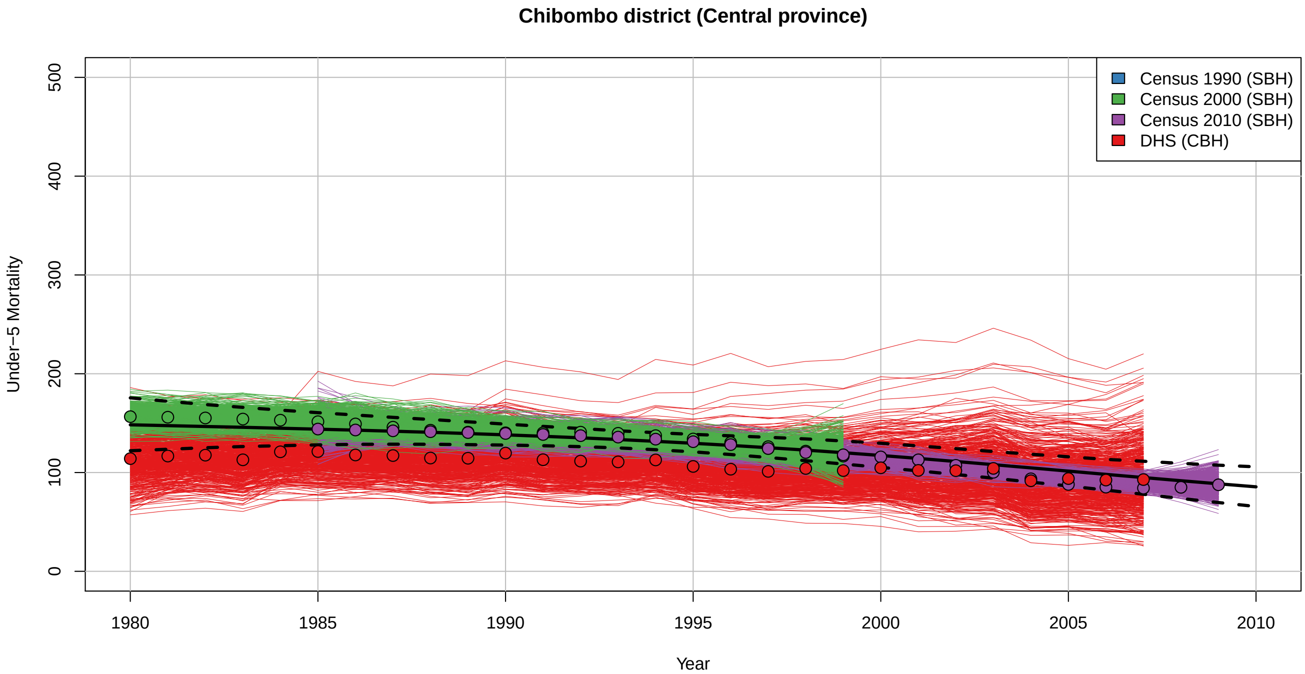

Figure A.9: Under-5 mortality estimates with uncertainty, Chibombo district (Central province)

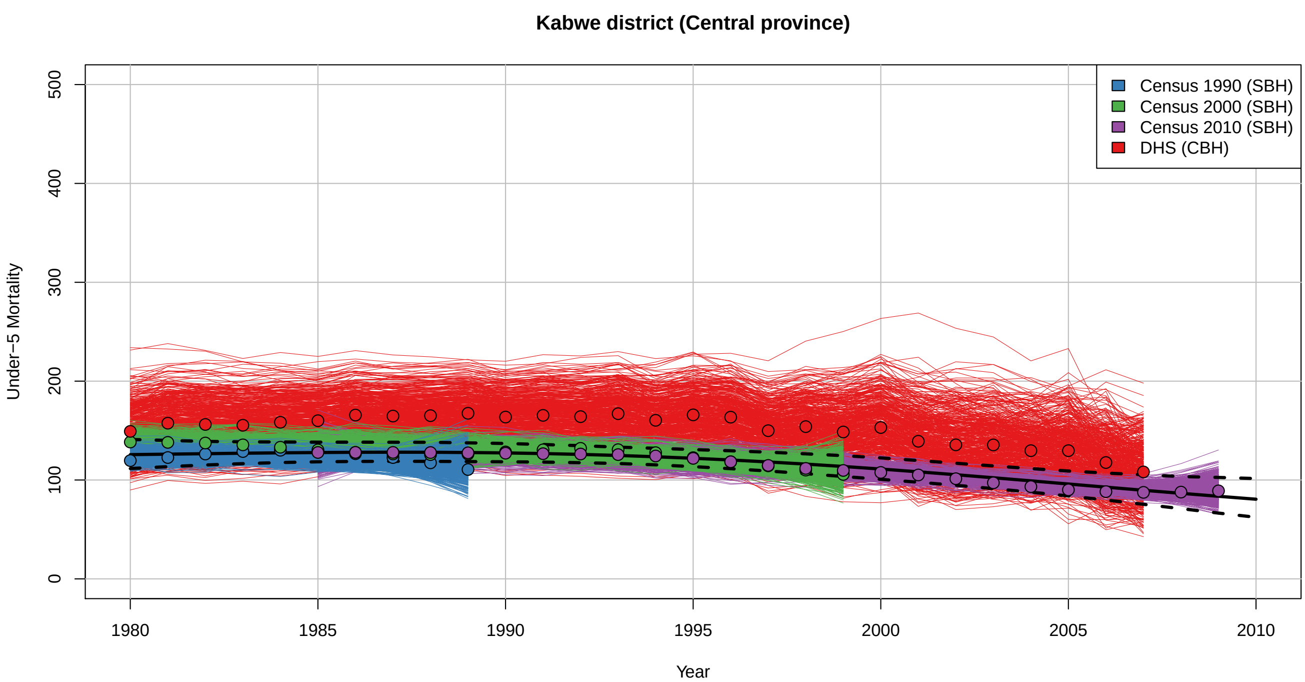

Figure A.10: Under-5 mortality estimates with uncertainty, Kabwe district (Central province)

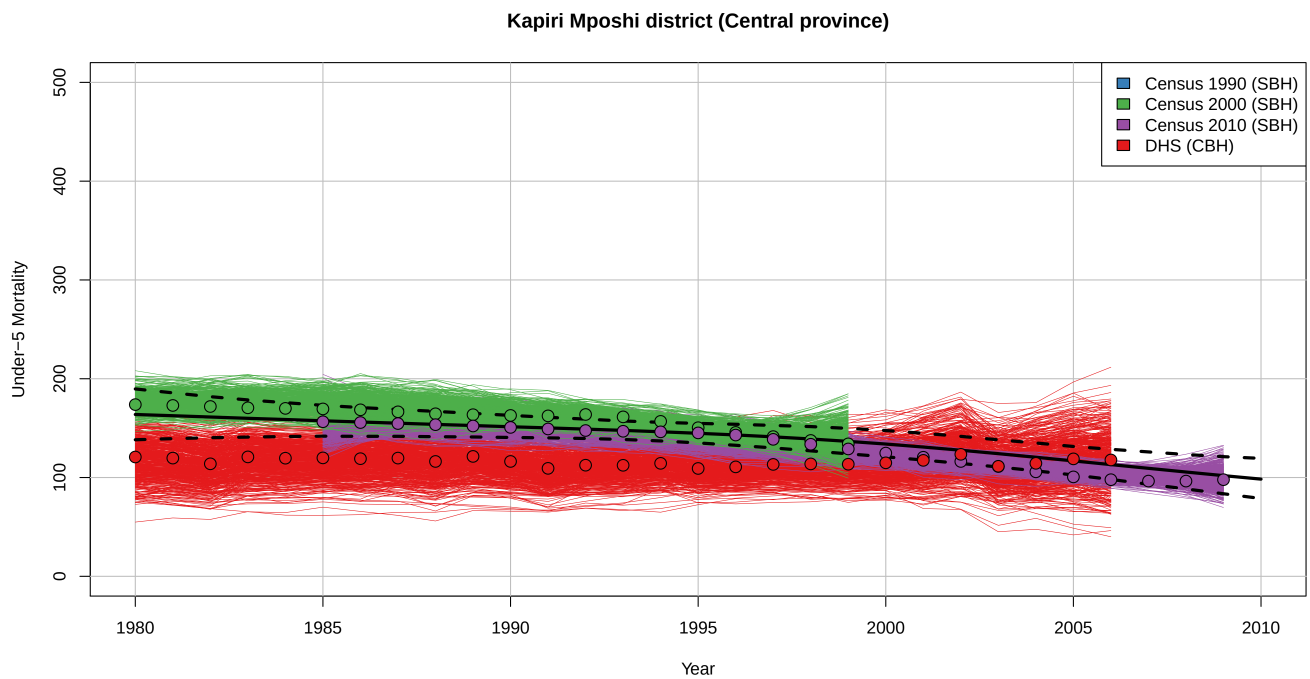

Figure A.11: Under-5 mortality estimates with uncertainty, Kapiri Mposhi district (Central province)

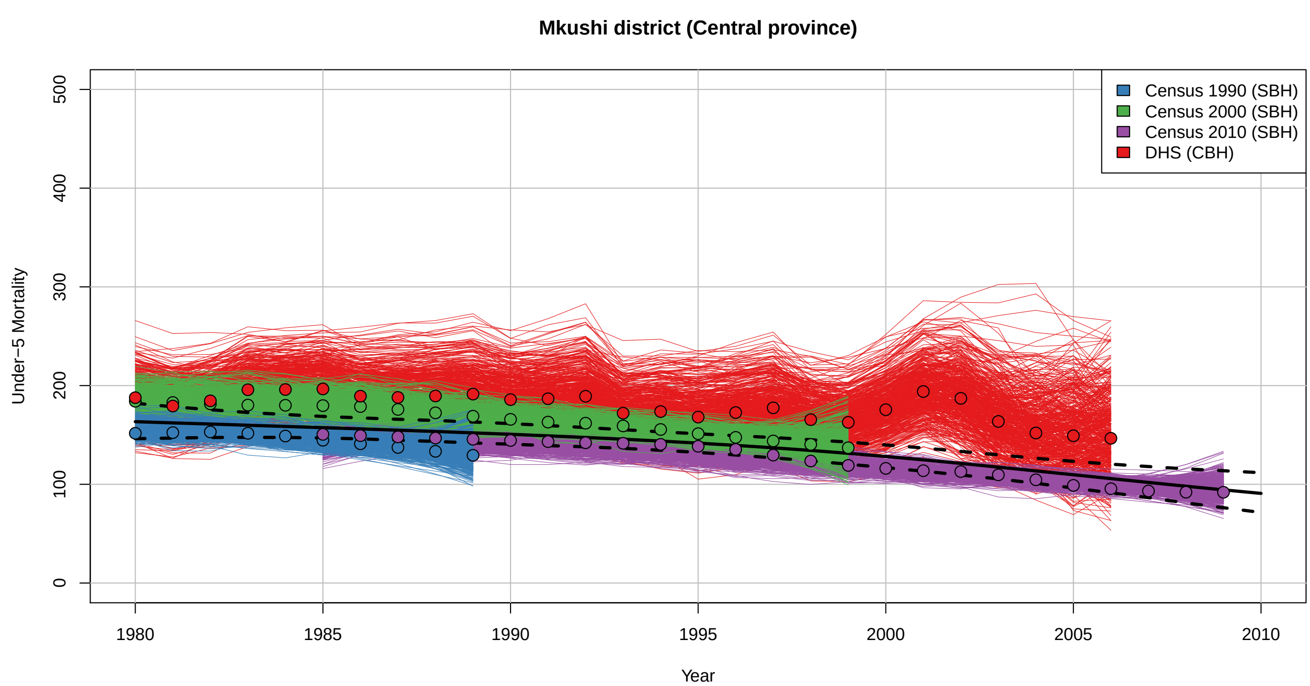

Figure A.12: Under-5 mortality estimates with uncertainty, Mkushi district (Central province)

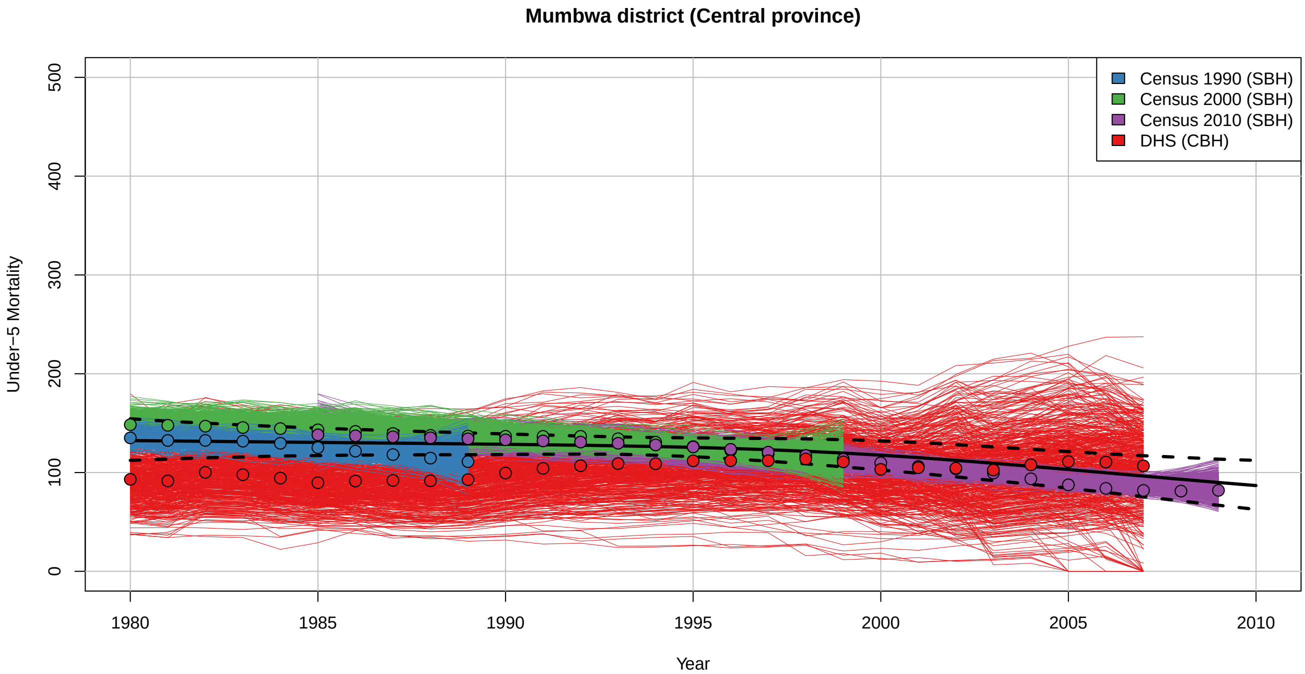

Figure A.13: Under-5 mortality estimates with uncertainty, Mumbwa district (Central province)

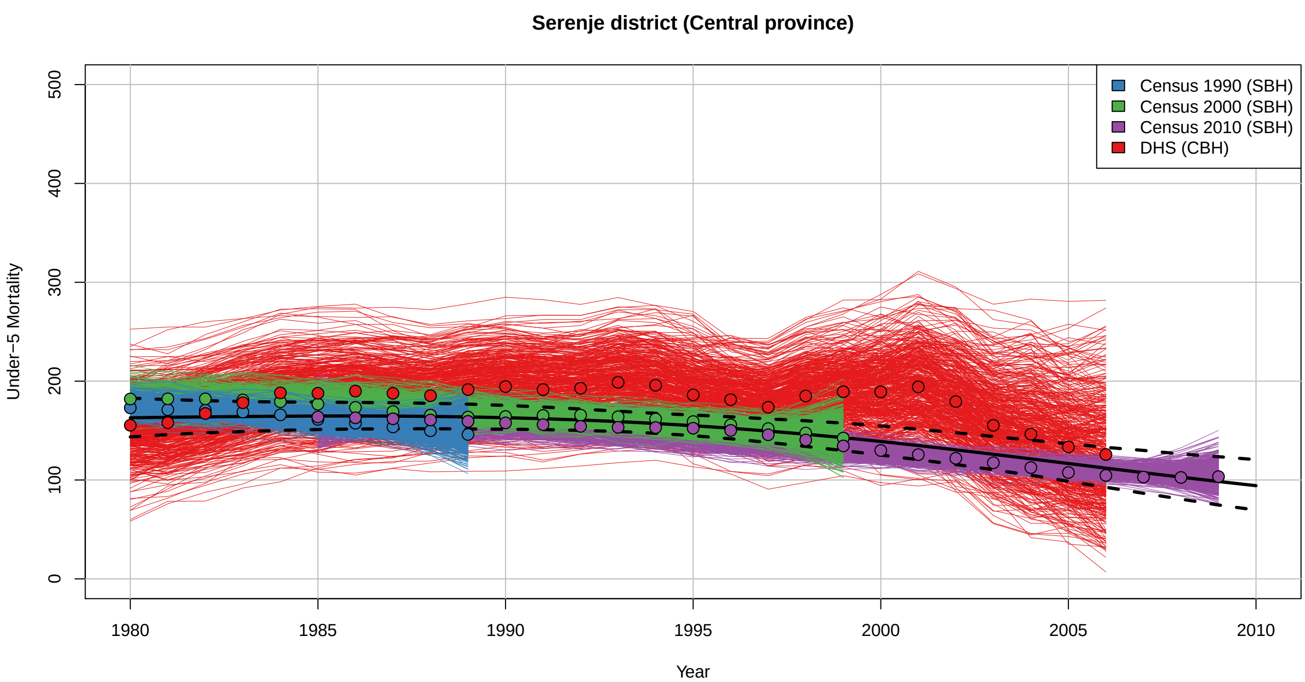

Figure A.14: Under-5 mortality estimates with uncertainty, Serenje district (Central province)

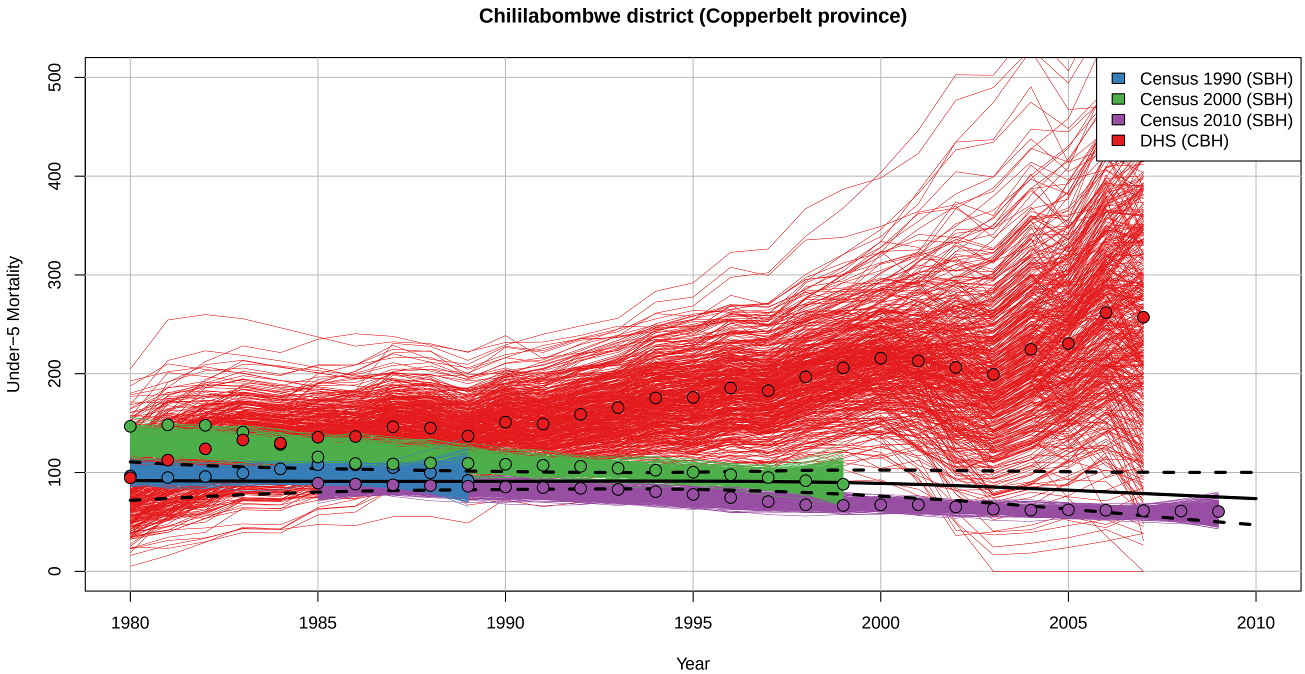

Figure A.15: Under-5 mortality estimates with uncertainty, Chililabombwe district (Copperbelt province)

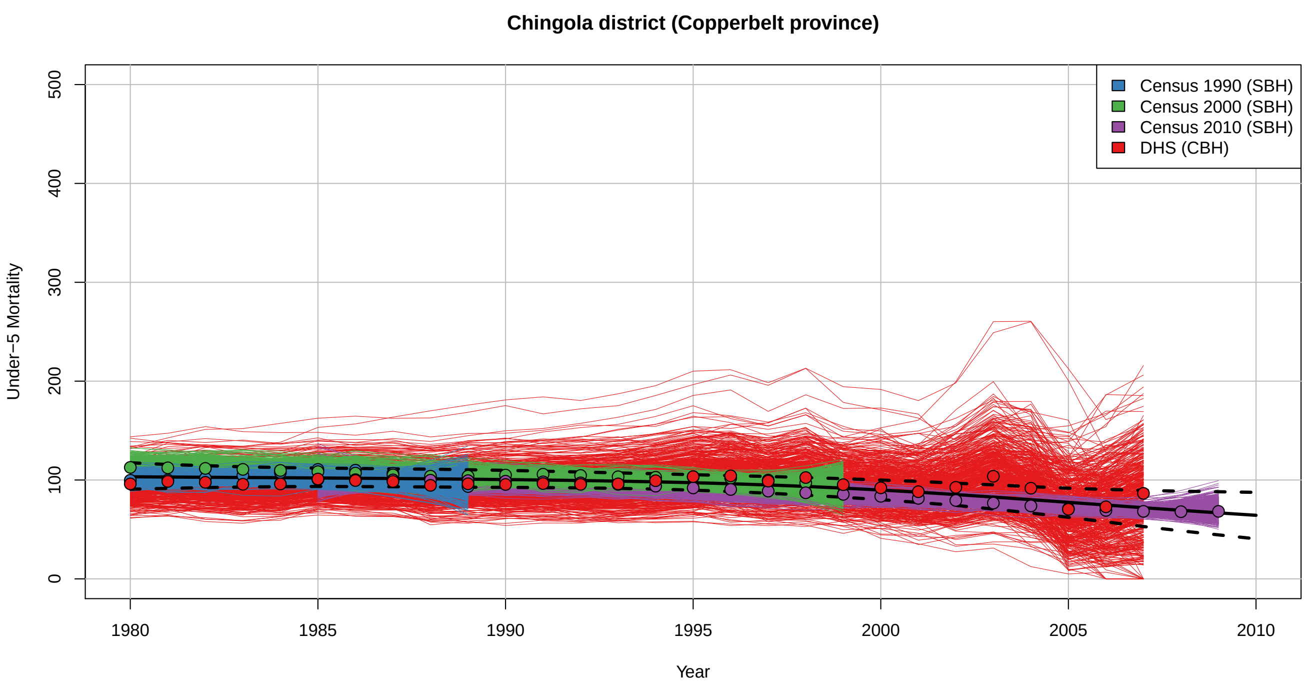

Figure A.16: Under-5 mortality estimates with uncertainty, Chingola district (Copperbelt province)

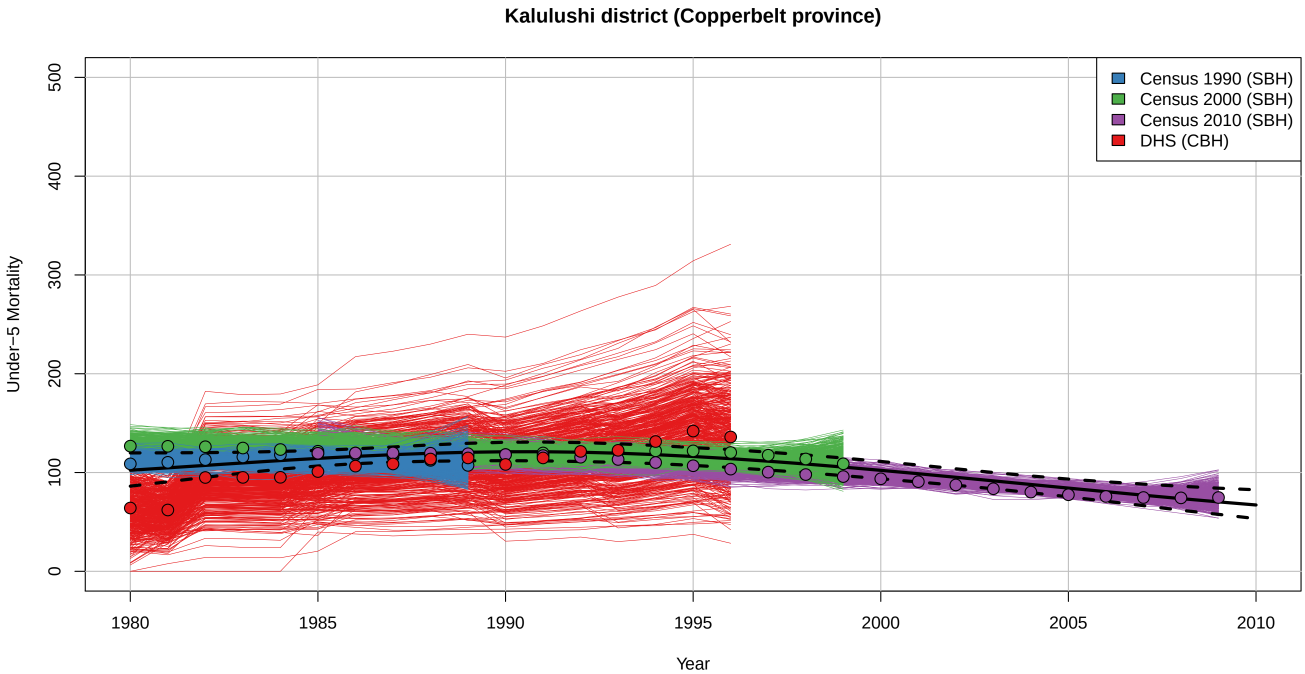

Figure A.17: Under-5 mortality estimates with uncertainty, Kalulushi district (Copperbelt province)

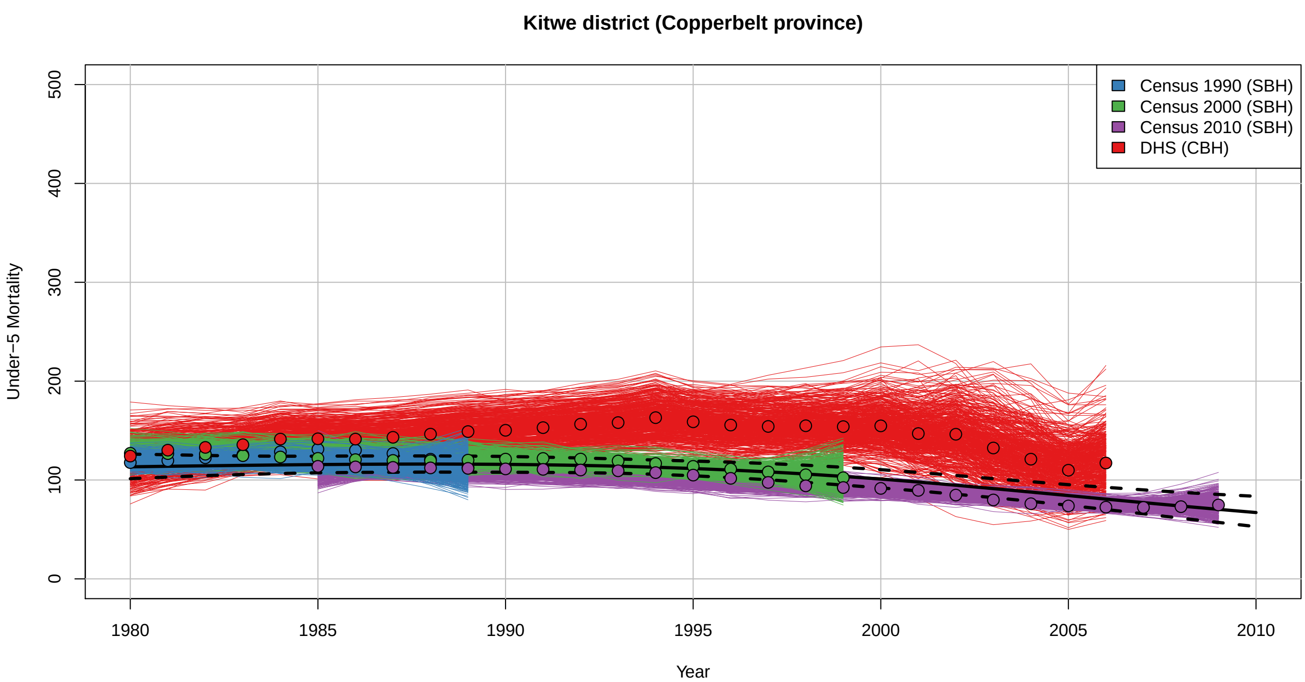

Figure A.18: Under-5 mortality estimates with uncertainty, Kitwe district (Copperbelt province)

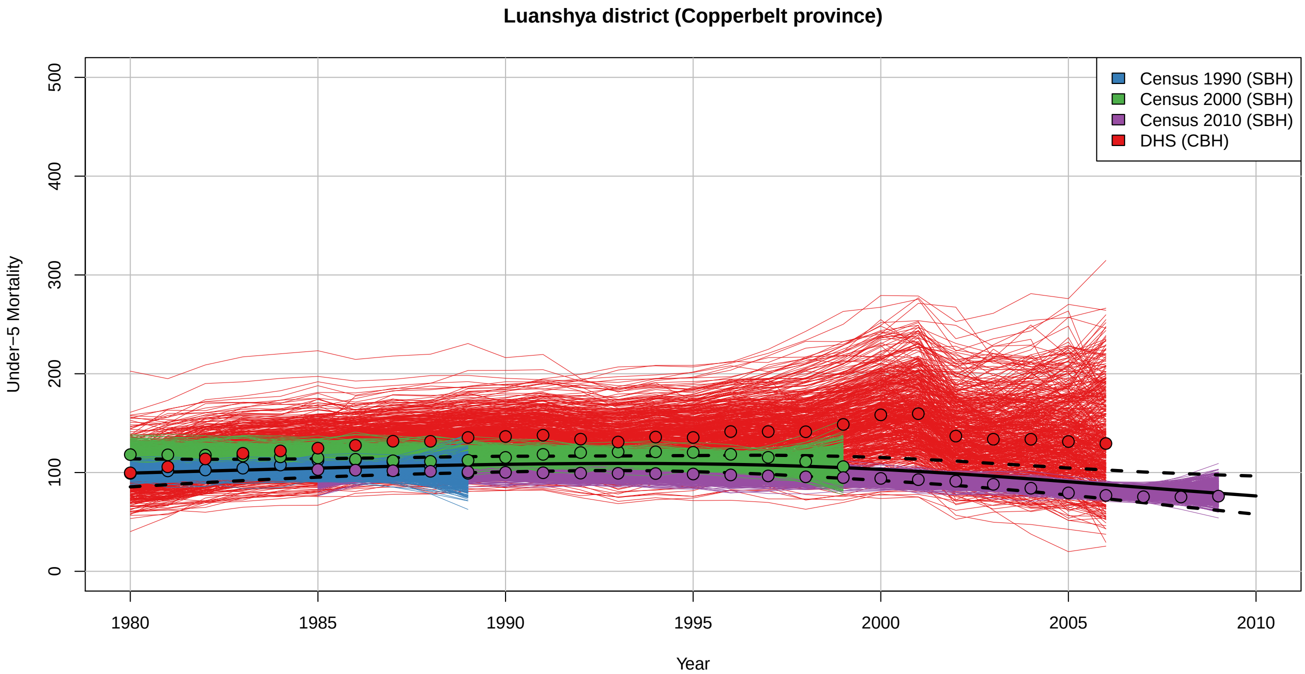

Figure A.19: Under-5 mortality estimates with uncertainty, Luanshya district (Copperbelt province)

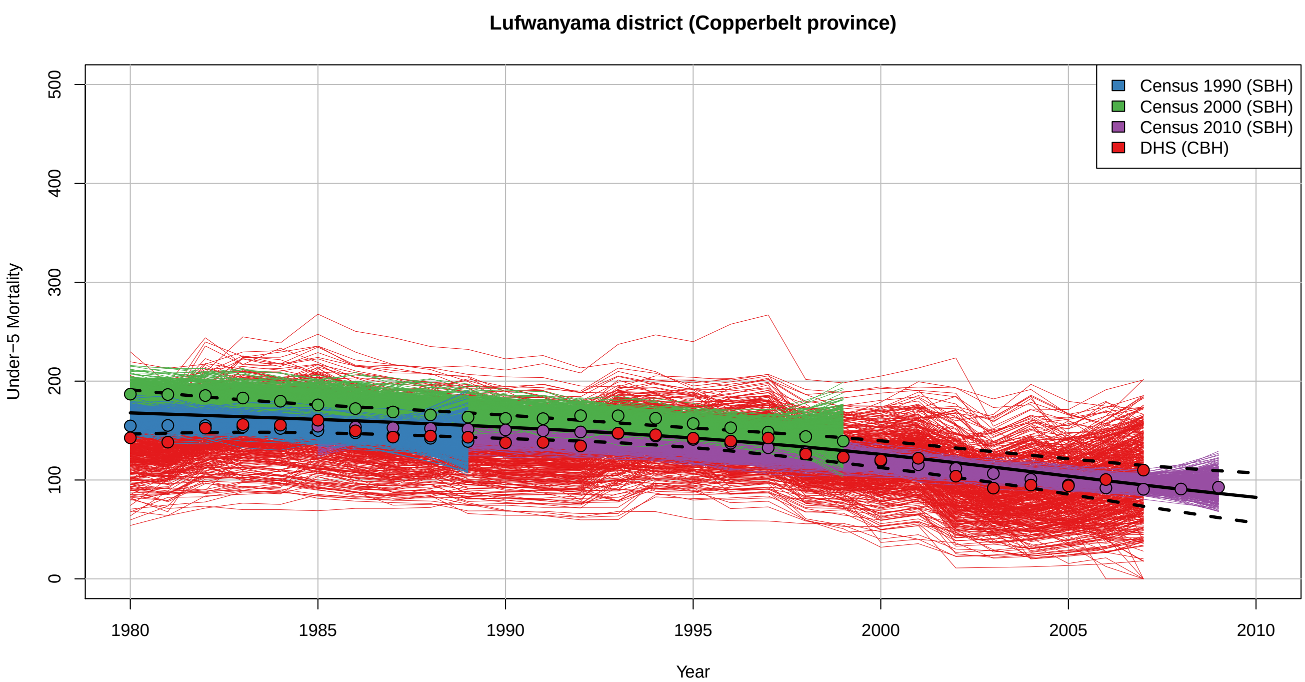

Figure A.20: Under-5 mortality estimates with uncertainty, Lufwanyama district (Copperbelt province)

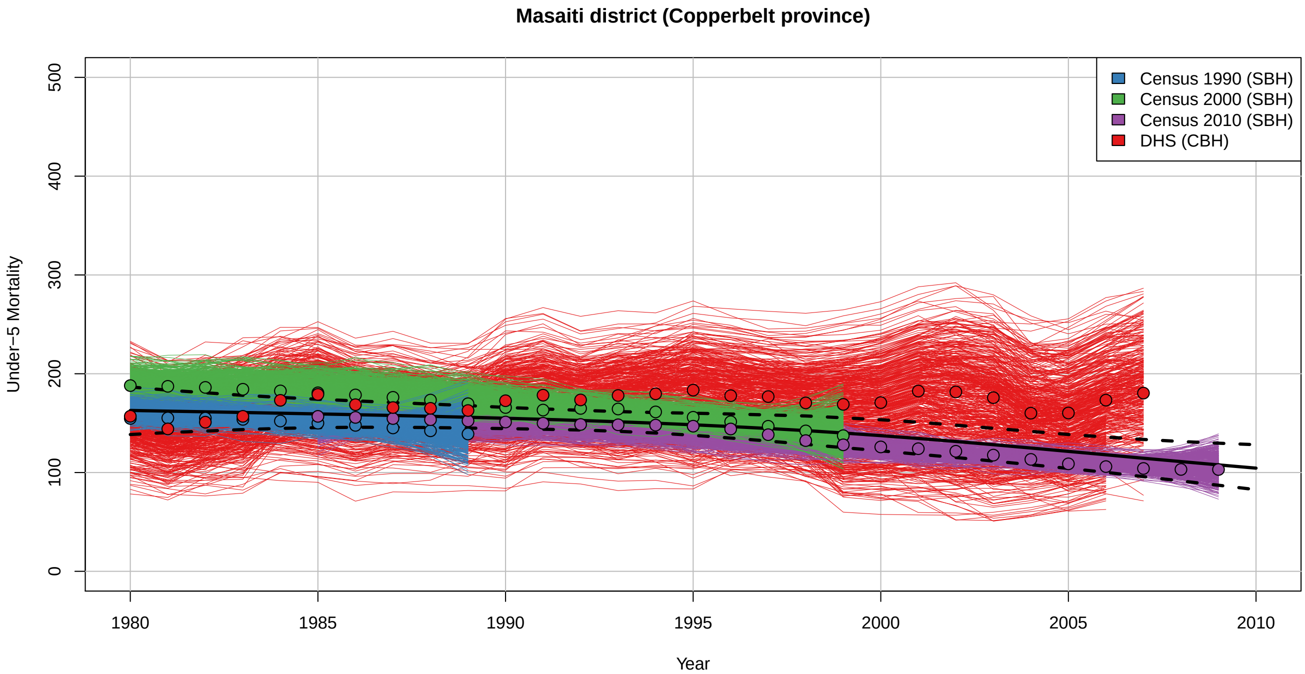

Figure A.21: Under-5 mortality estimates with uncertainty, Masaiti district (Copperbelt province)

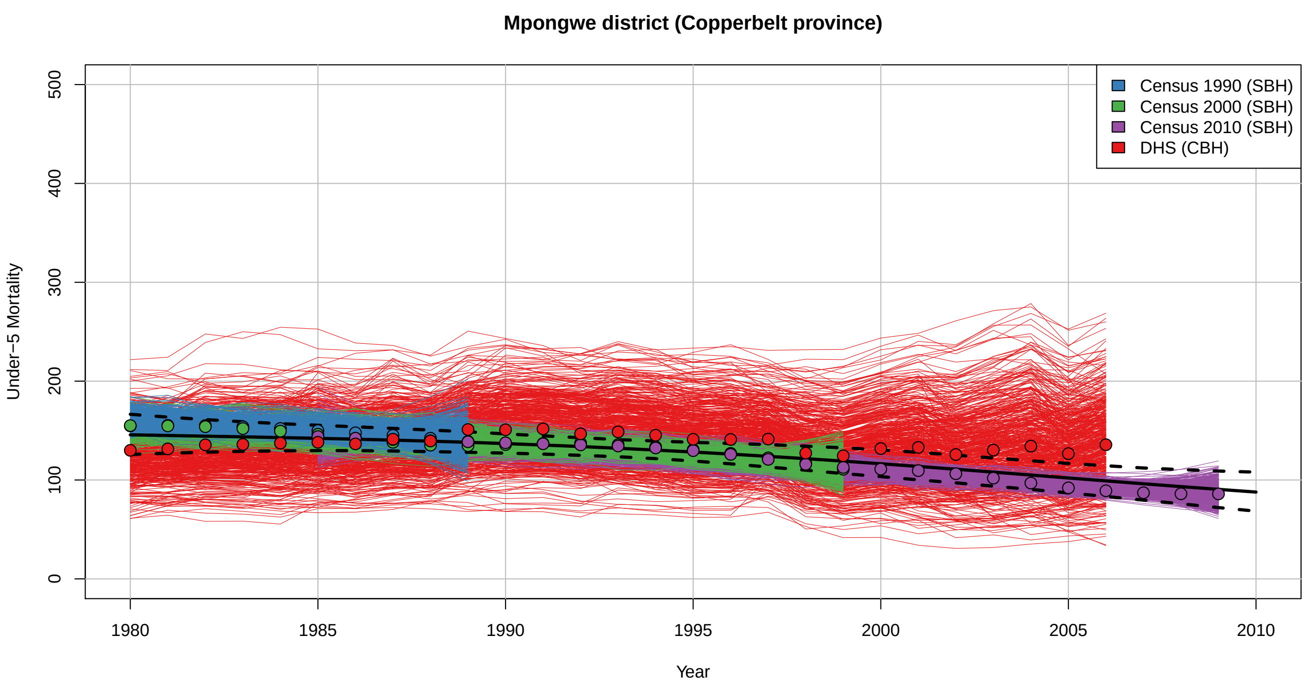

Figure A.22: Under-5 mortality estimates with uncertainty, Mpongwe district (Copperbelt province)

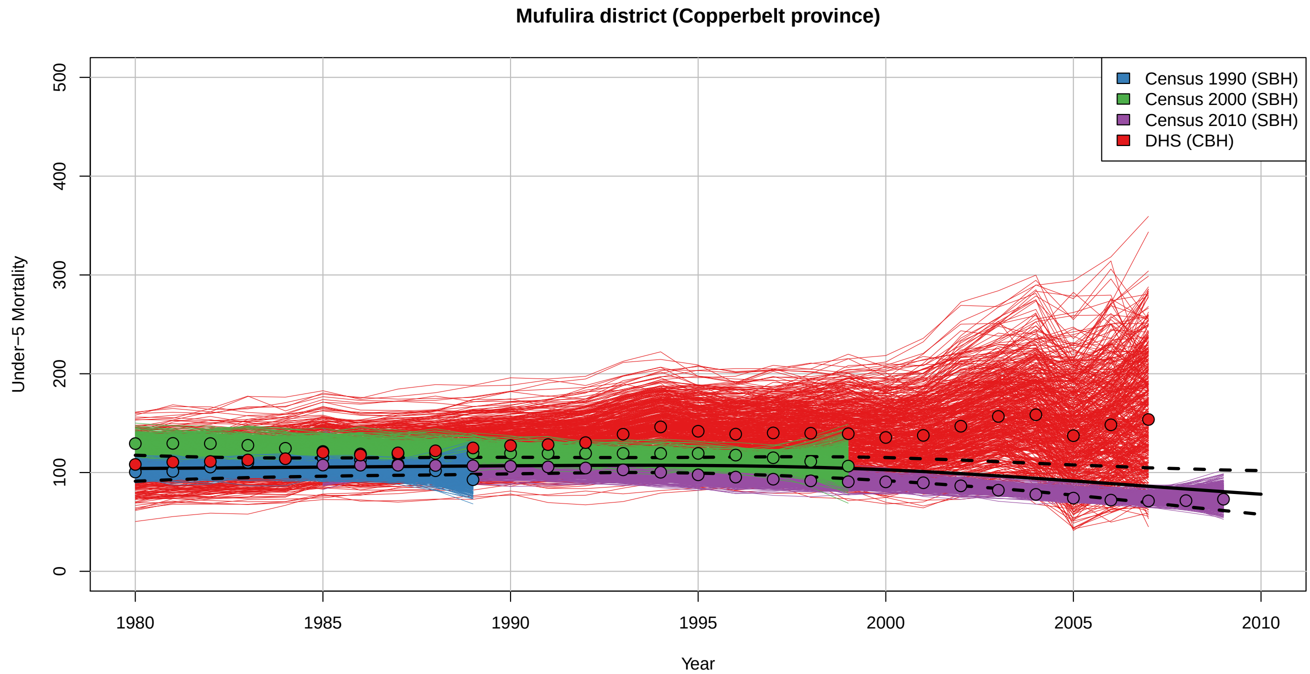

Figure A.23: Under-5 mortality estimates with uncertainty, Mufulira district (Copperbelt province)

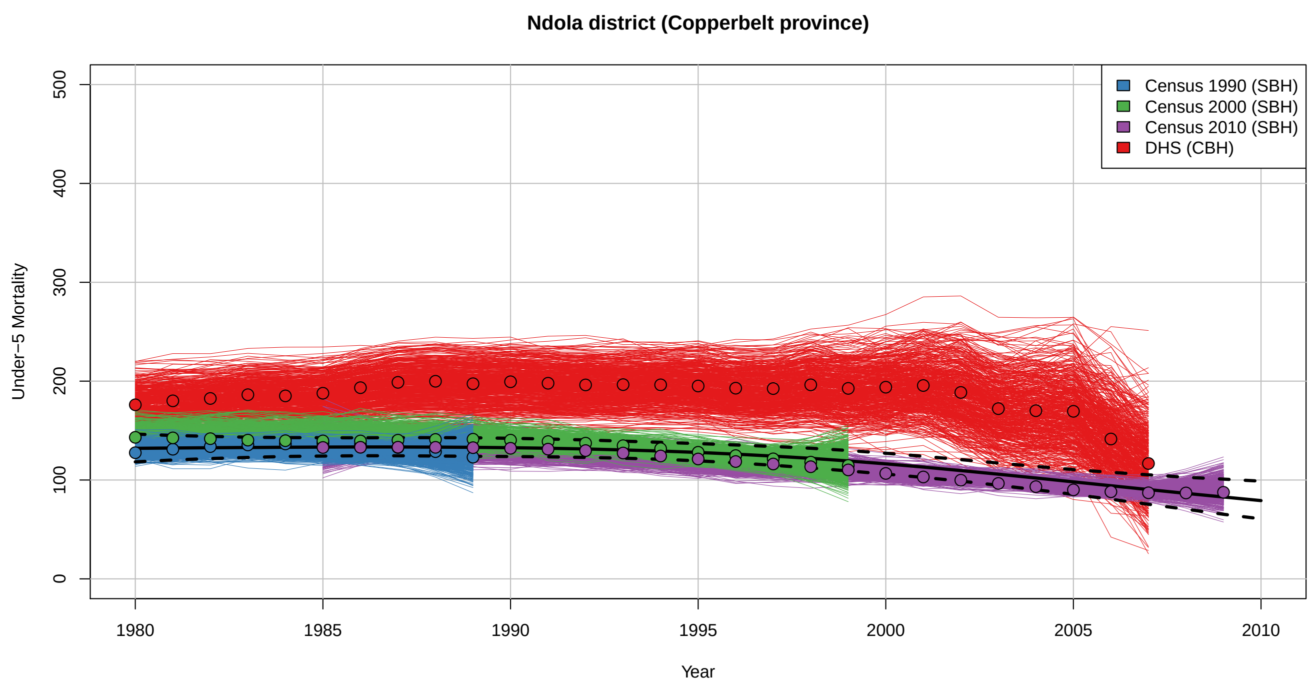

Figure A.24: Under-5 mortality estimates with uncertainty, Ndola district (Copperbelt province)

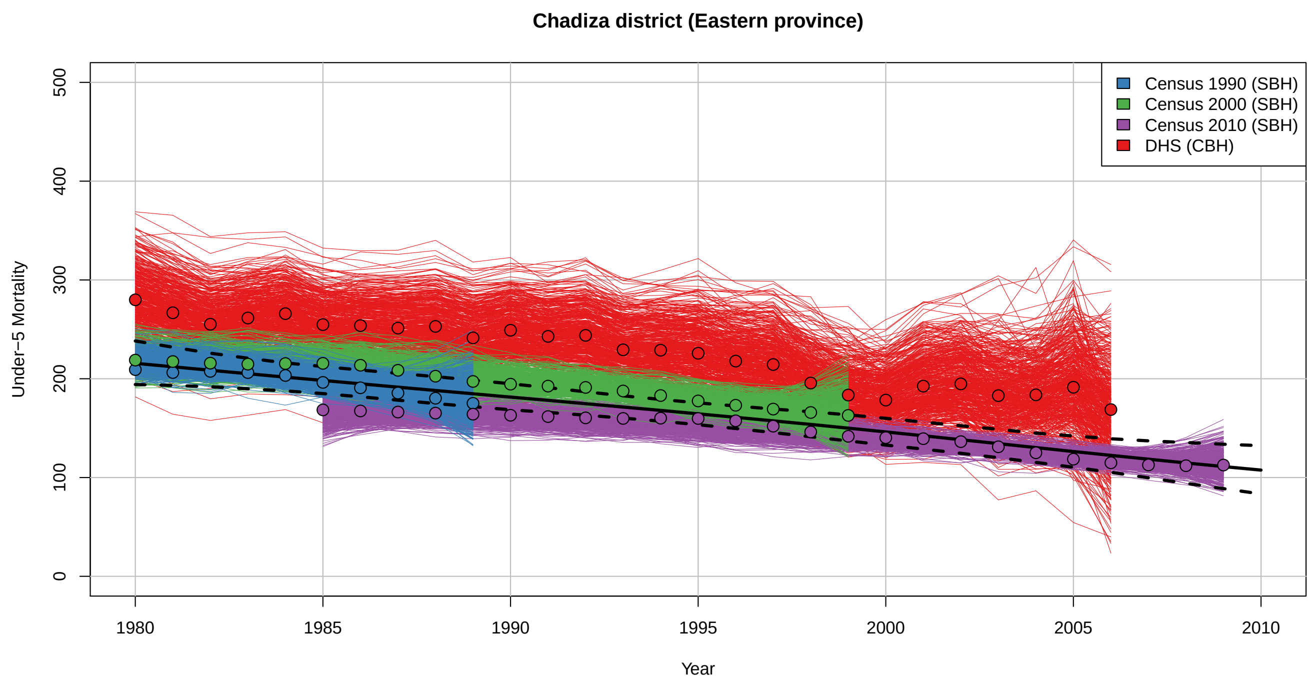

Figure A.25: Under-5 mortality estimates with uncertainty, Chadiza district (Eastern province)

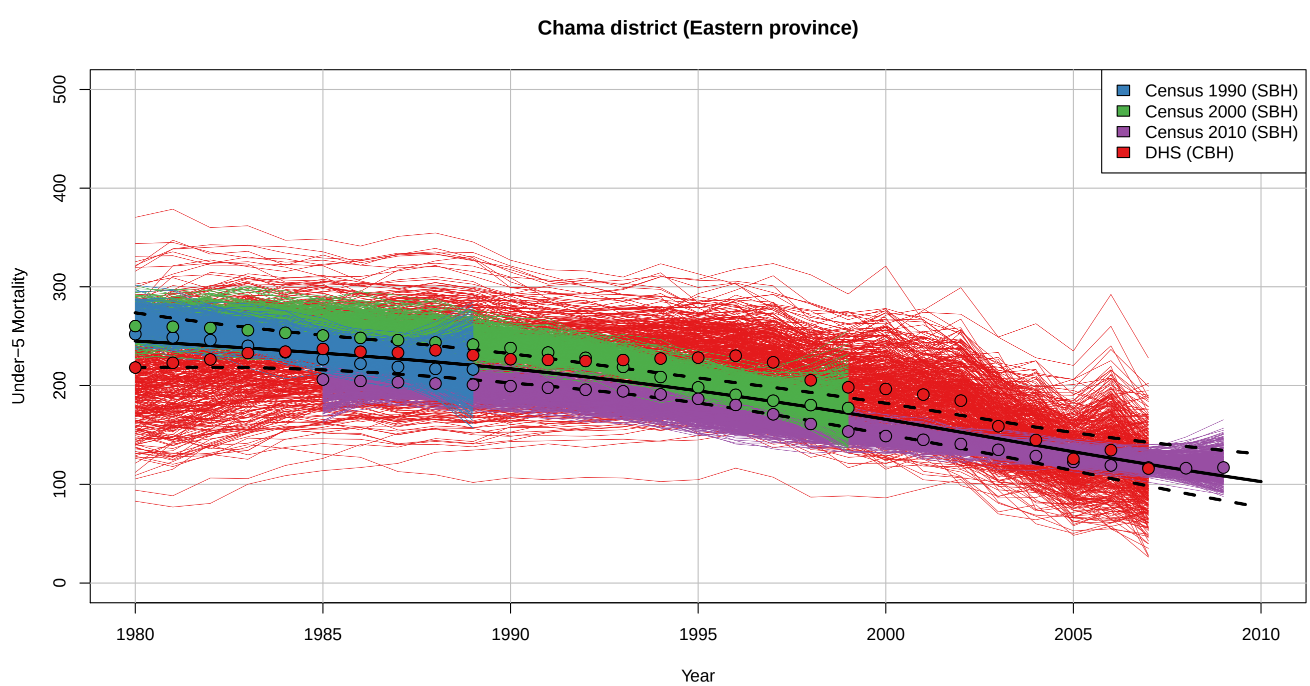

Figure A.26: Under-5 mortality estimates with uncertainty, Chama district (Eastern province)

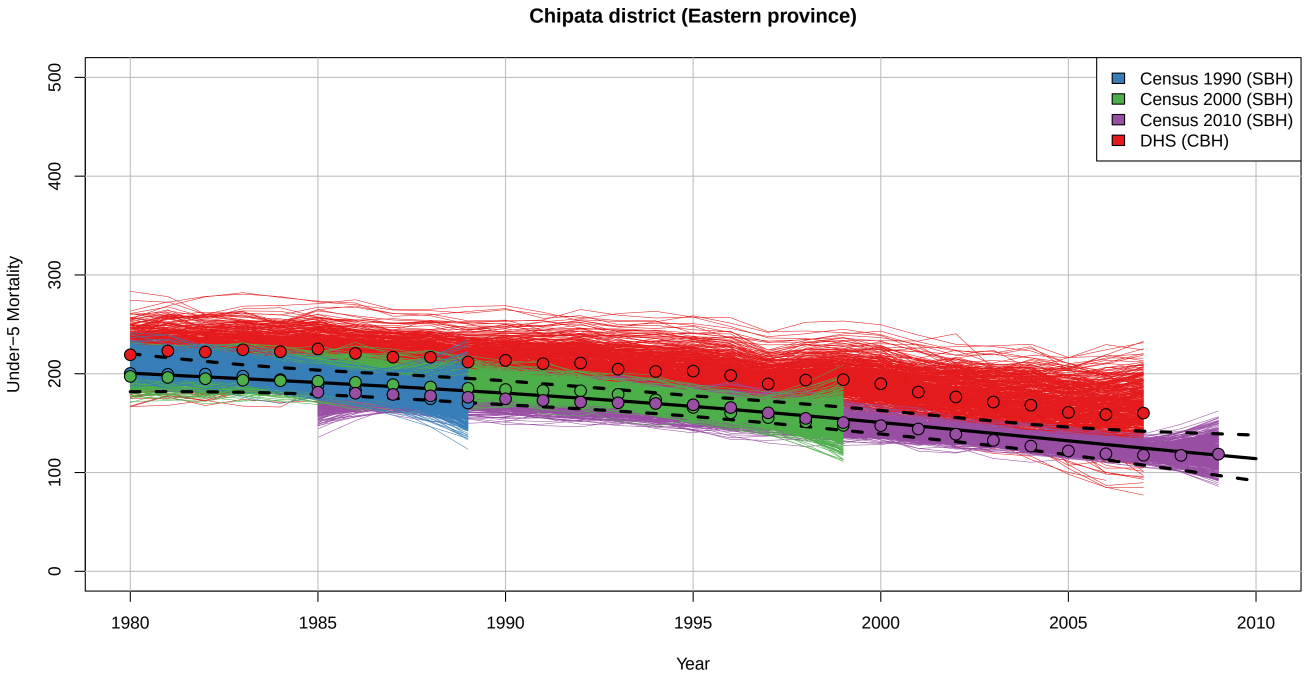

Figure A.27: Under-5 mortality estimates with uncertainty, Chipata district (Eastern province)

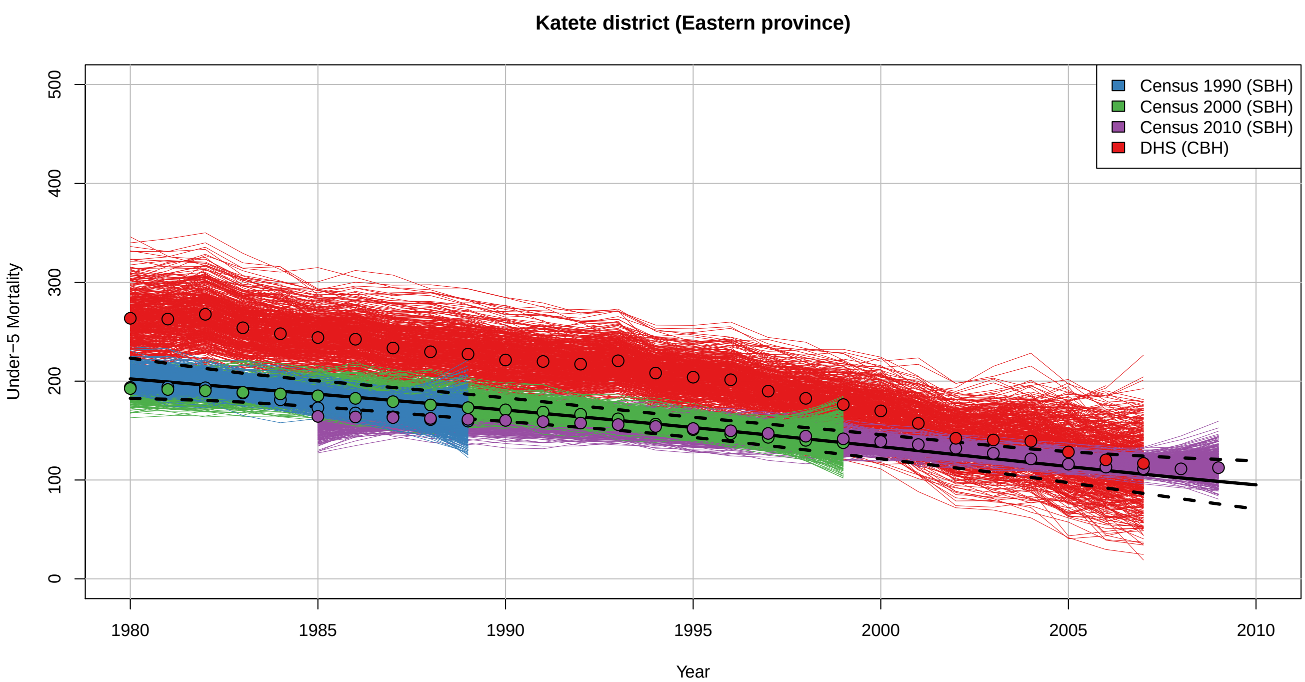

Figure A.28: Under-5 mortality estimates with uncertainty, Katete district (Eastern province)

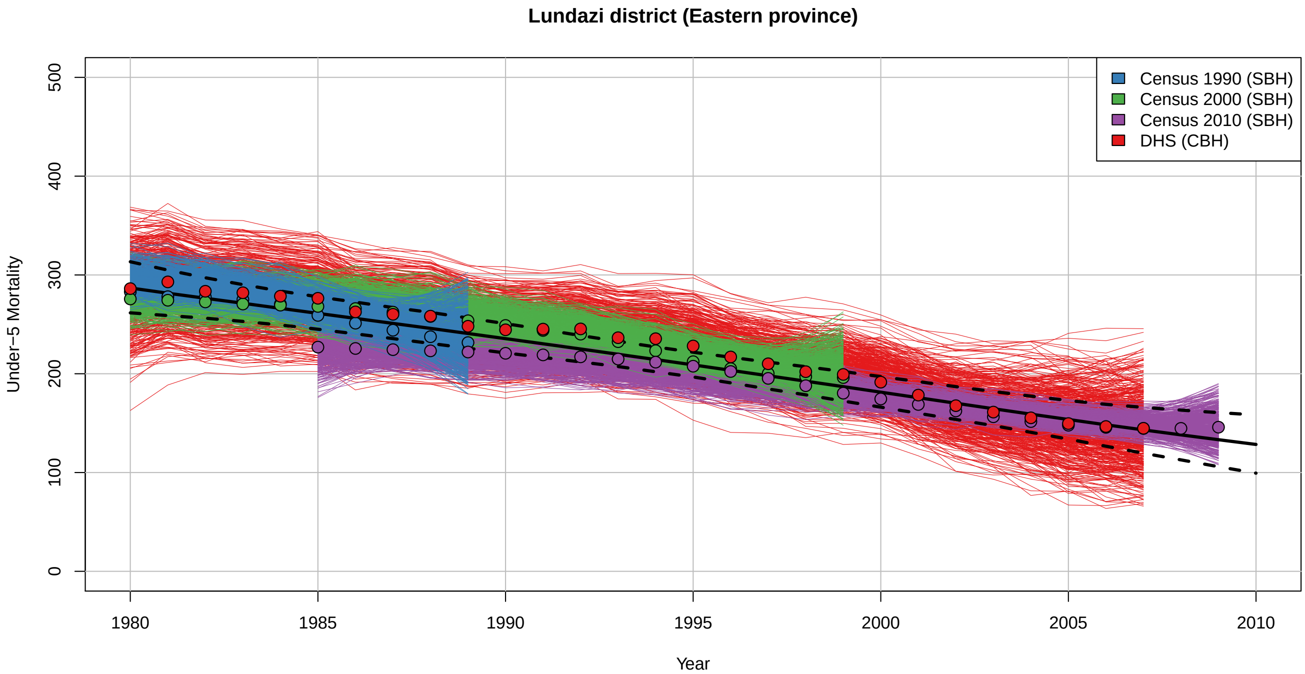

Figure A.29: Under-5 mortality estimates with uncertainty, Lundazi district (Eastern province)

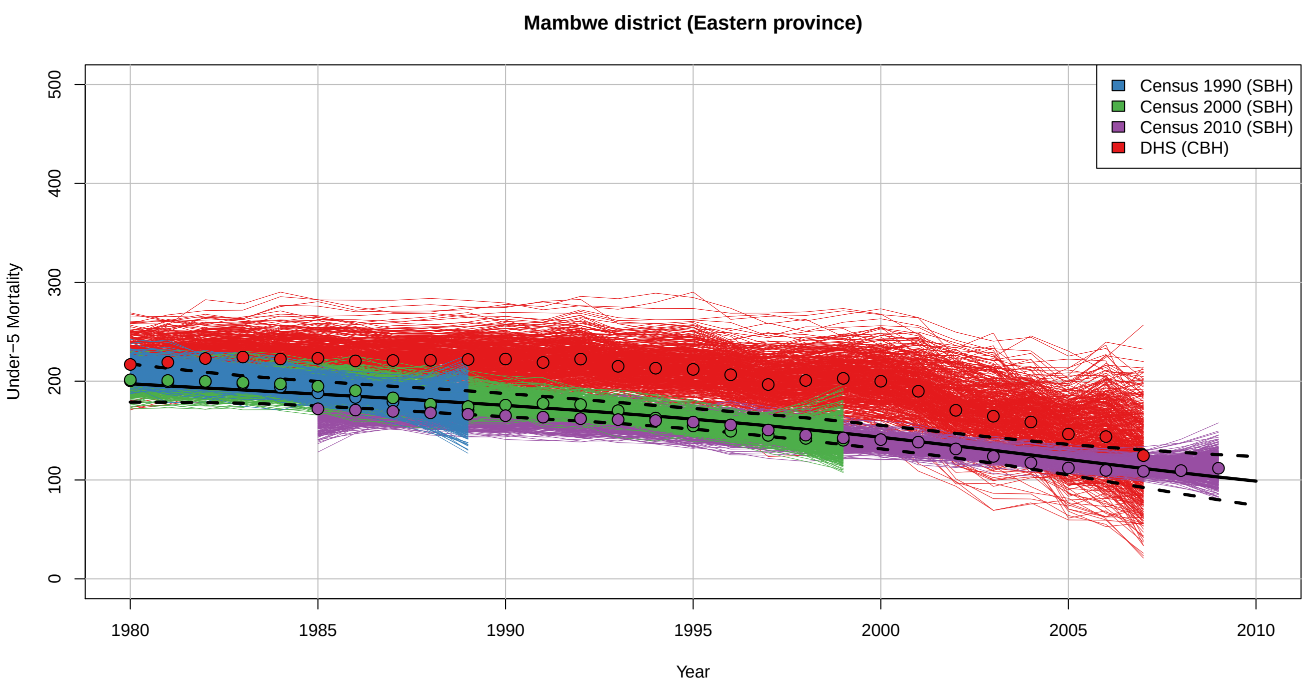

Figure A.30: Under-5 mortality estimates with uncertainty, Mambwe district (Eastern province)

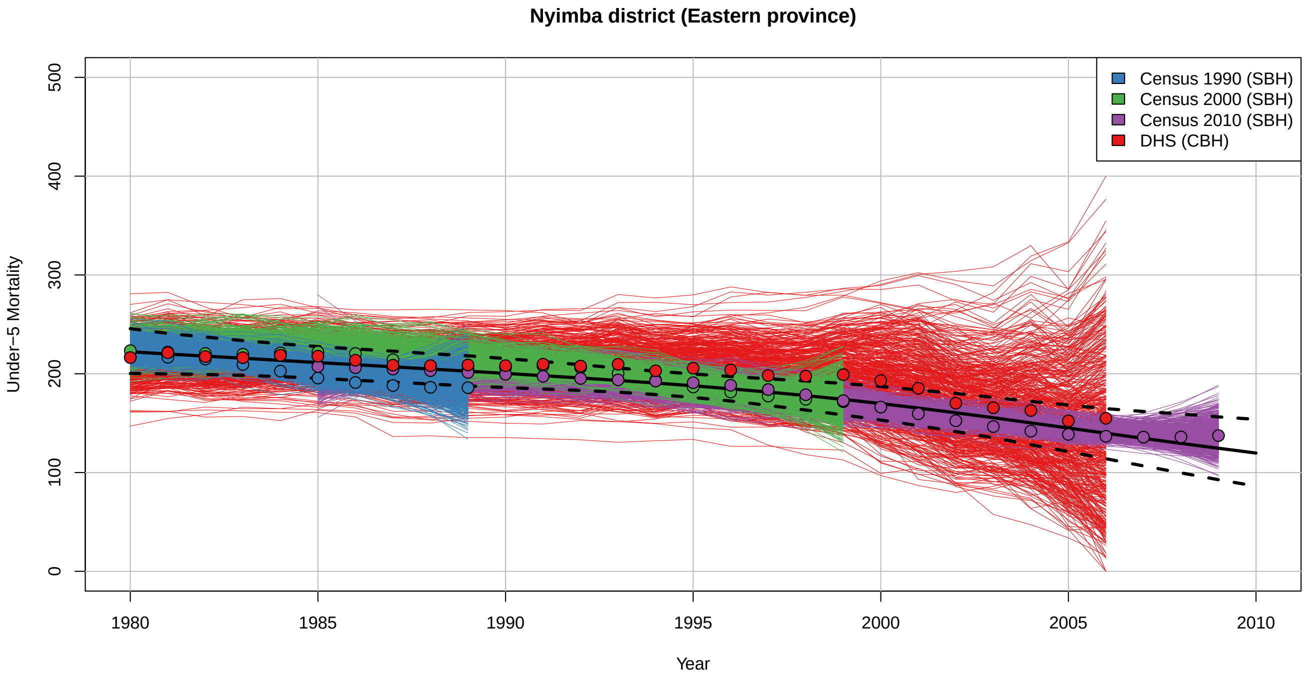

Figure A.31: Under-5 mortality estimates with uncertainty, Nyimba district (Eastern province)

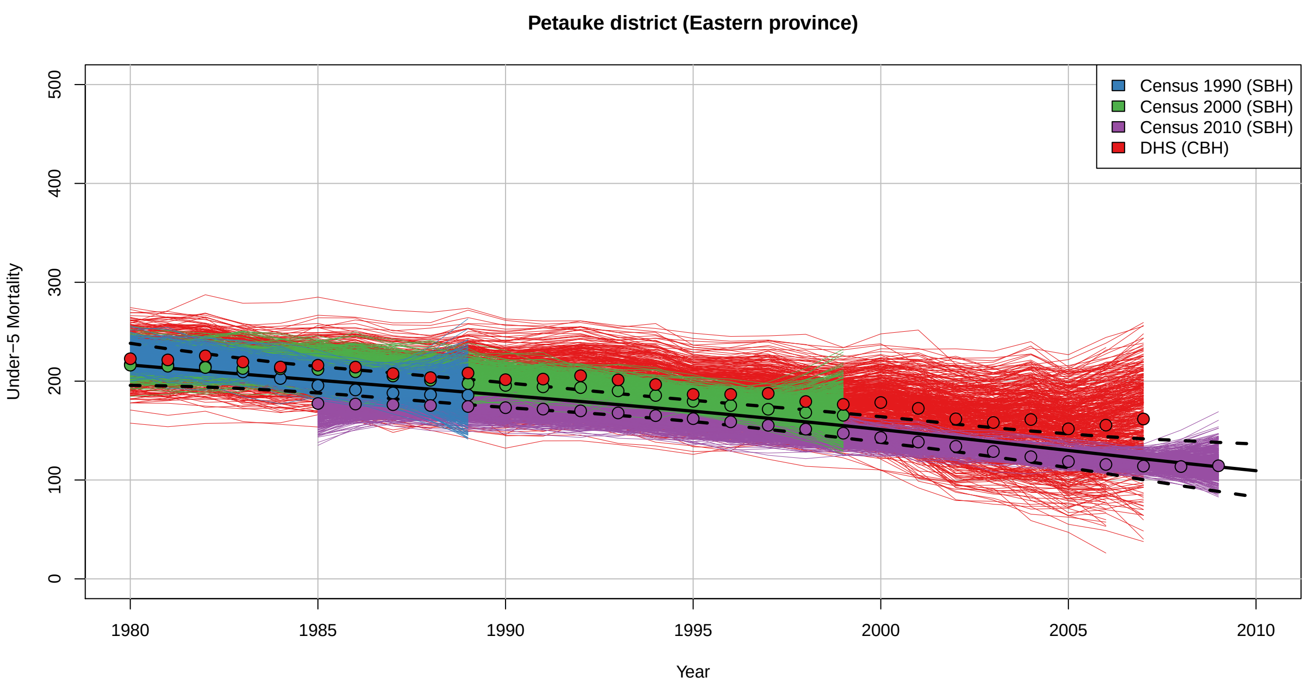

Figure A.32: Under-5 mortality estimates with uncertainty, Petauke district (Eastern province)

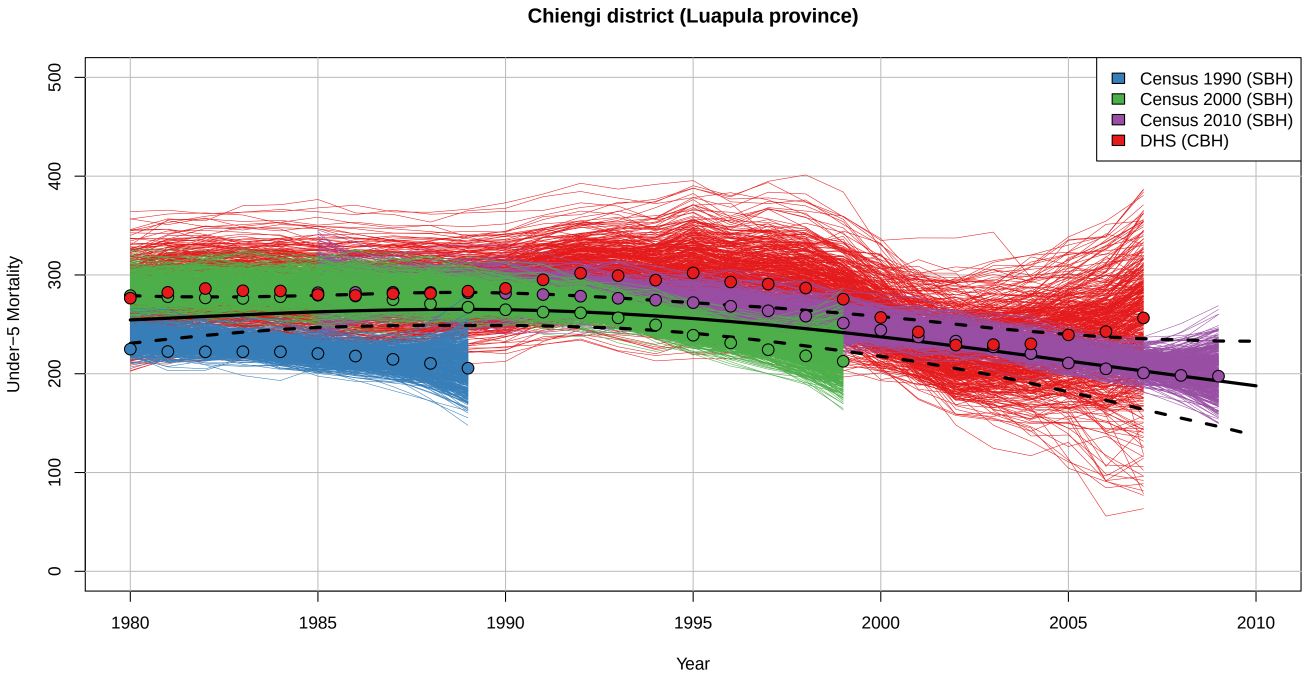

Figure A.33: Under-5 mortality estimates with uncertainty, Chiengi district (Luapula province)

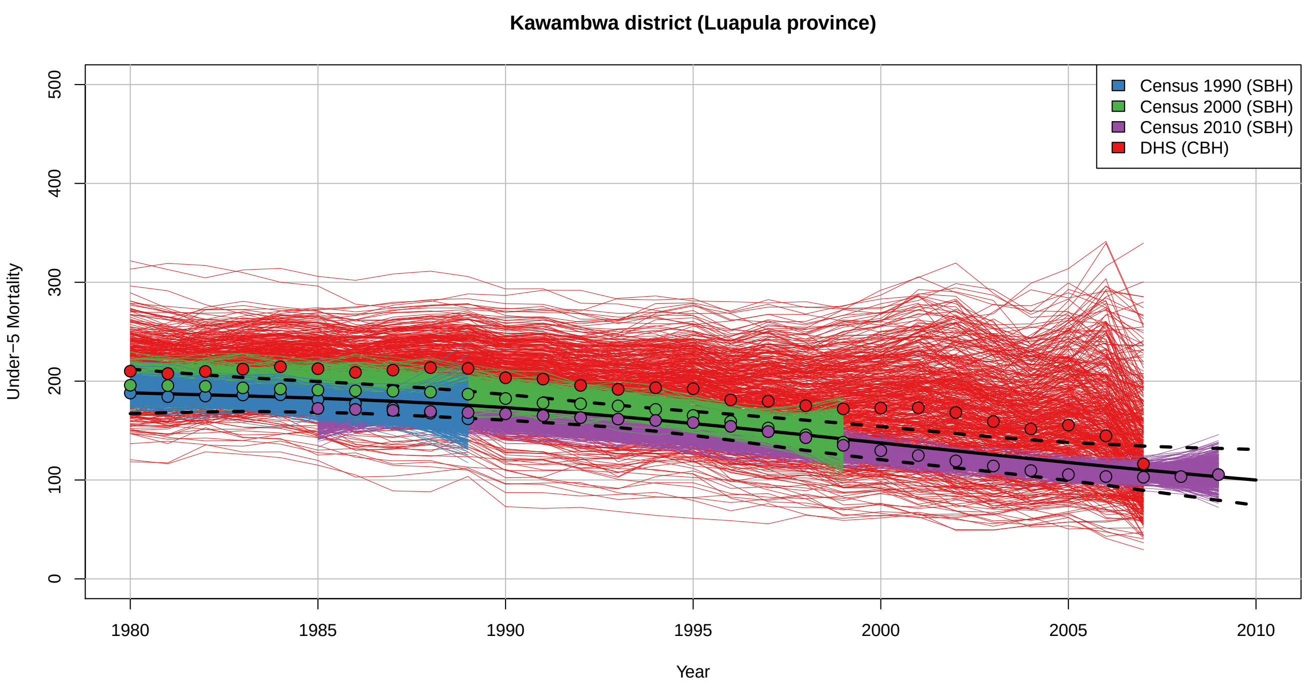

Figure A.34: Under-5 mortality estimates with uncertainty, Kawambwa district (Luapula province)

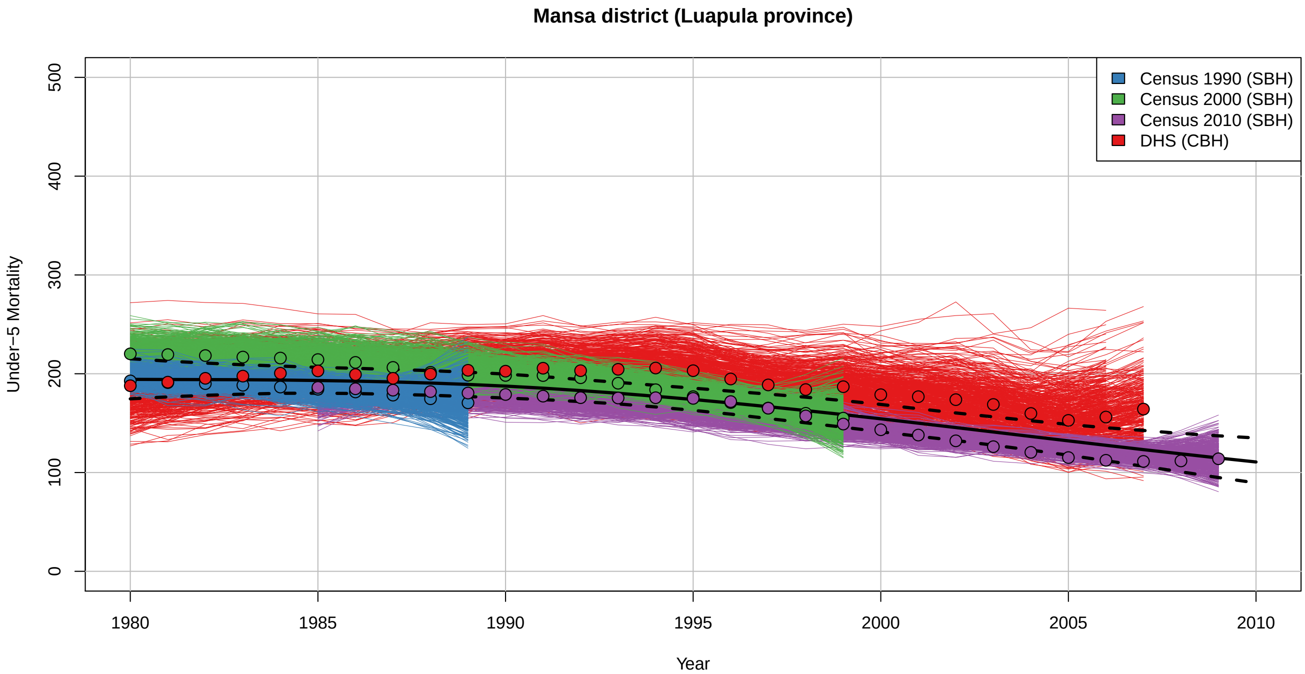

Figure A.35: Under-5 mortality estimates with uncertainty, Mansa district (Luapula province)

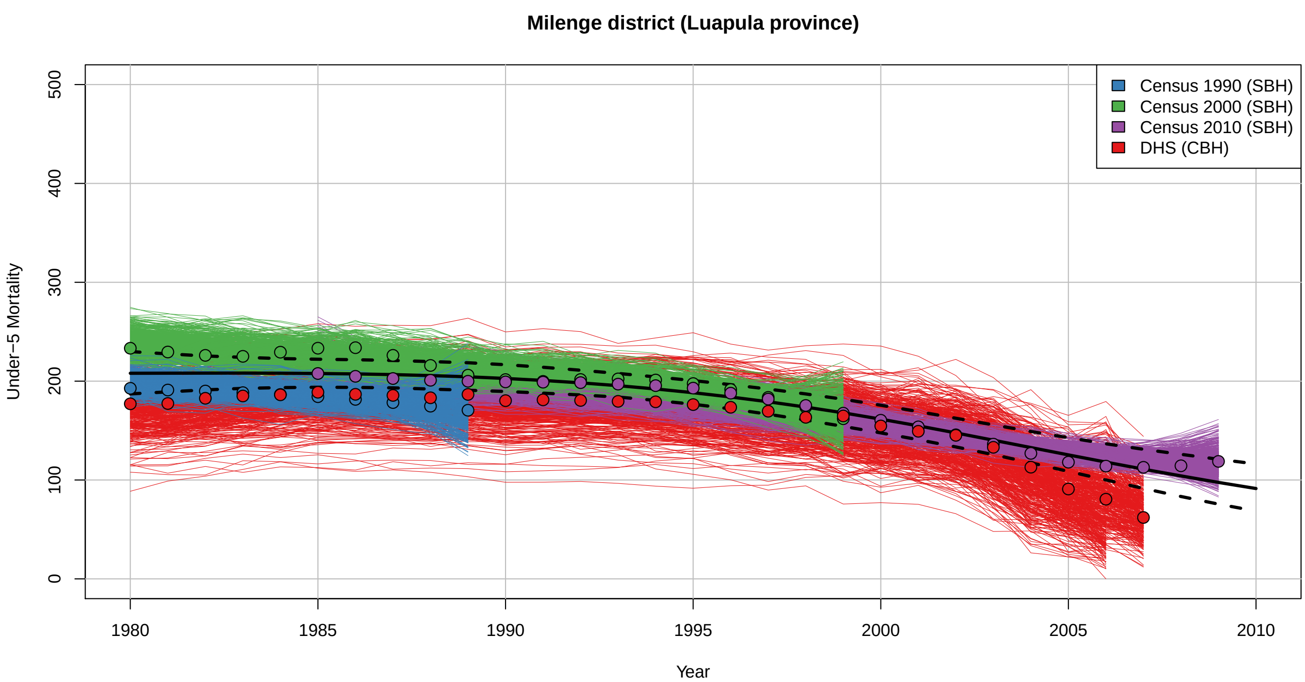

Figure A.36: Under-5 mortality estimates with uncertainty, Milenge district (Luapula province)

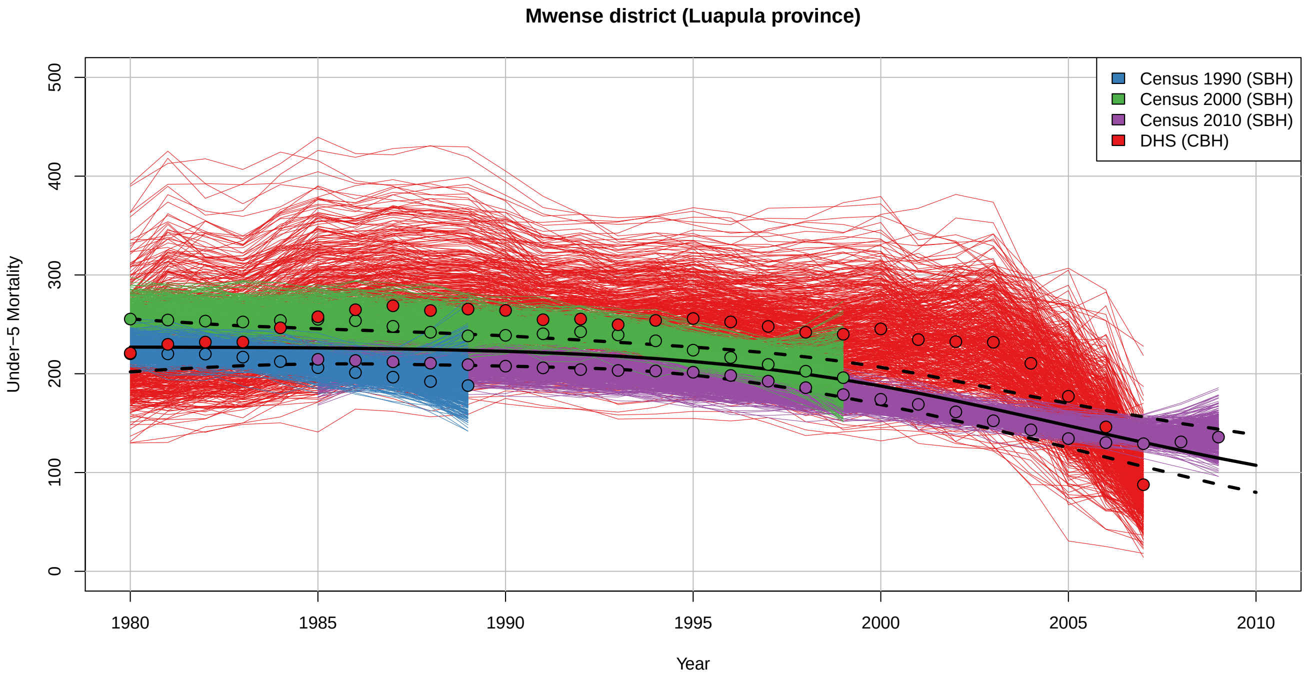

Figure A.37: Under-5 mortality estimates with uncertainty, Mwense district (Luapula province)

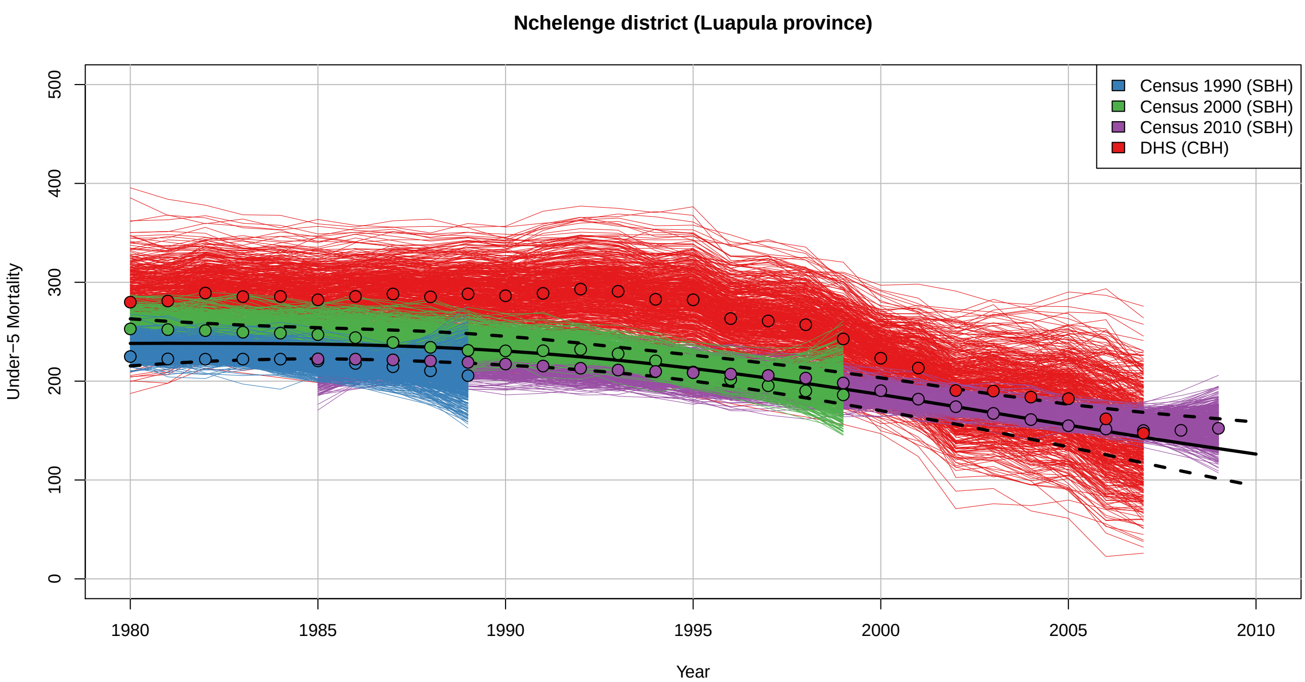

Figure A.38: Under-5 mortality estimates with uncertainty, Nchelenge district (Luapula province)

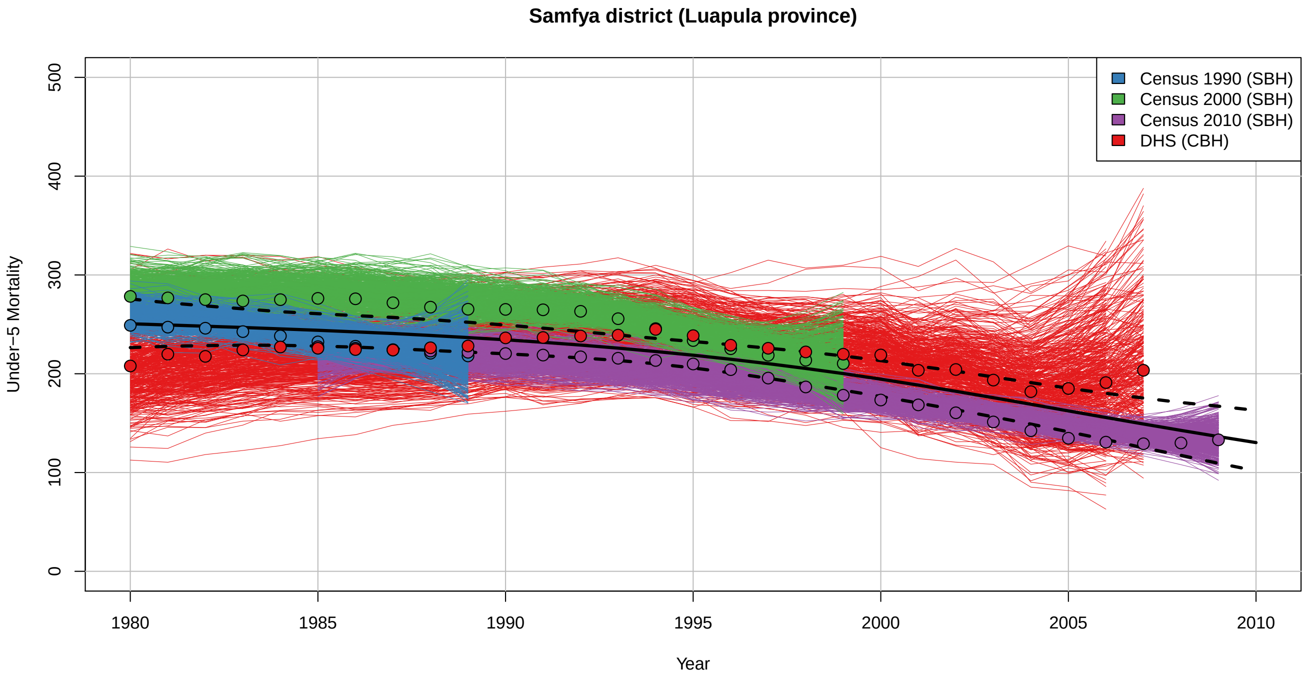

Figure A.39: Under-5 mortality estimates with uncertainty, Samfya district (Luapula province)

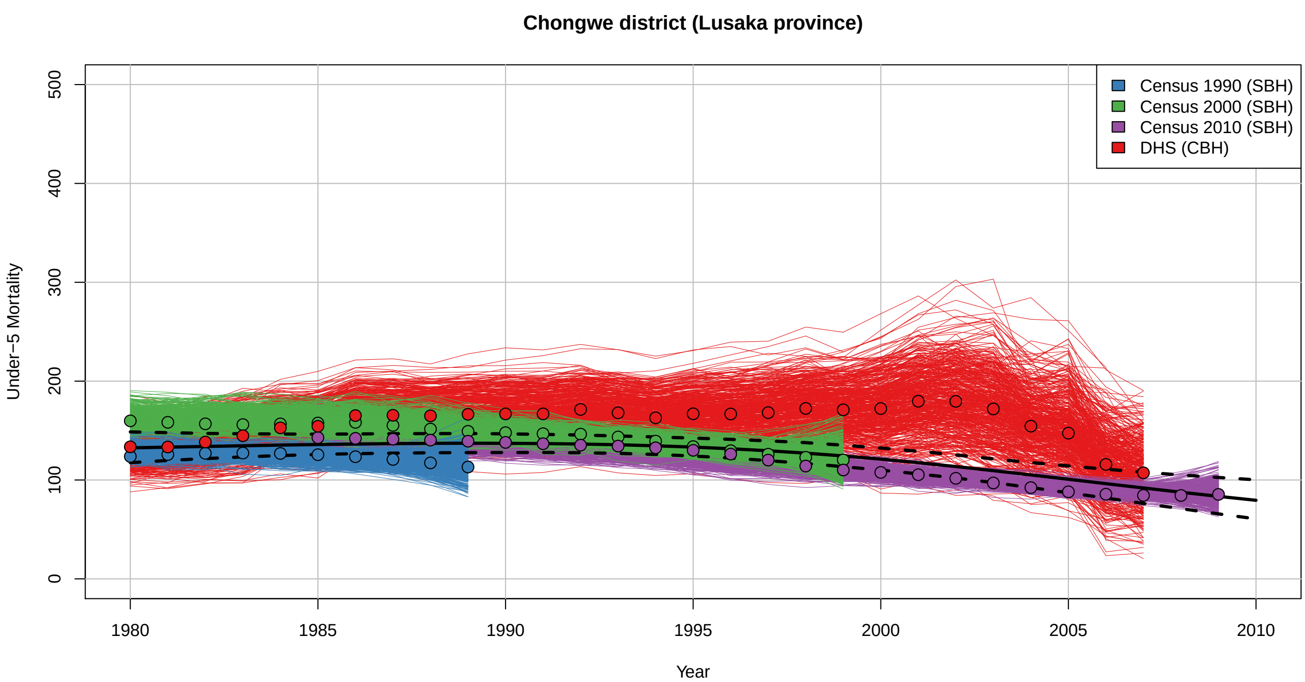

Figure A.40: Under-5 mortality estimates with uncertainty, Chongwe district (Lusaka province)

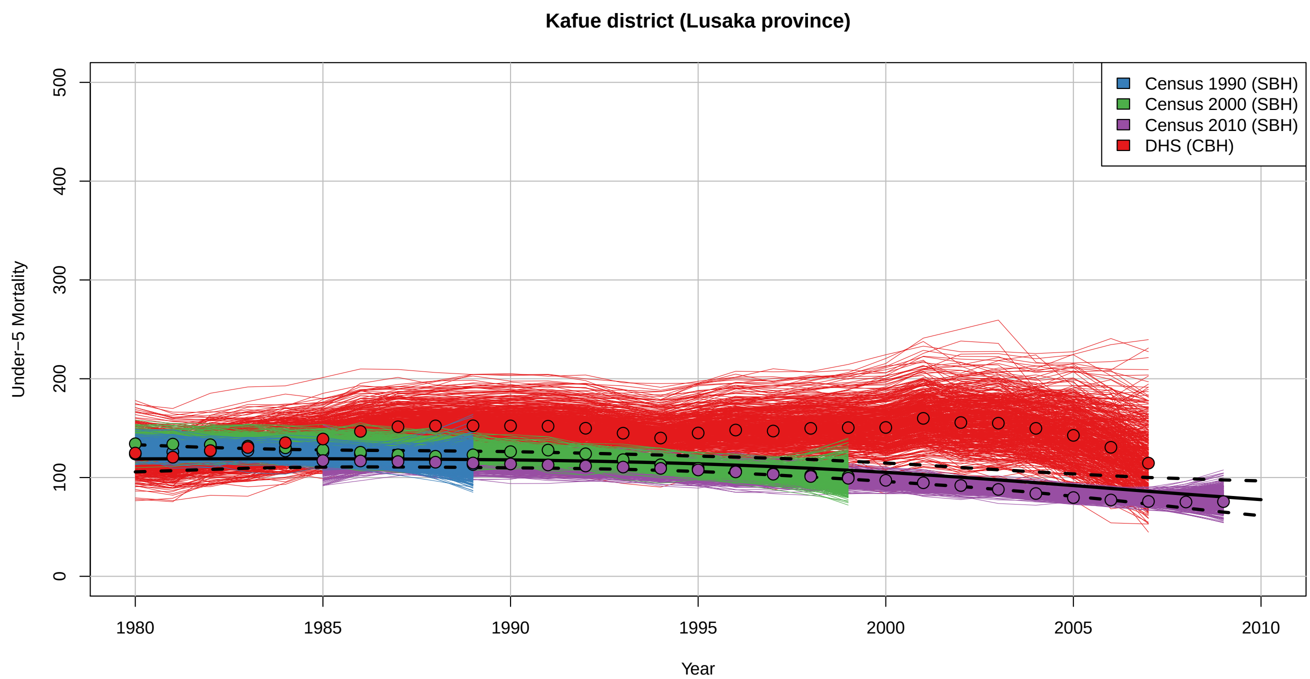

Figure A.41: Under-5 mortality estimates with uncertainty, Kafue district (Lusaka province)

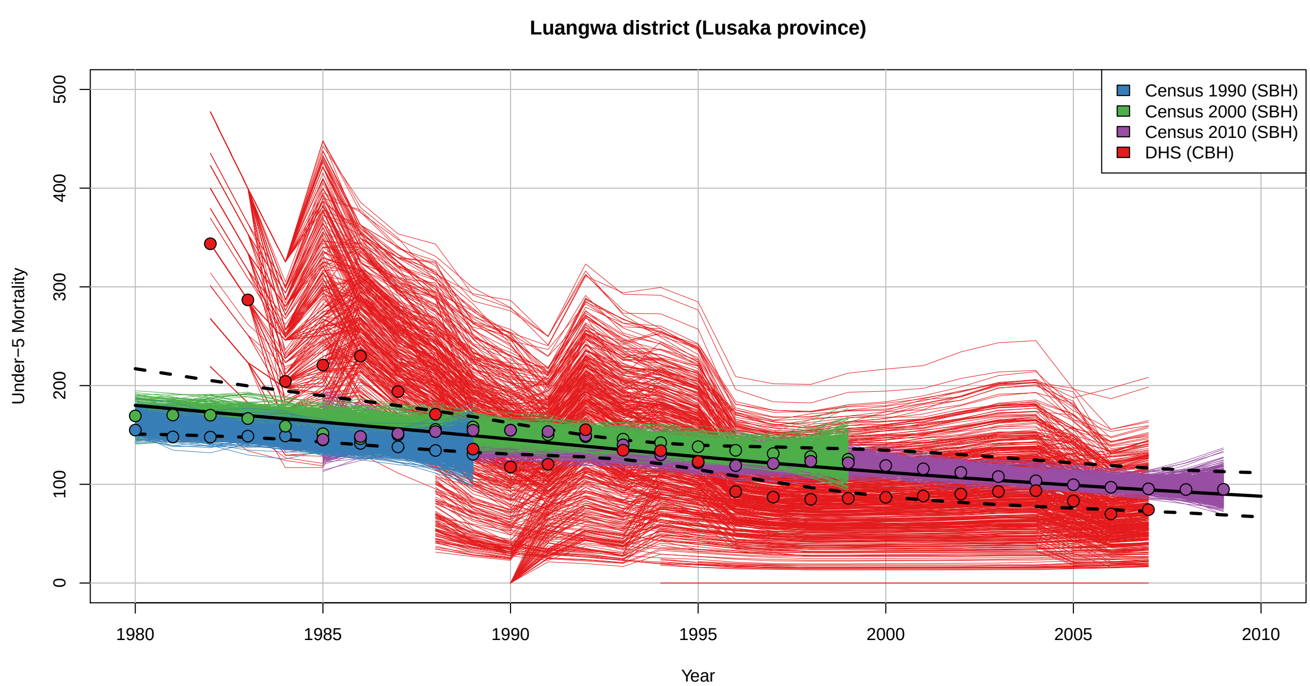

Figure A.42: Under-5 mortality estimates with uncertainty, Luangwa district (Lusaka province)

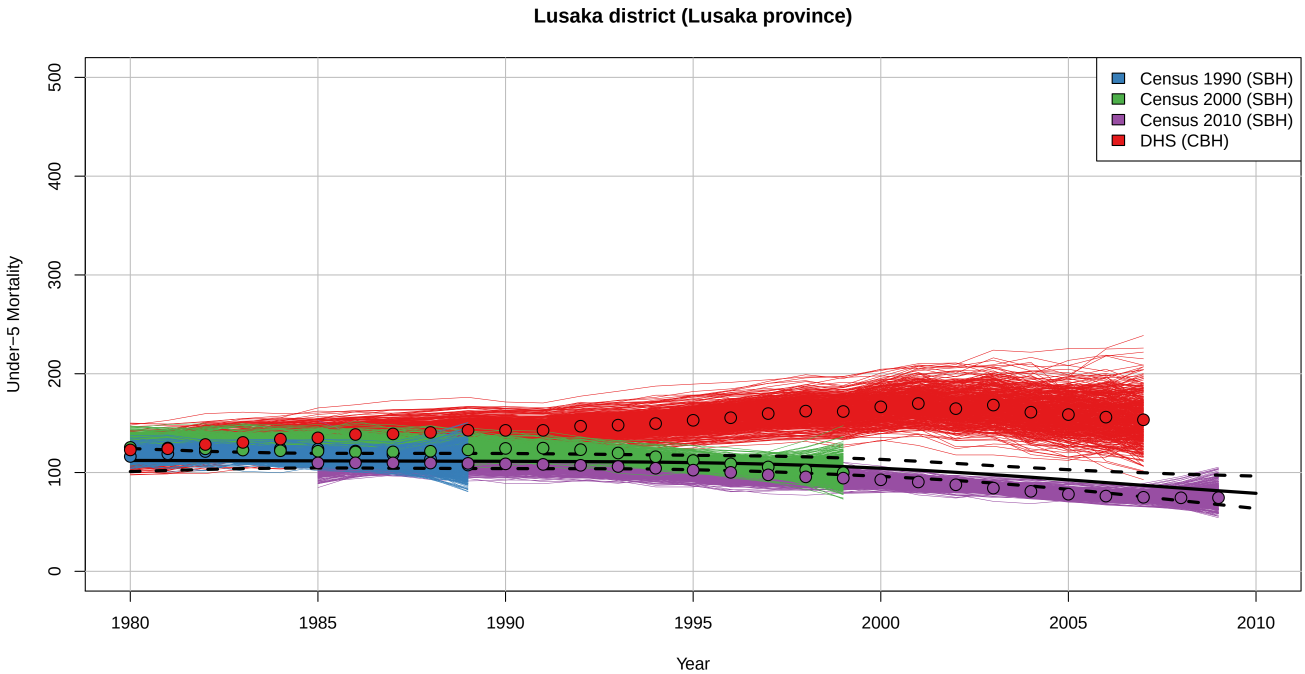

Figure A.43: Under-5 mortality estimates with uncertainty, Lusaka district (Lusaka province)

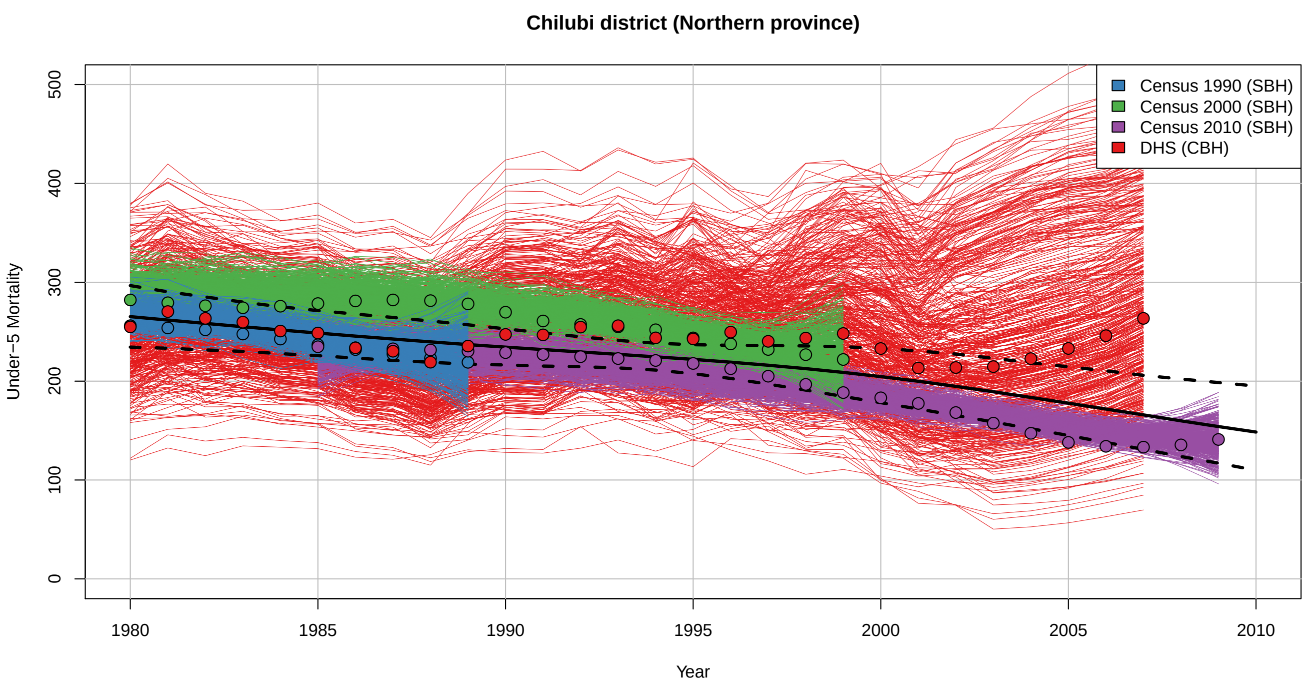

Figure A.44: Under-5 mortality estimates with uncertainty, Chilubi district (Northern province)

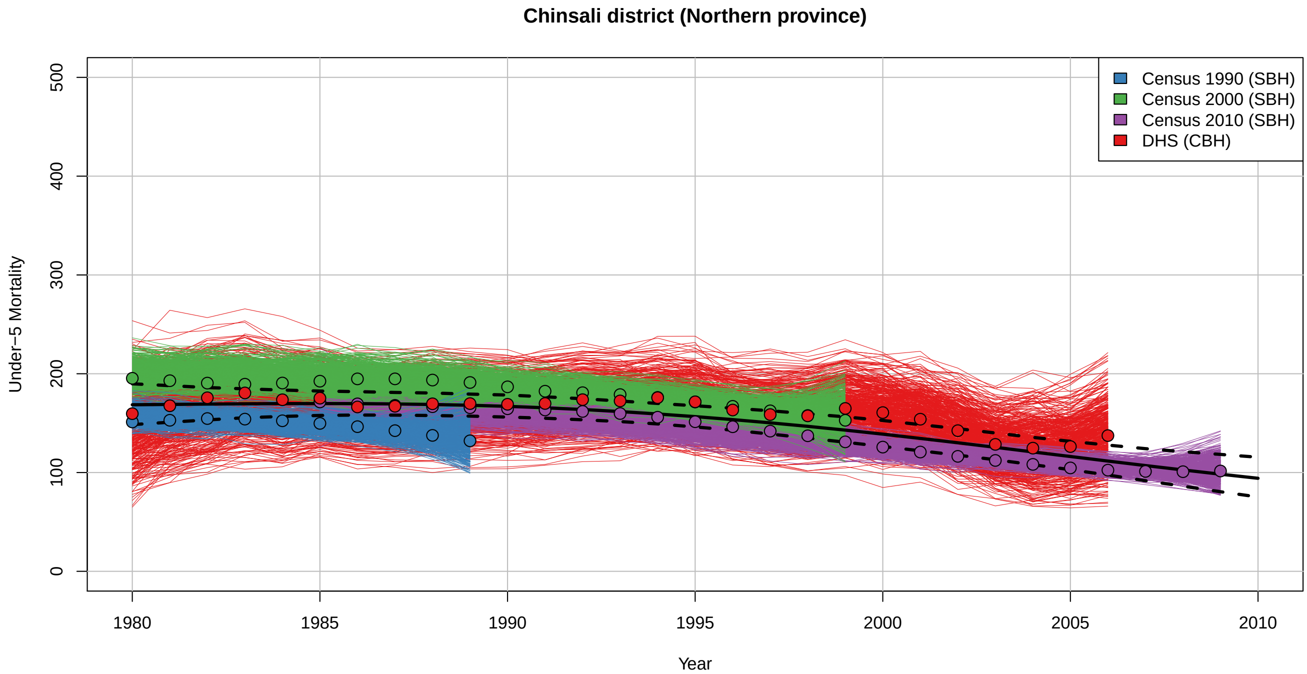

Figure A.45: Under-5 mortality estimates with uncertainty, Chinsali district (Northern province)

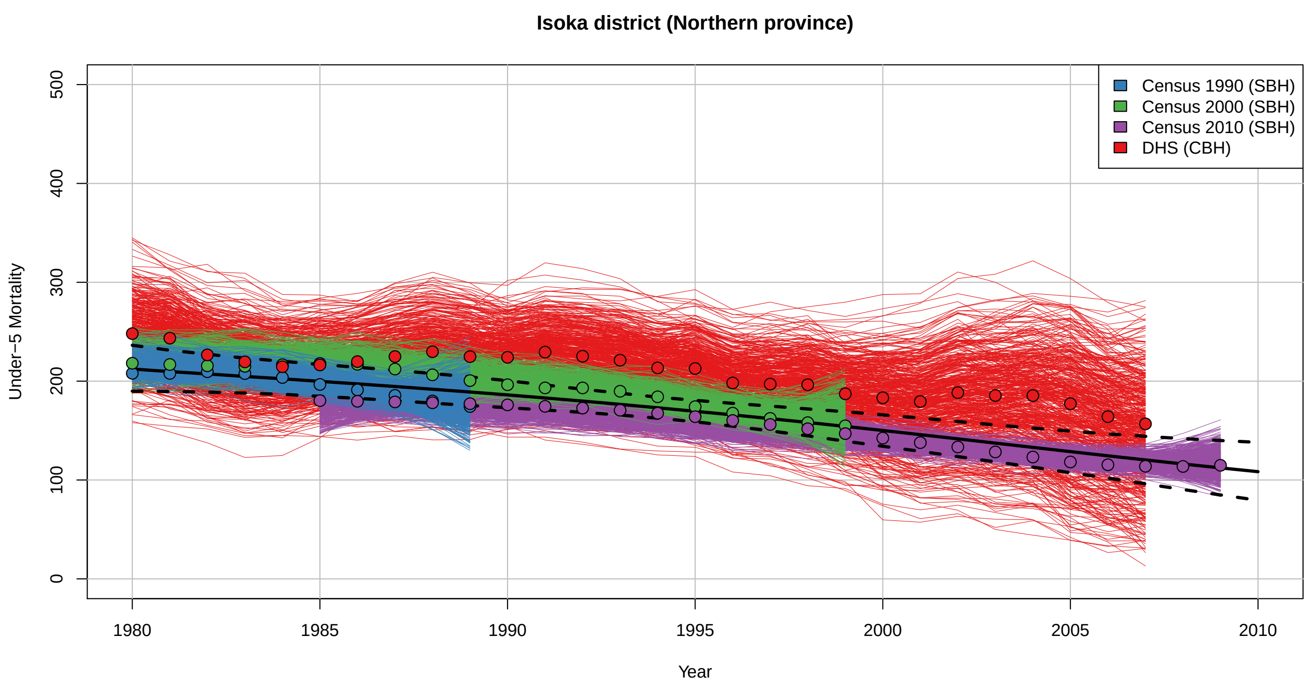

Figure A.46: Under-5 mortality estimates with uncertainty, Isoka district (Northern province)

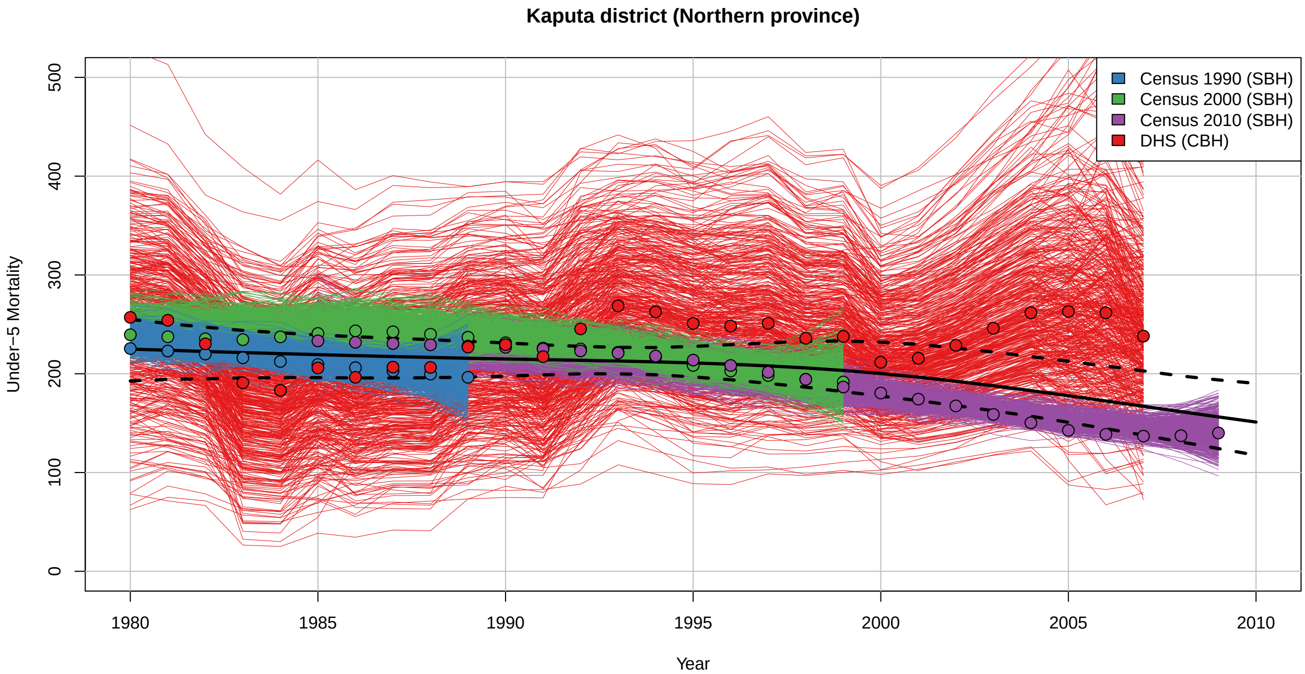

Figure A.47: Under-5 mortality estimates with uncertainty, Kaputa district (Northern province)

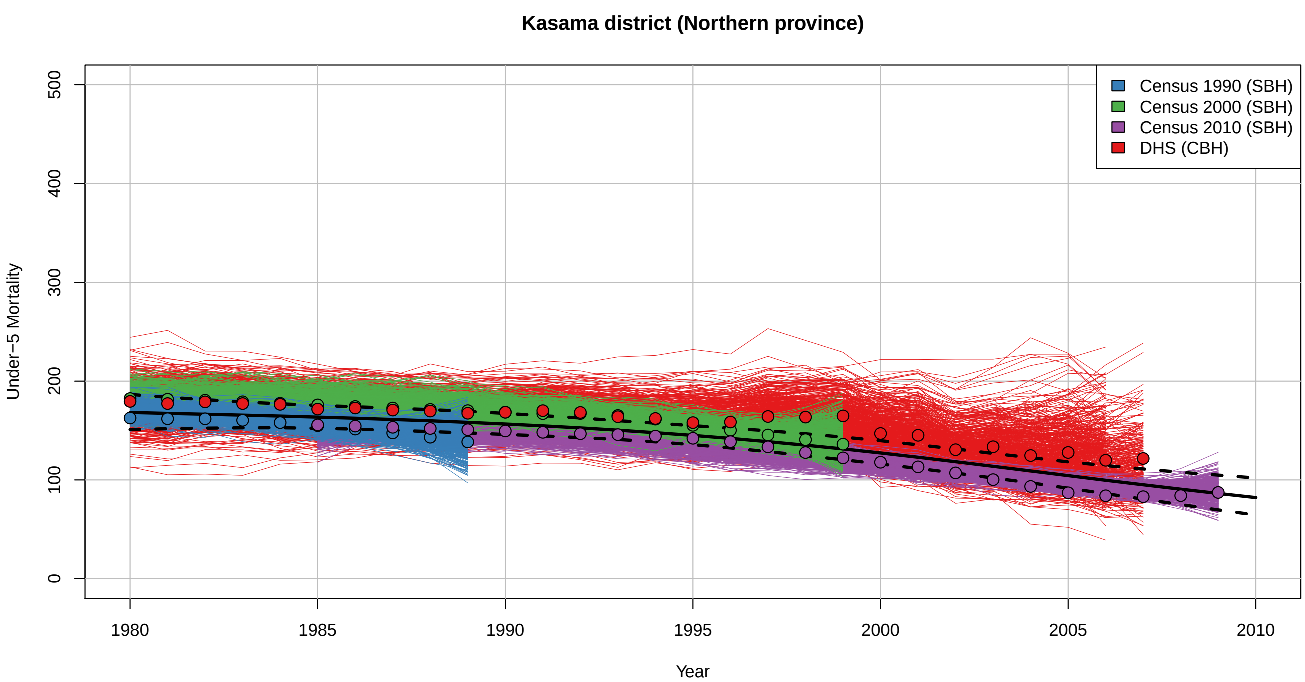

Figure A.48: Under-5 mortality estimates with uncertainty, Kasama district (Northern province)

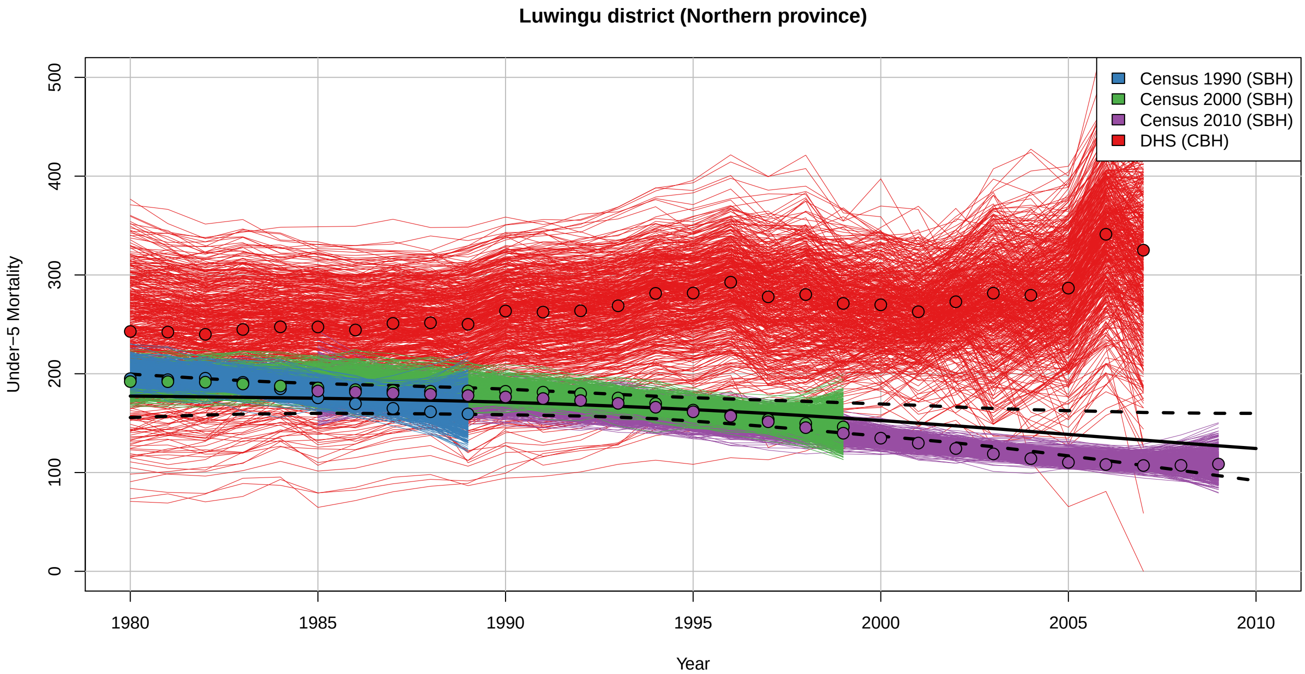

Figure A.49: Under-5 mortality estimates with uncertainty, Luwingu district (Northern province)

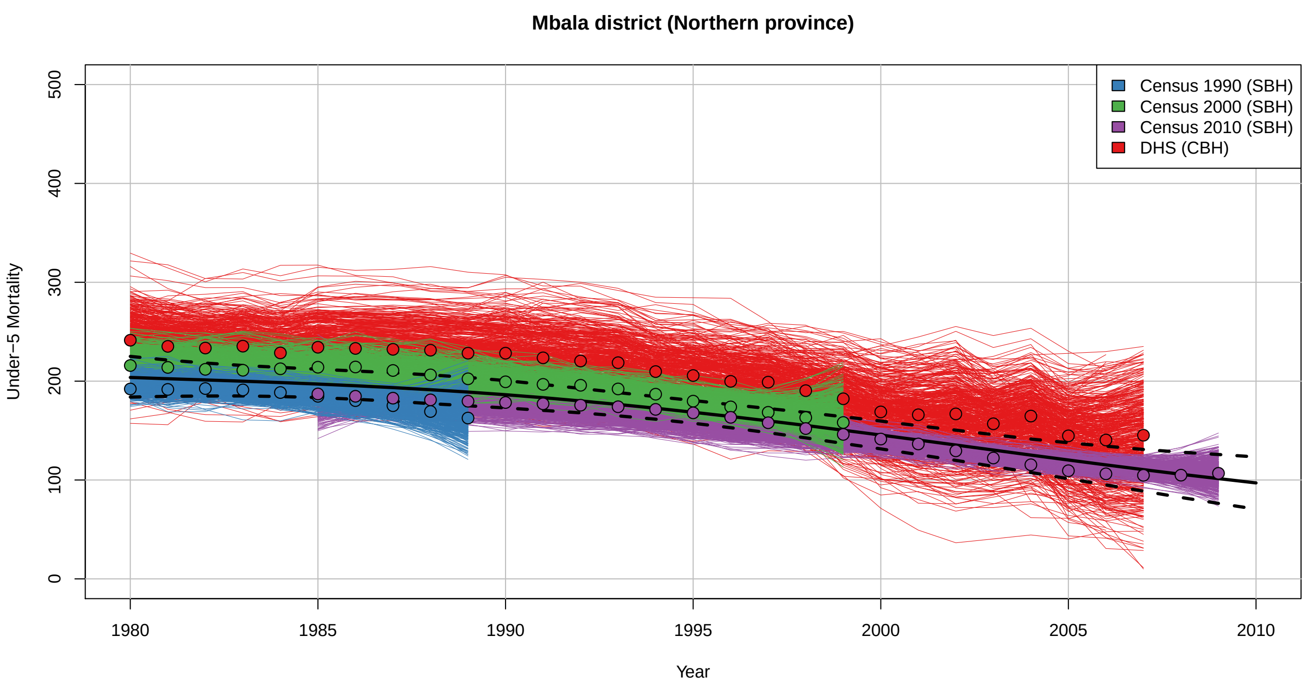

Figure A.50: Under-5 mortality estimates with uncertainty, Mbala district (Northern province)

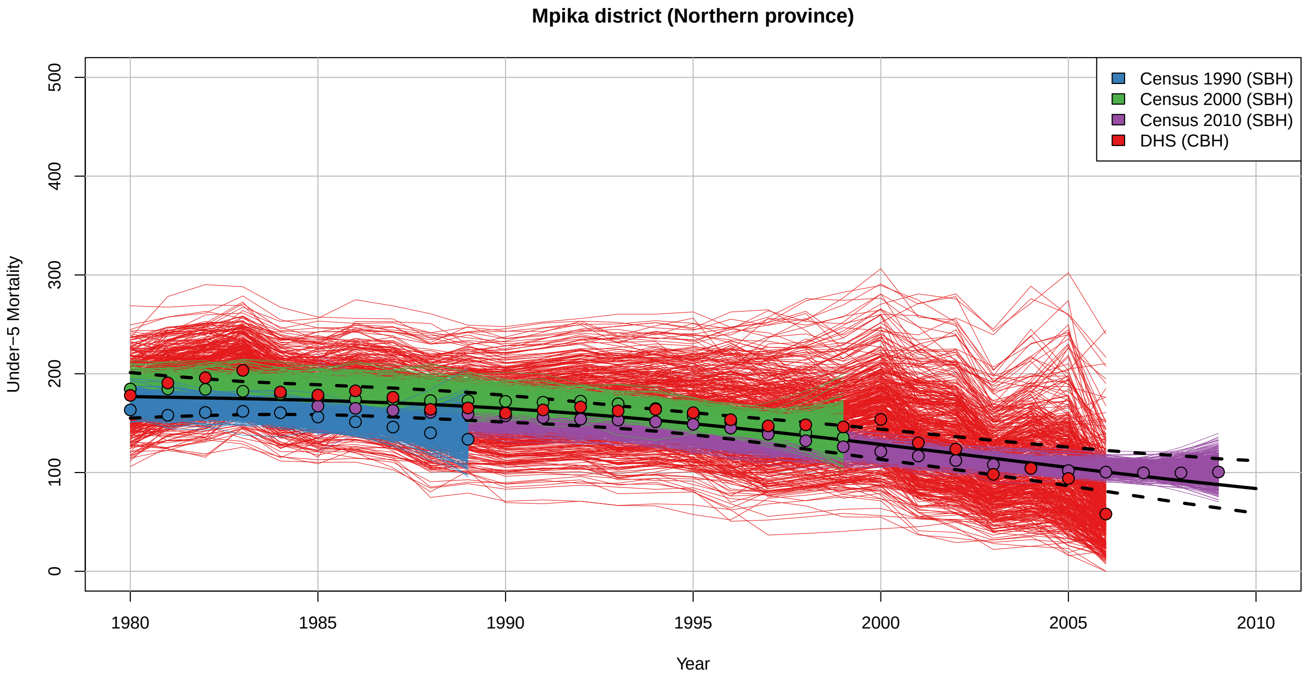

Figure A.51: Under-5 mortality estimates with uncertainty, Mpika district (Northern province)

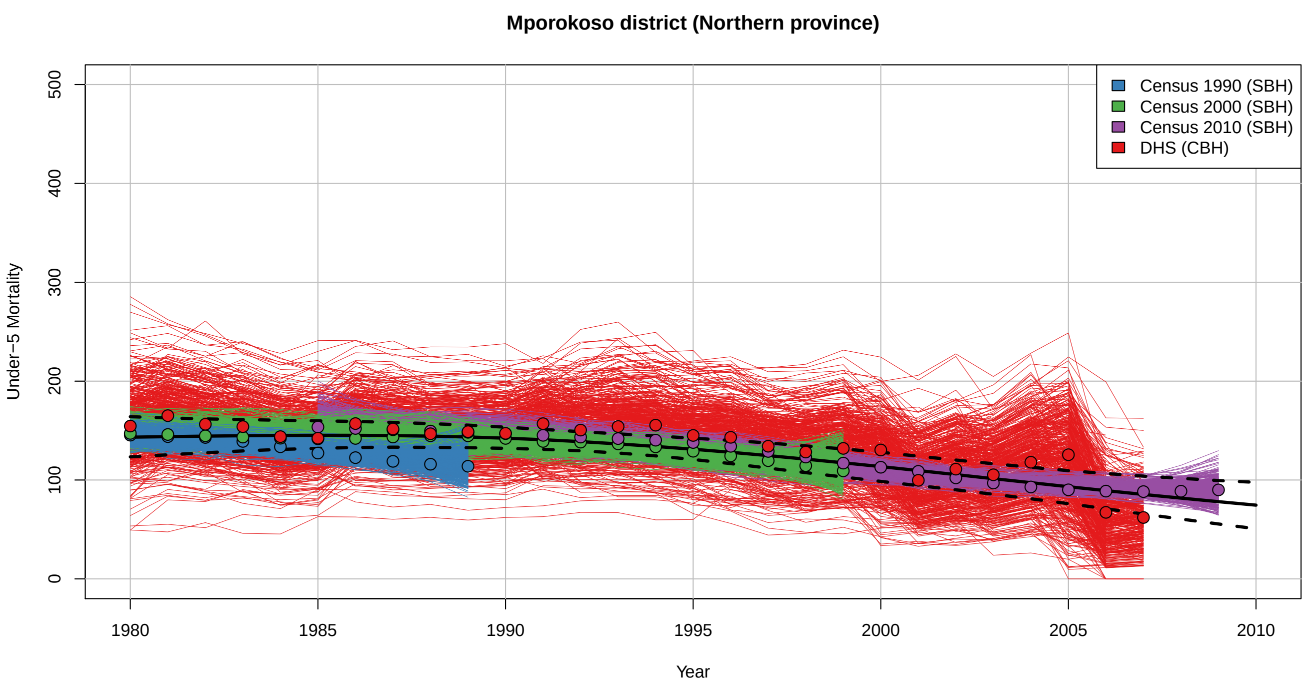

Figure A.52: Under-5 mortality estimates with uncertainty, Mporokoso district (Northern province)

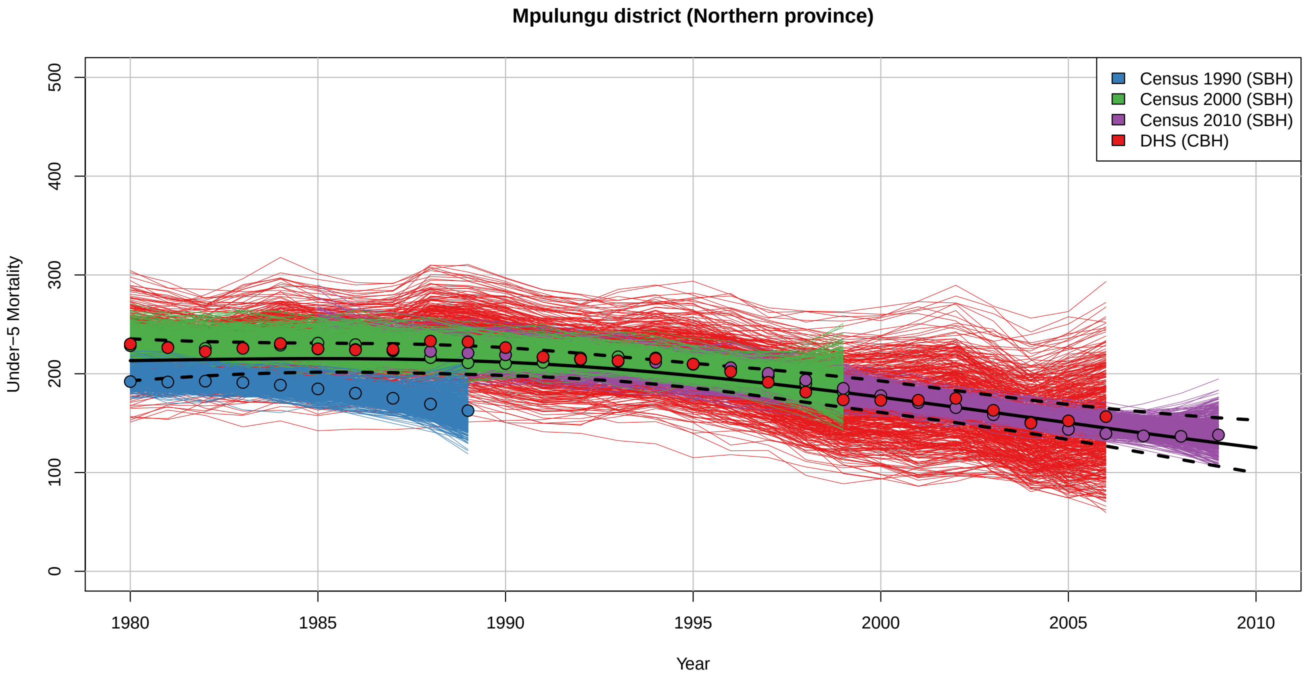

Figure A.53: Under-5 mortality estimates with uncertainty, Mpulungu district (Northern province)

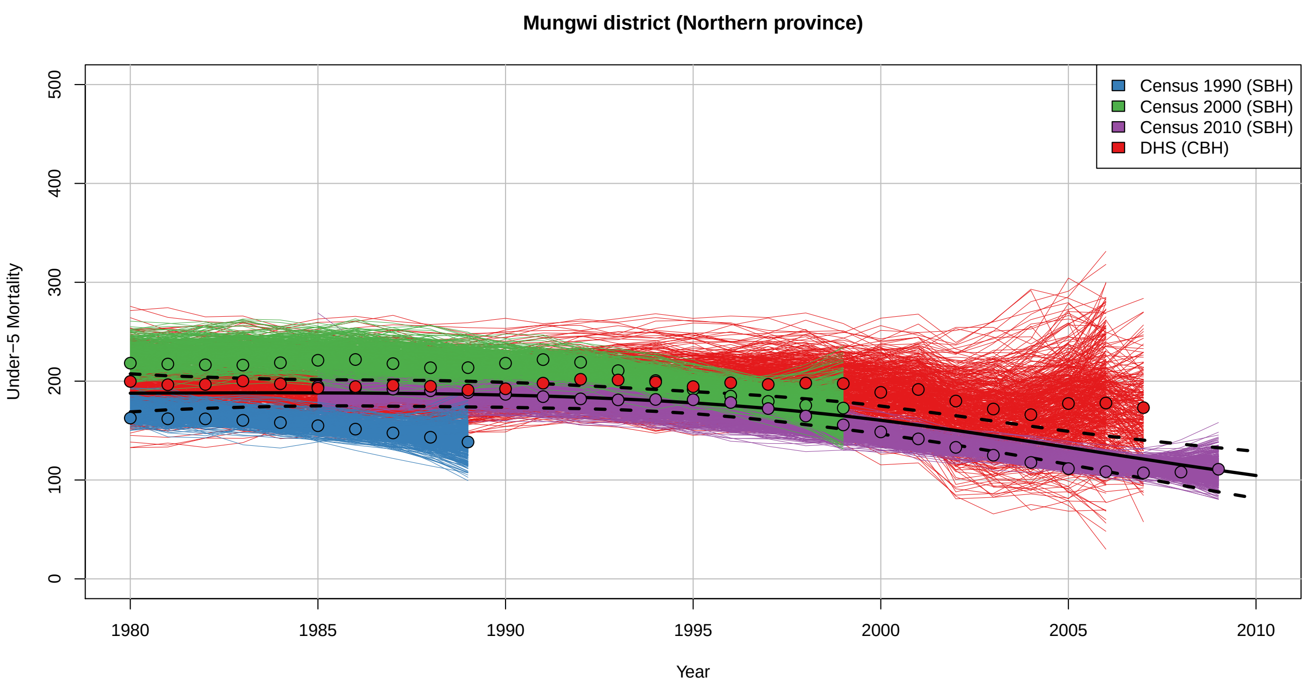

Figure A.54: Under-5 mortality estimates with uncertainty, Mungwi district (Northern province)

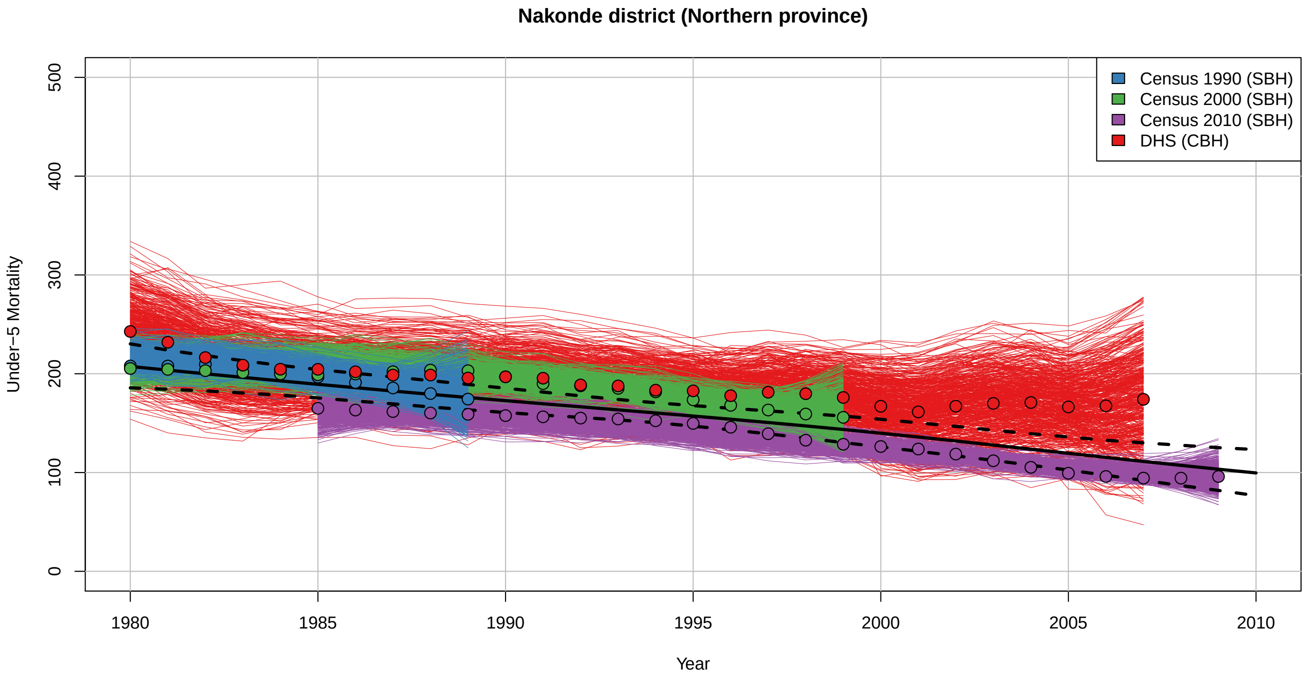

Figure A.55: Under-5 mortality estimates with uncertainty, Nakonde district (Northern province)

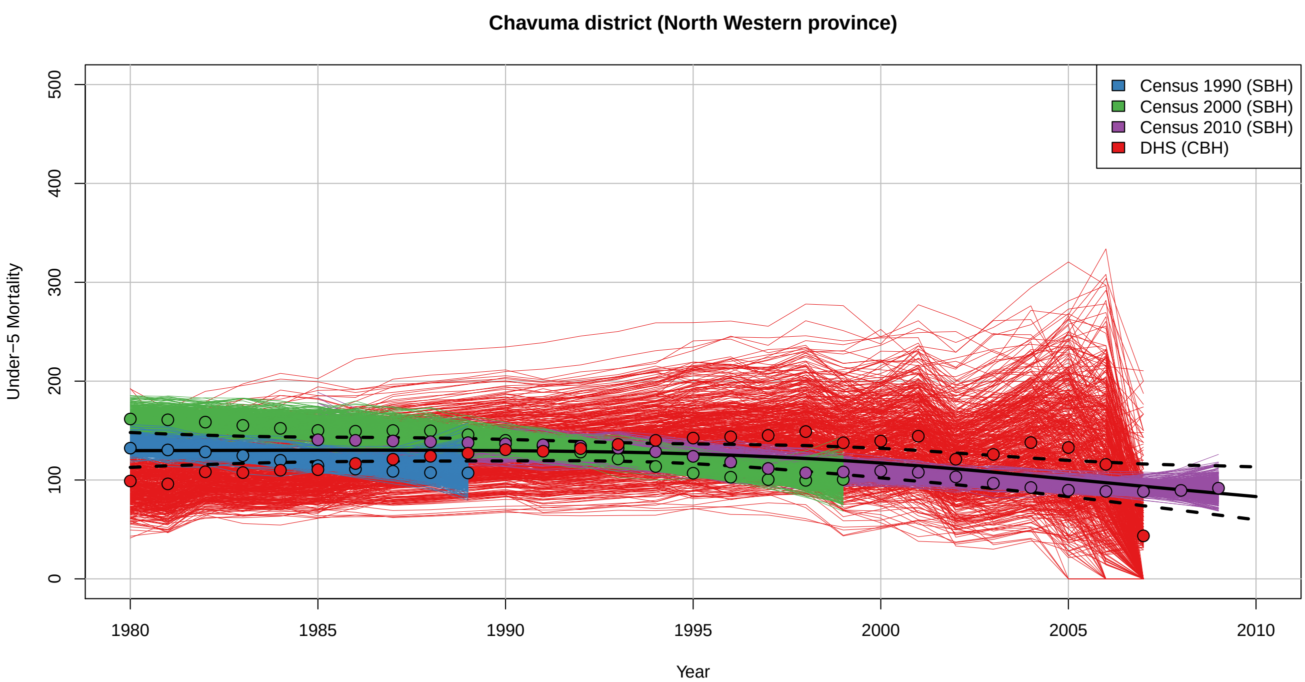

Figure A.56: Under-5 mortality estimates with uncertainty, Chavuma district (North Western province)

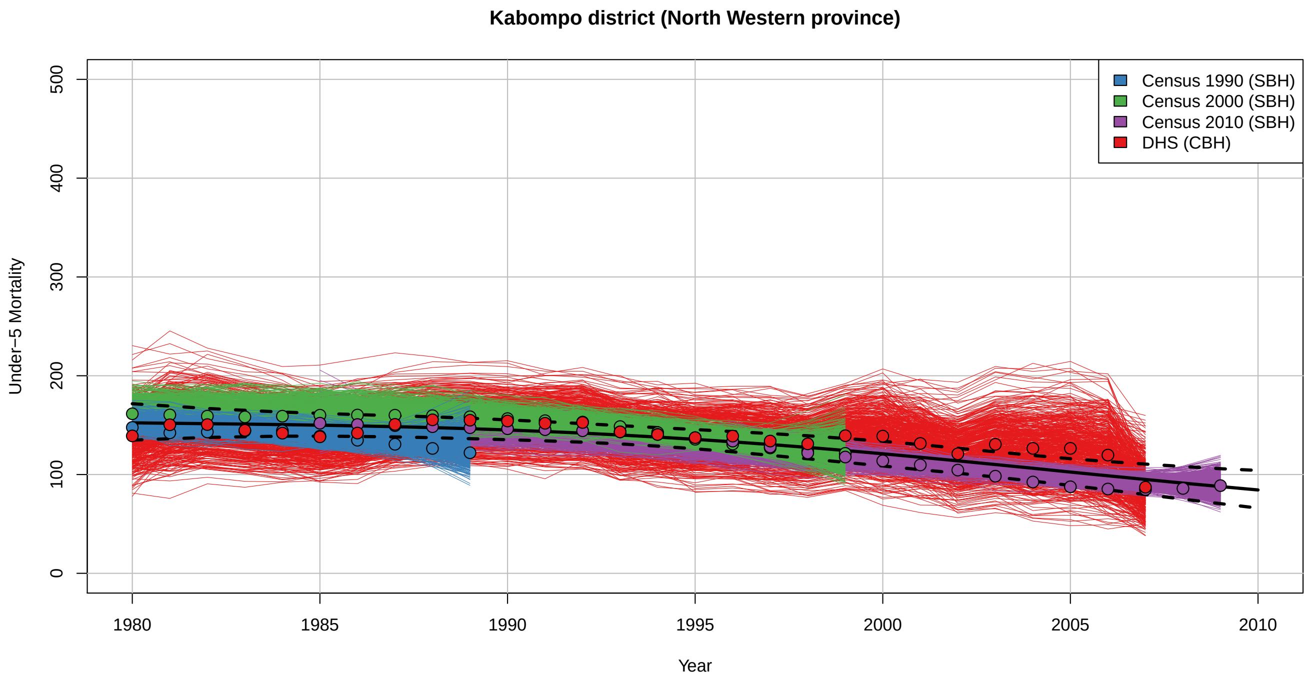

Figure A.57: Under-5 mortality estimates with uncertainty, Kabompo district (North Western province)

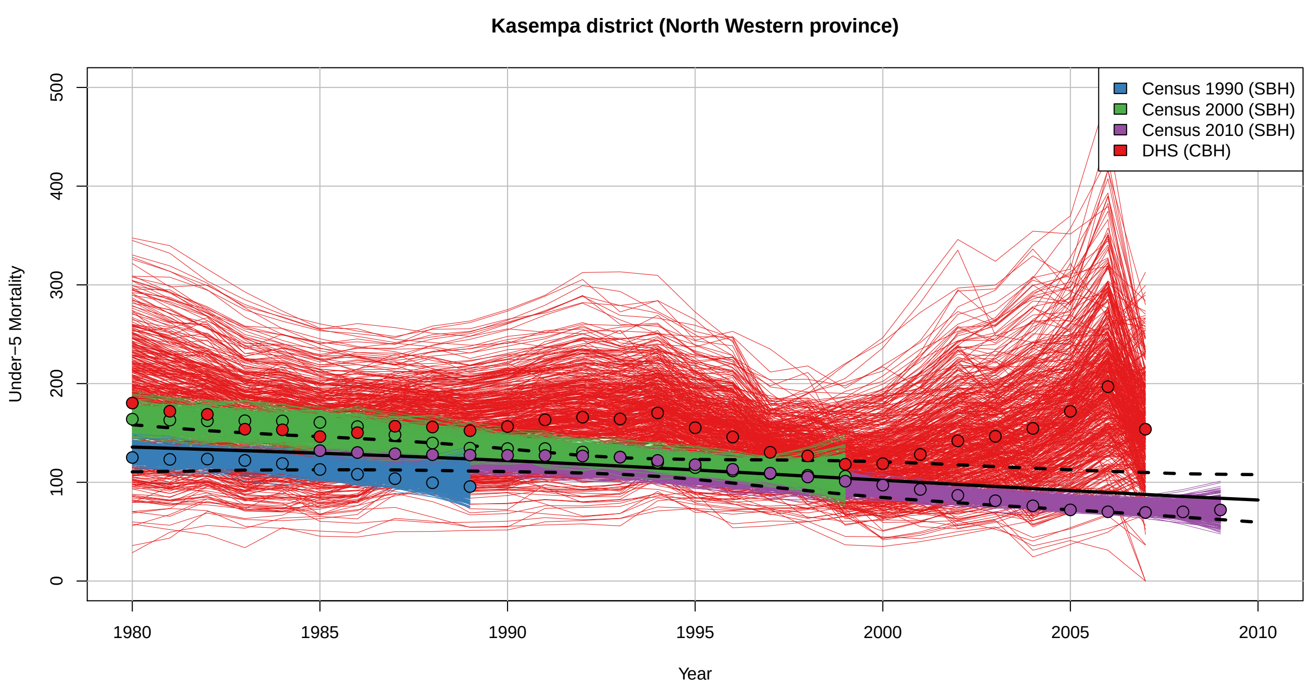

Figure A.58: Under-5 mortality estimates with uncertainty, Kasempa district (North Western province)

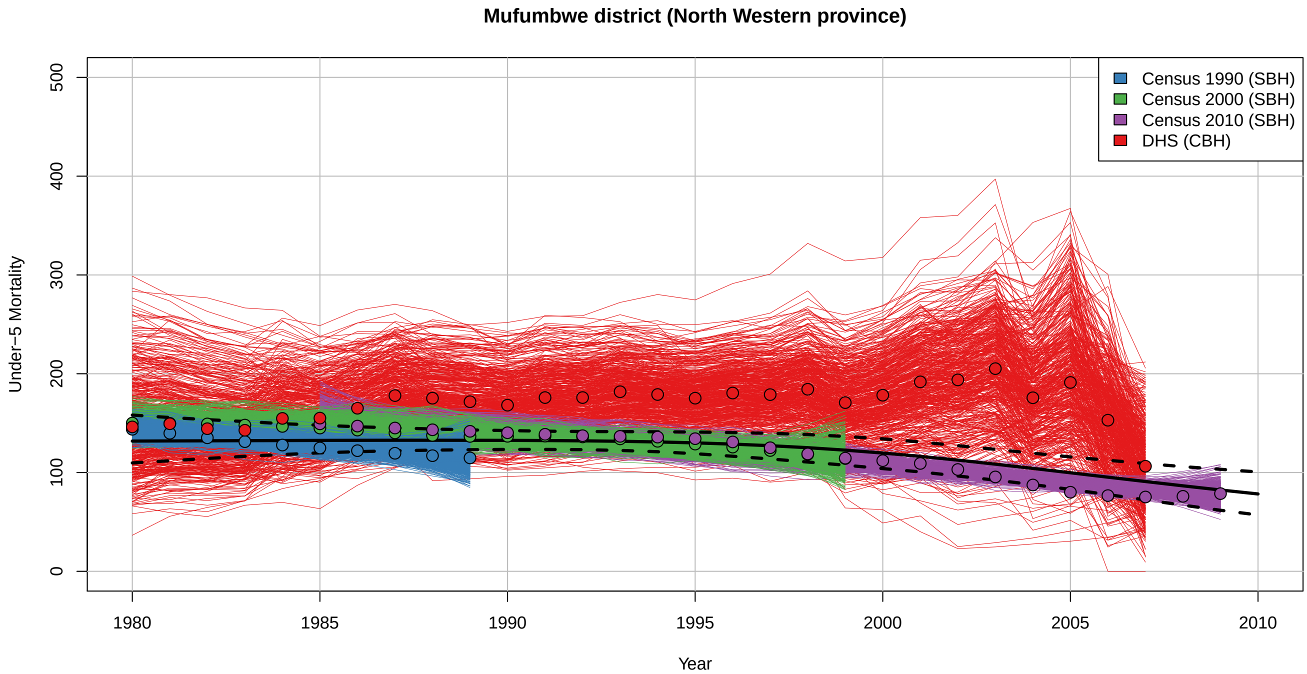

Figure A.59: Under-5 mortality estimates with uncertainty, Mufumbwe district (North Western province)

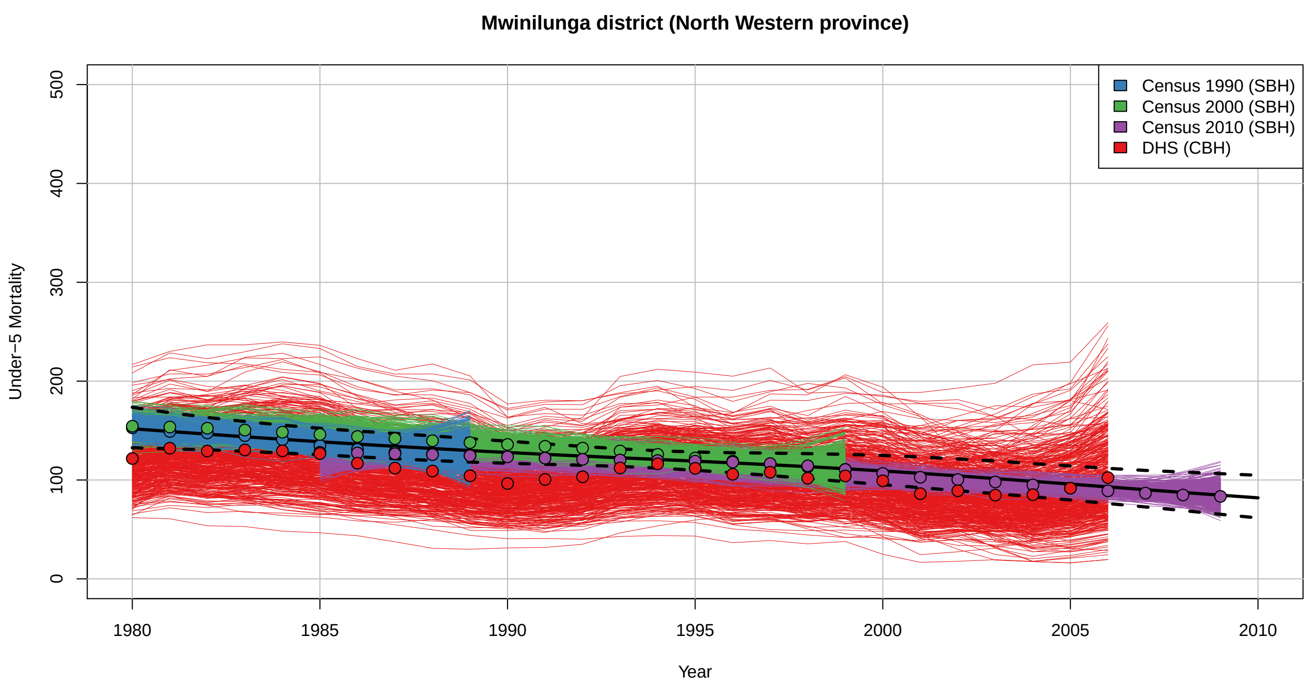

Figure A.60: Under-5 mortality estimates with uncertainty, Mwinilunga district (North Western province)

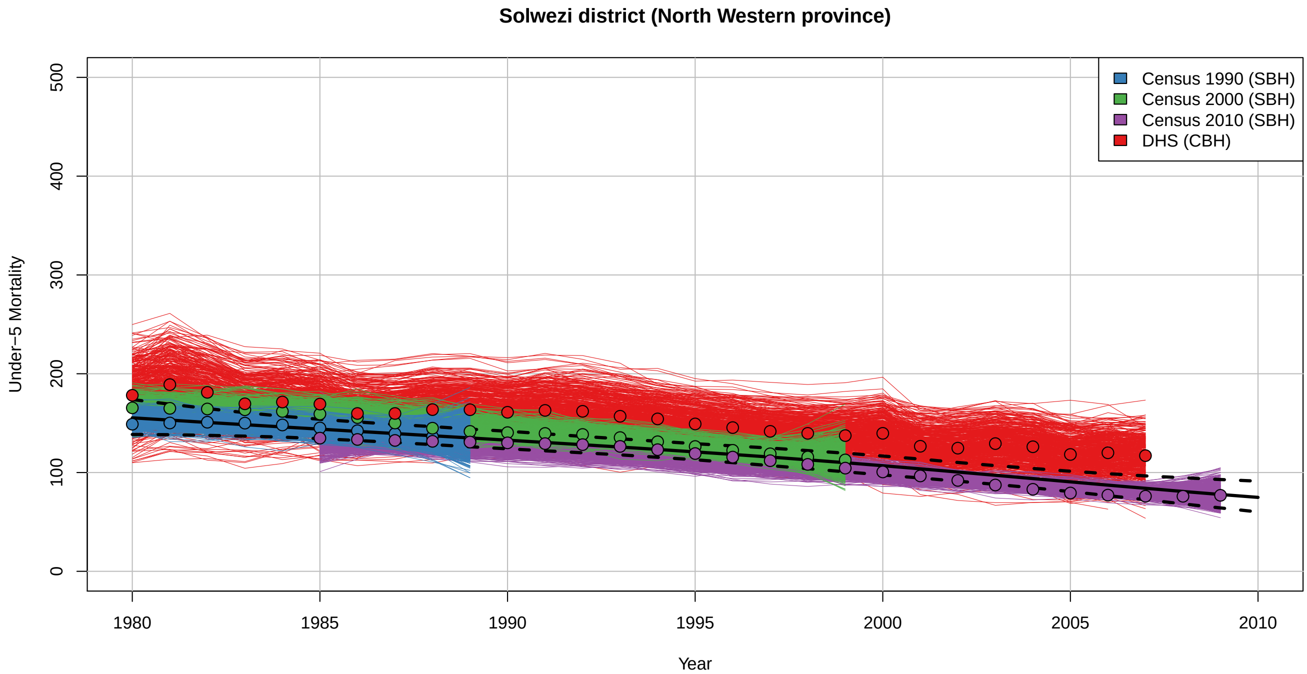

Figure A.61: Under-5 mortality estimates with uncertainty, Solwezi district (North Western province)

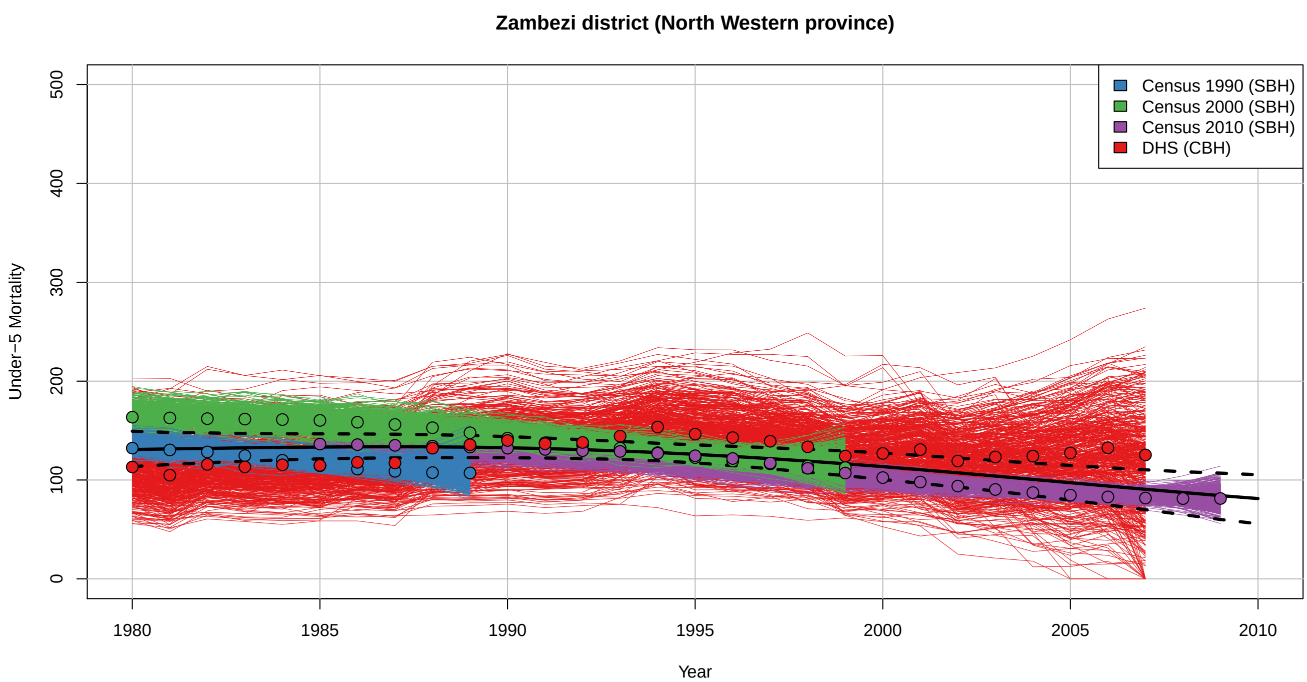

Figure A.62: Under-5 mortality estimates with uncertainty, Zambezi district (North Western province)

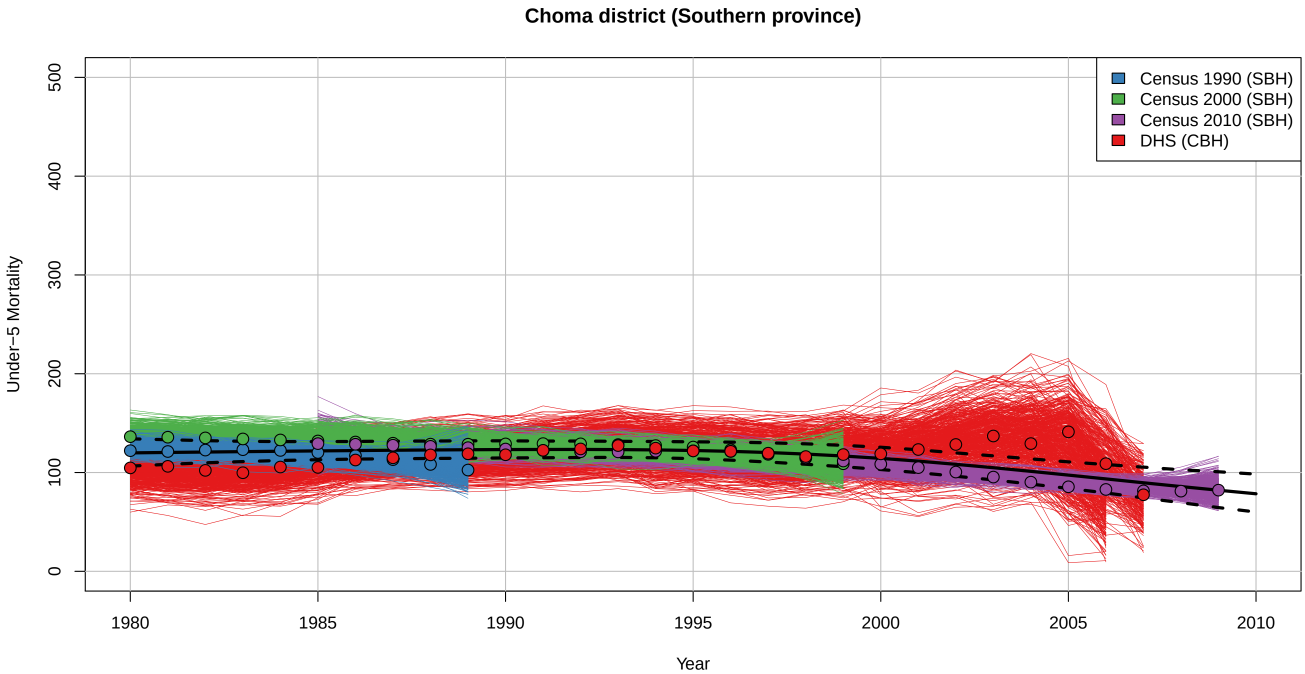

Figure A.63: Under-5 mortality estimates with uncertainty, Choma district (Southern province)

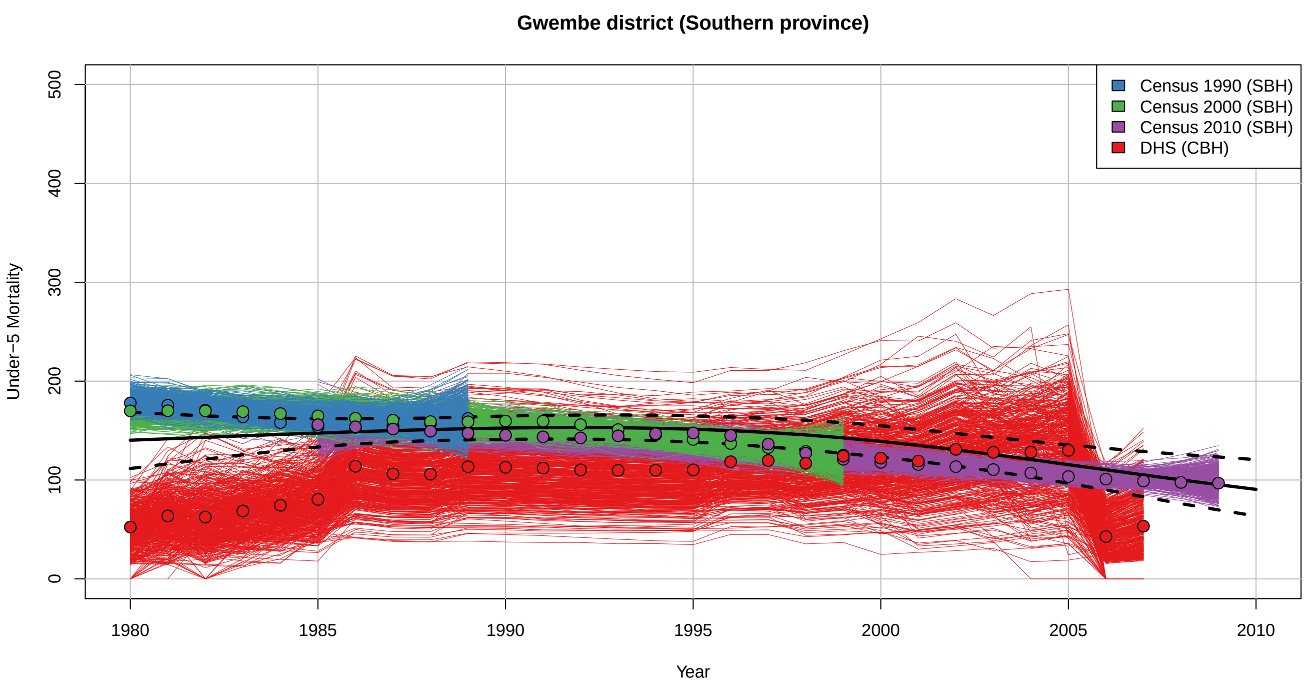

Figure A.64: Under-5 mortality estimates with uncertainty, Gwembe district (Southern province)

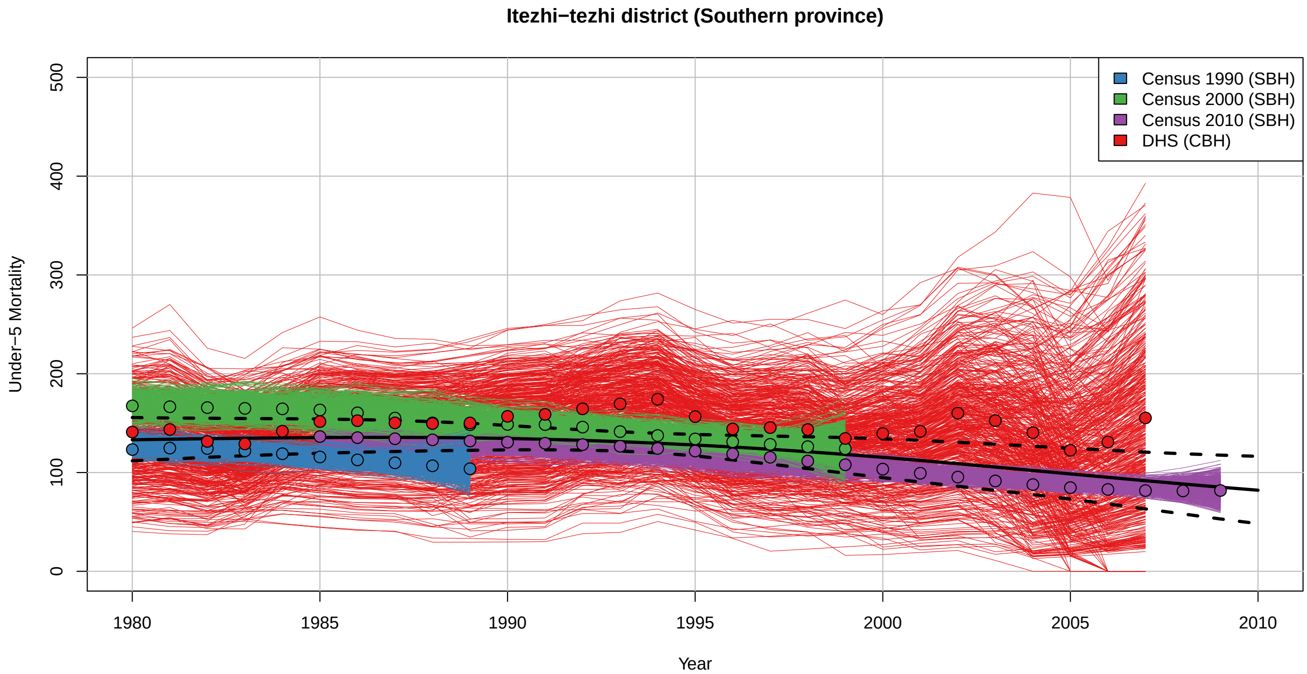

Figure A.65: Under-5 mortality estimates with uncertainty, Itezhi-tezhi district (Southern province)

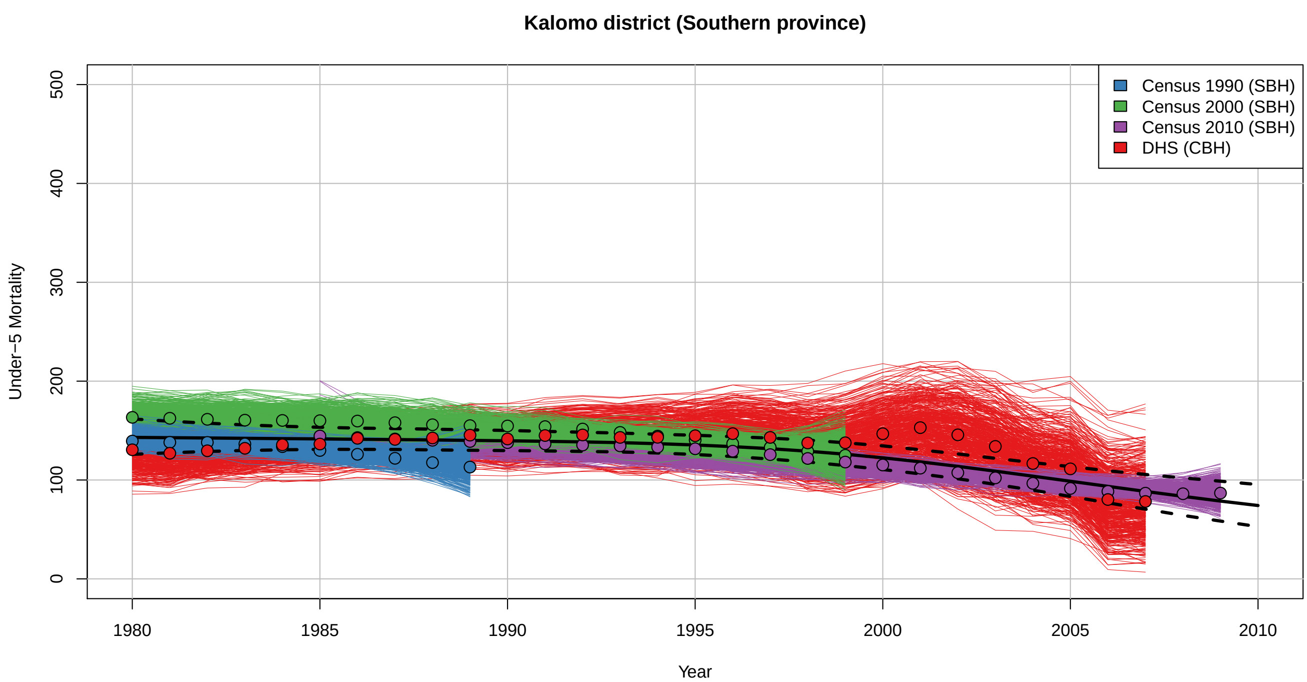

Figure A.66: Under-5 mortality estimates with uncertainty, Kalomo district (Southern province)

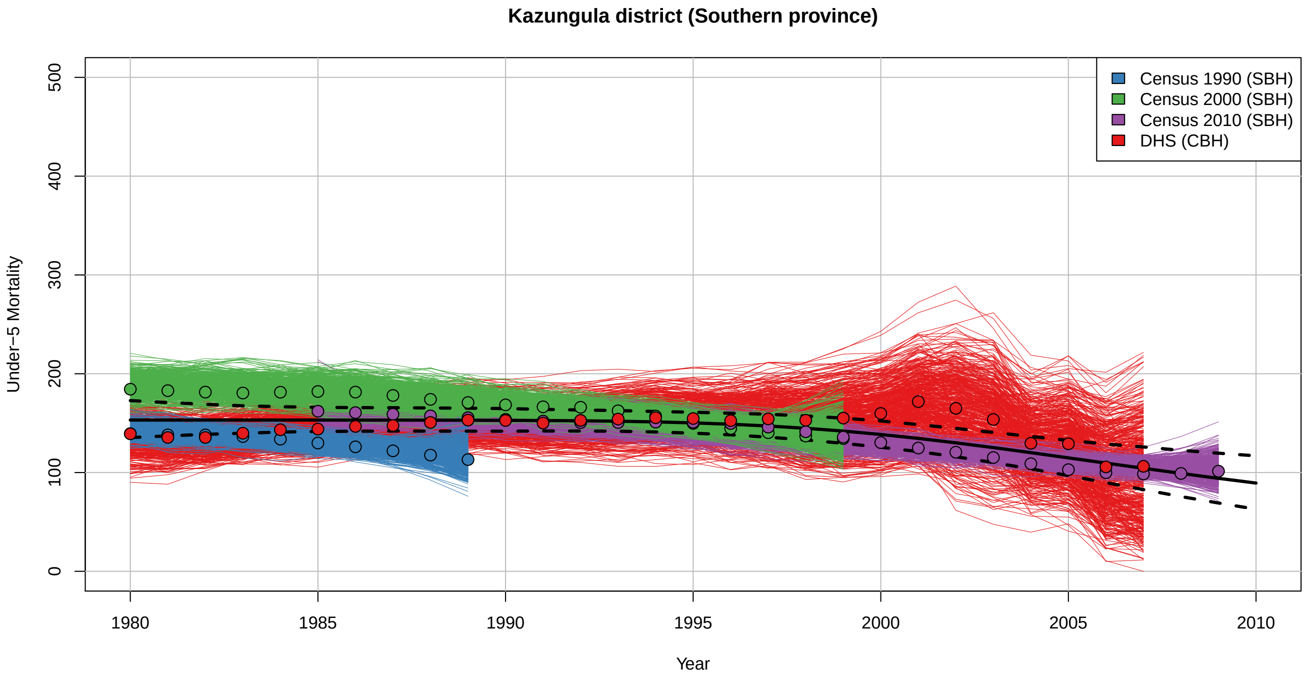

Figure A.67: Under-5 mortality estimates with uncertainty, Kazungula district (Southern province)

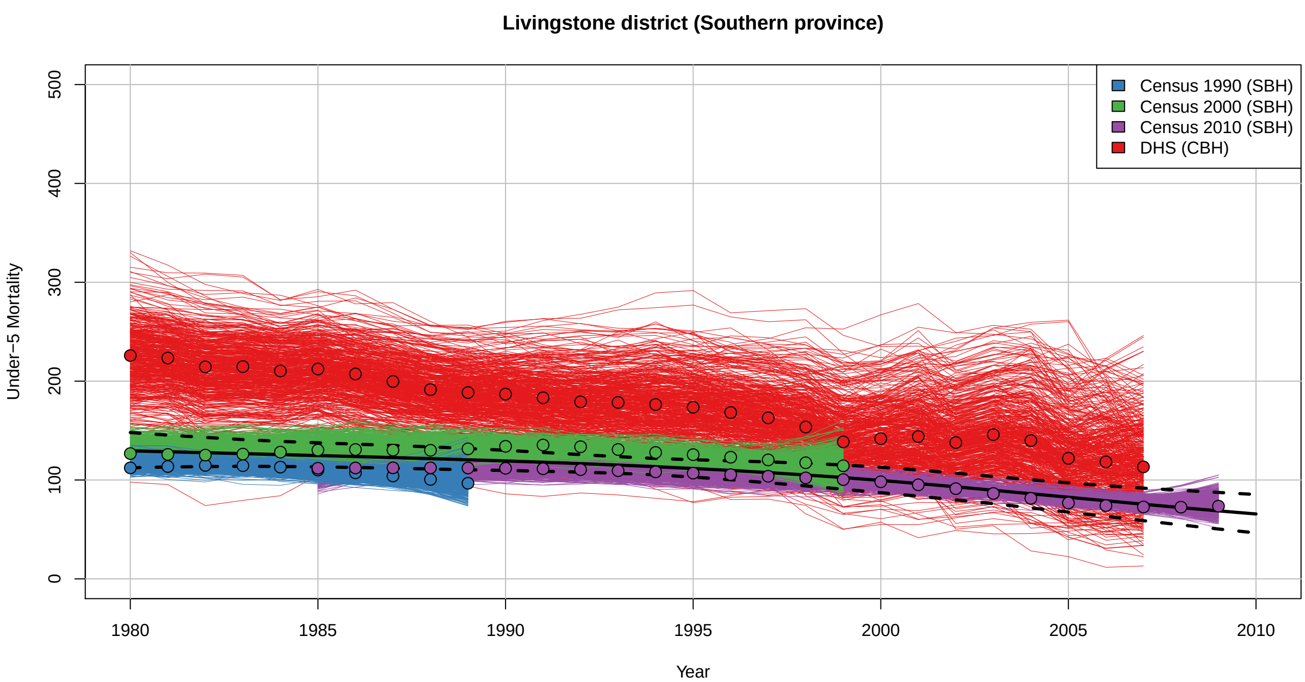

Figure A.68: Under-5 mortality estimates with uncertainty, Livingstone district (Southern province)

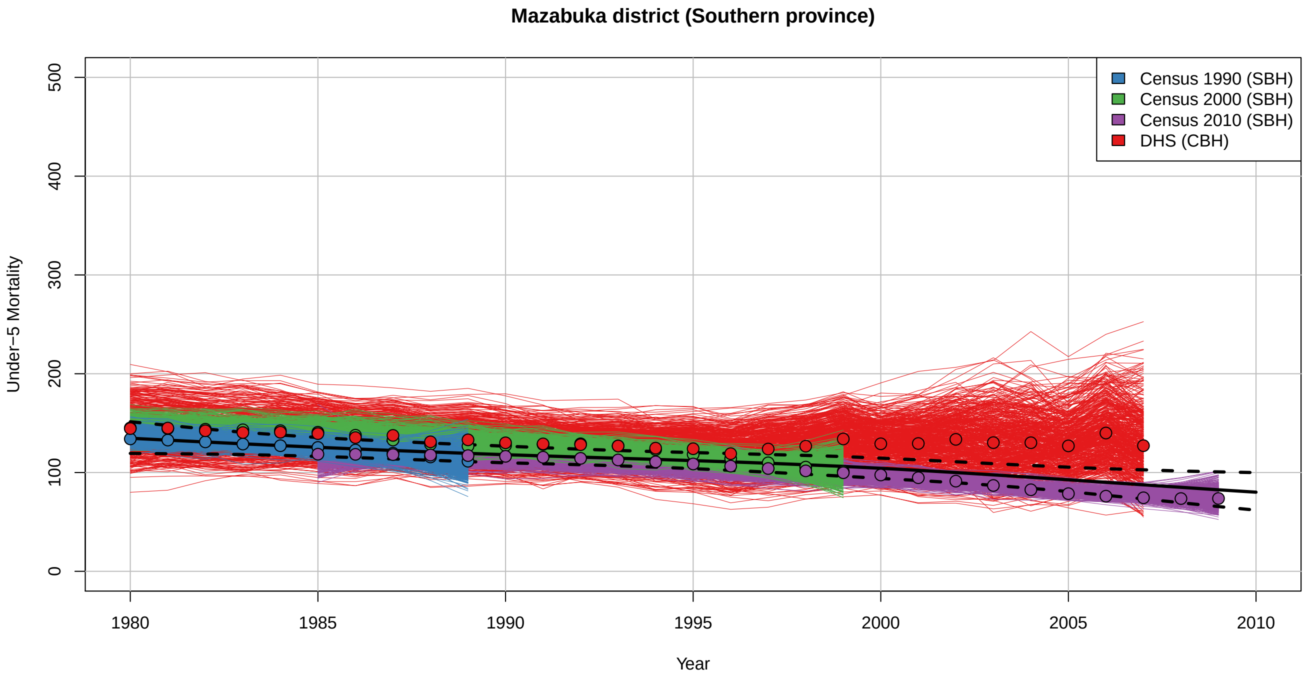

Figure A.69: Under-5 mortality estimates with uncertainty, Mazabuka district (Southern province)

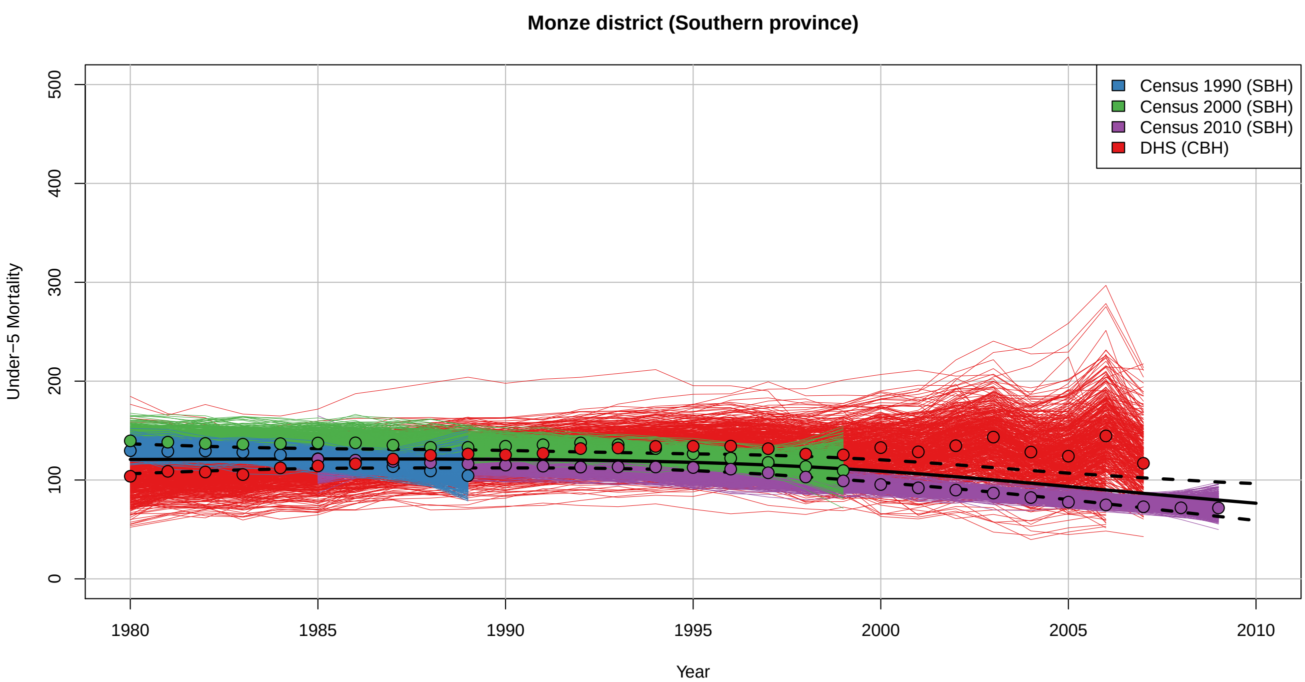

Figure A.70: Under-5 mortality estimates with uncertainty, Monze district (Southern province)

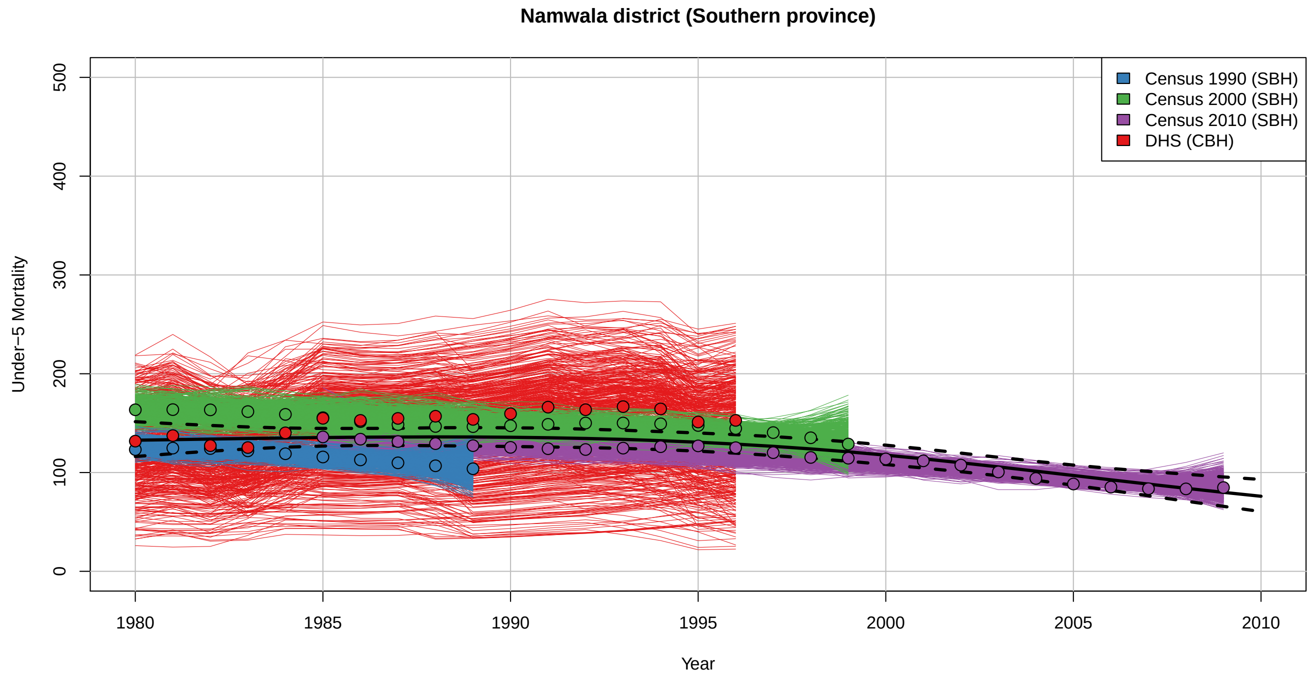

Figure A.71: Under-5 mortality estimates with uncertainty, Namwala district (Southern province)

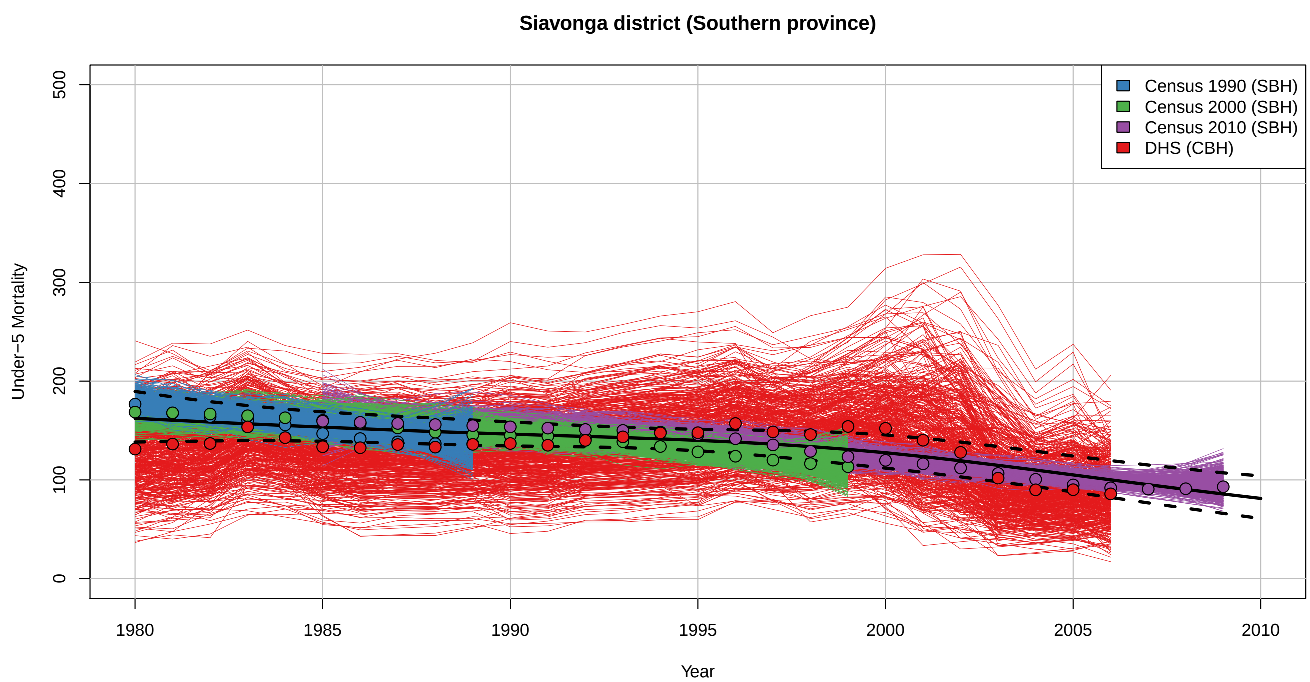

Figure A.72: Under-5 mortality estimates with uncertainty, Siavonga district (Southern province)

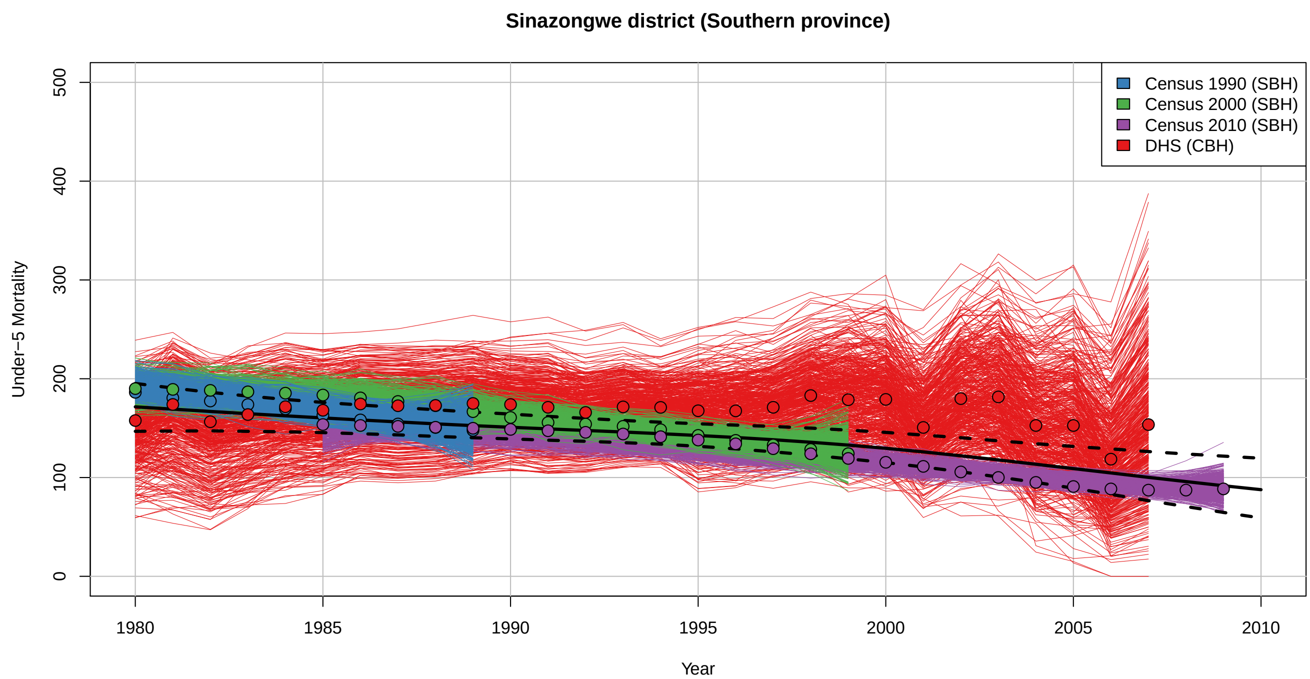

Figure A.73: Under-5 mortality estimates with uncertainty, Sinazongwe district (Southern province)

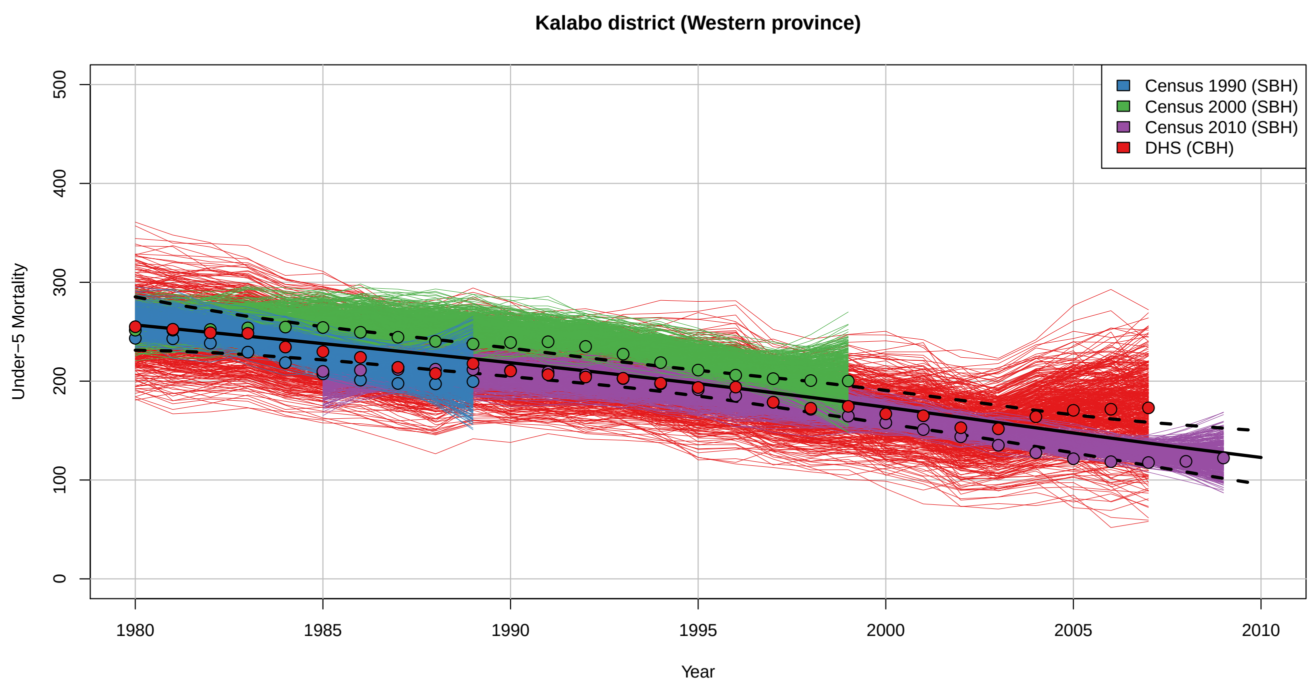

Figure A.74: Under-5 mortality estimates with uncertainty, Kalabo district (Western province)

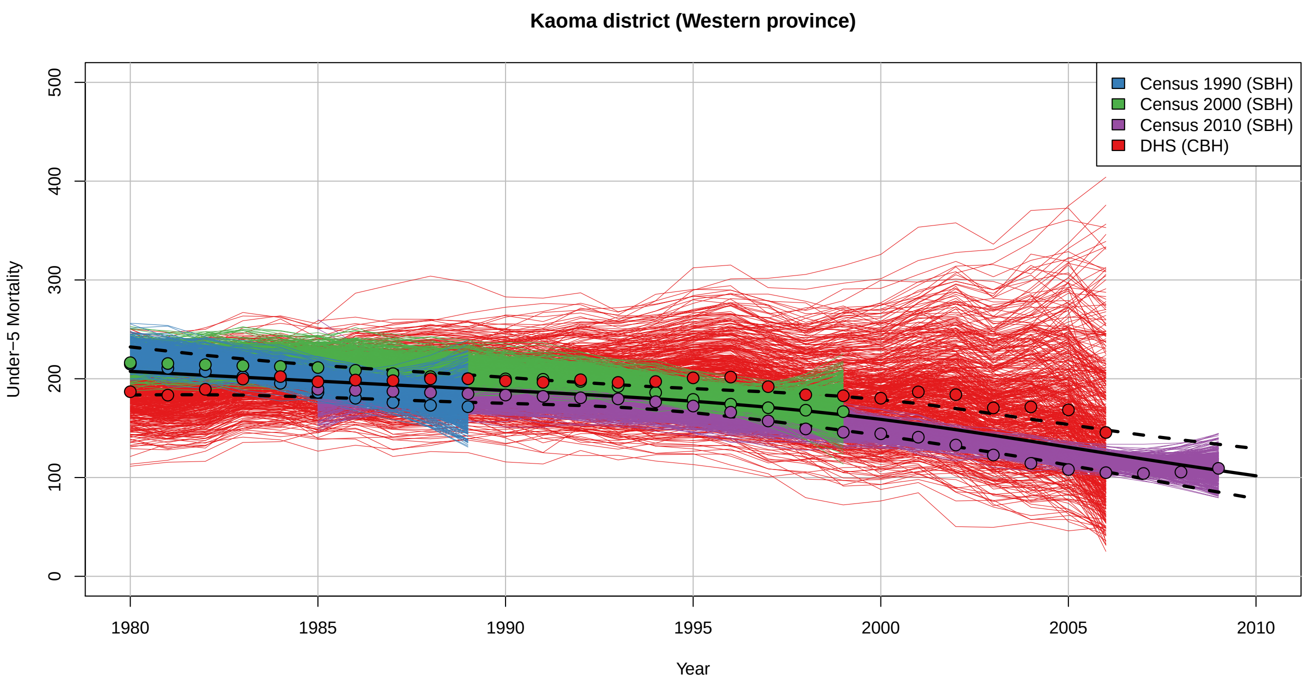

Figure A.75: Under-5 mortality estimates with uncertainty, Kaoma district (Western province)

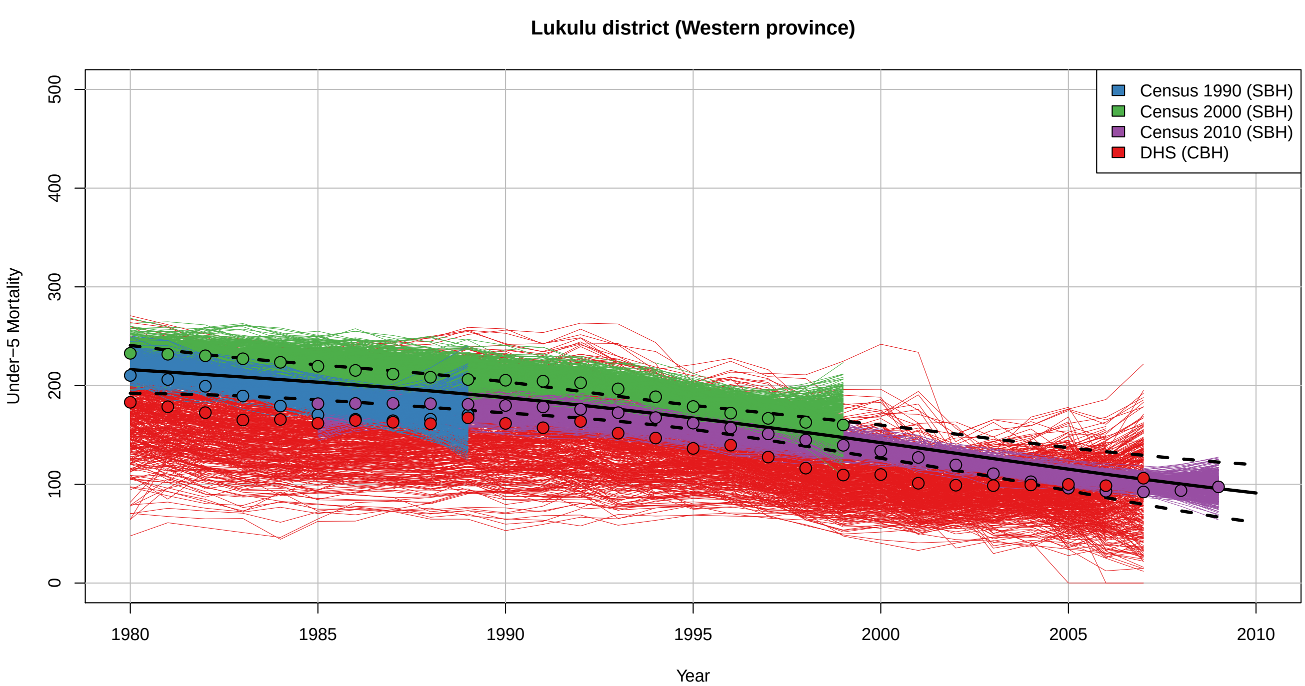

Figure A.76: Under-5 mortality estimates with uncertainty, Lukulu district (Western province)

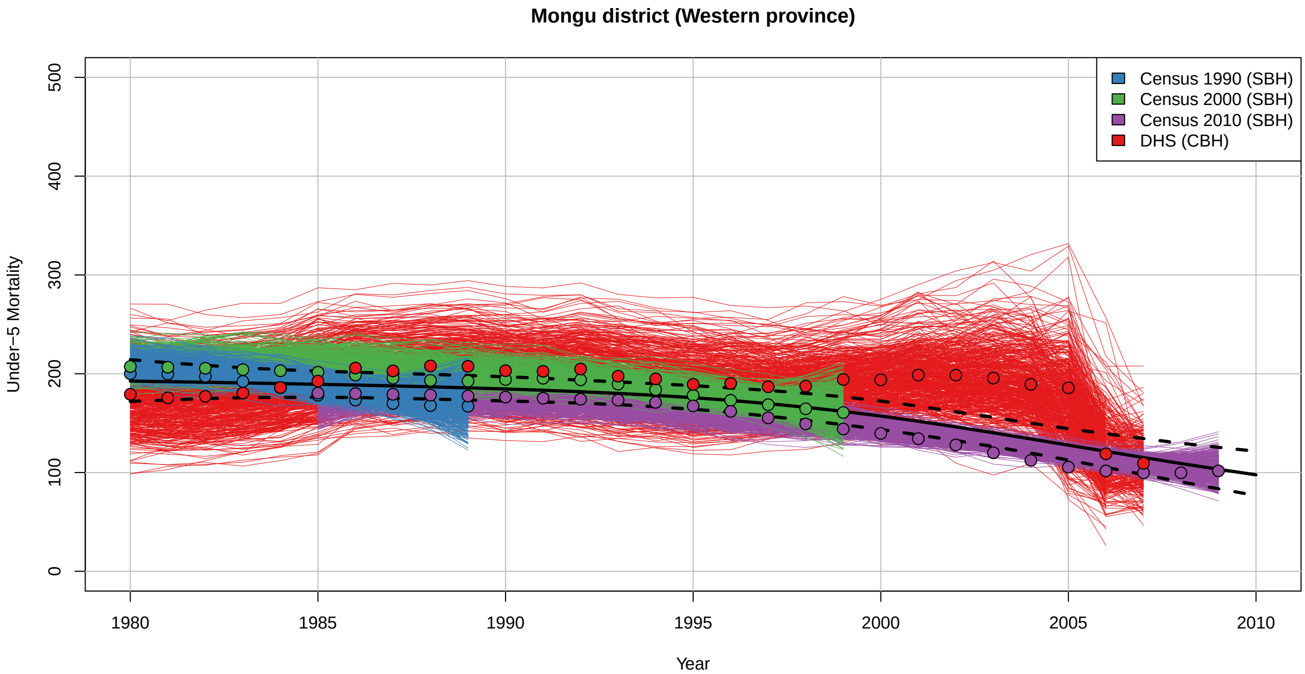

Figure A.77: Under-5 mortality estimates with uncertainty, Mongu district (Western province)

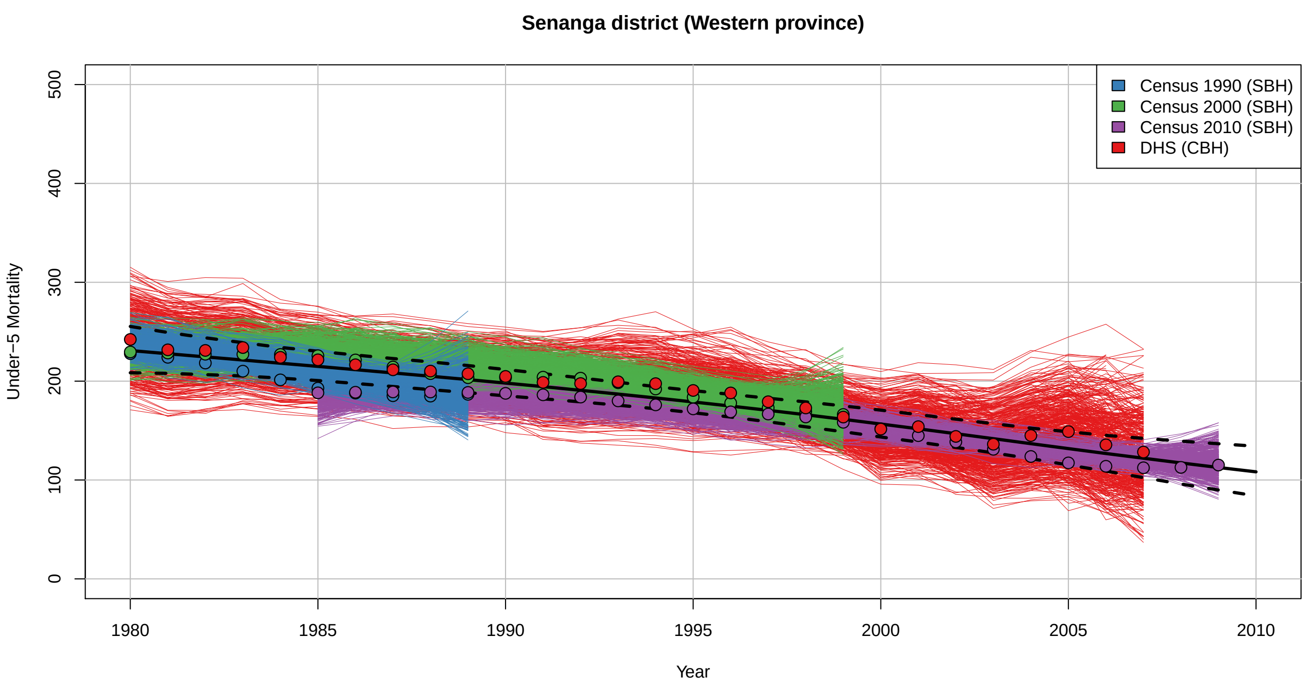

Figure A.78: Under-5 mortality estimates with uncertainty, Senanga district (Western province)

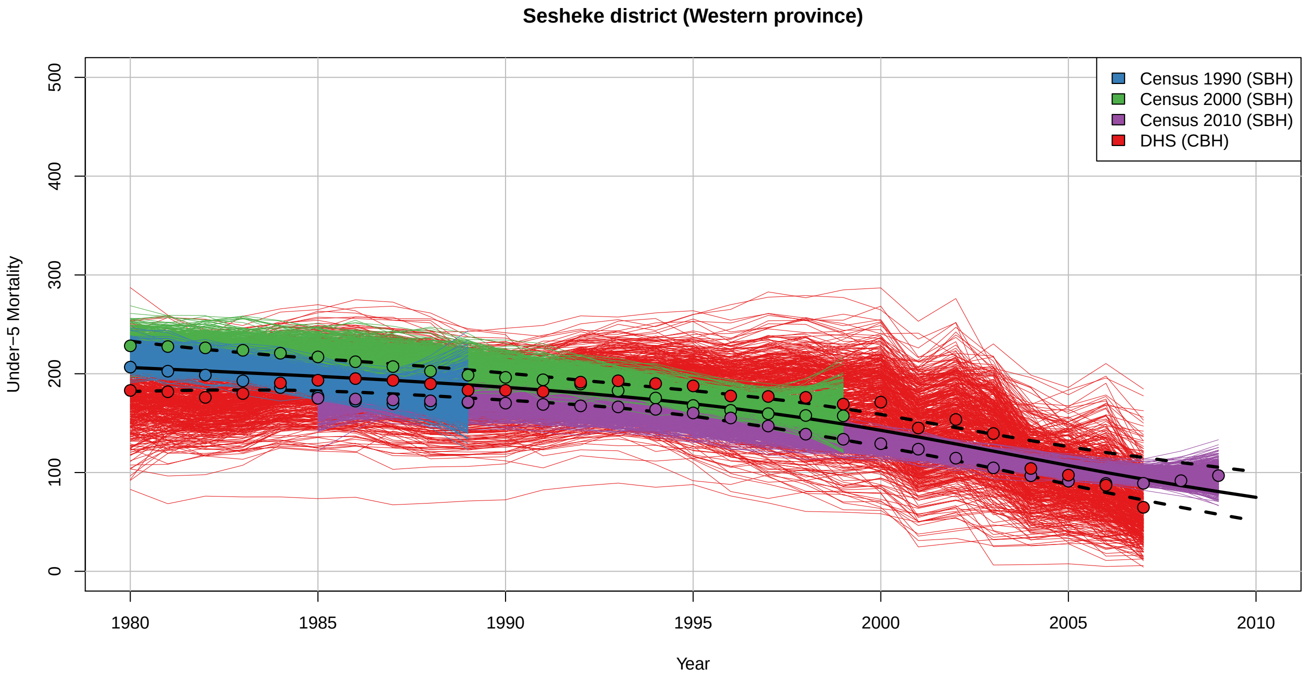

Figure A.79: Under-5 mortality estimates with uncertainty, Sesheke district (Western province)

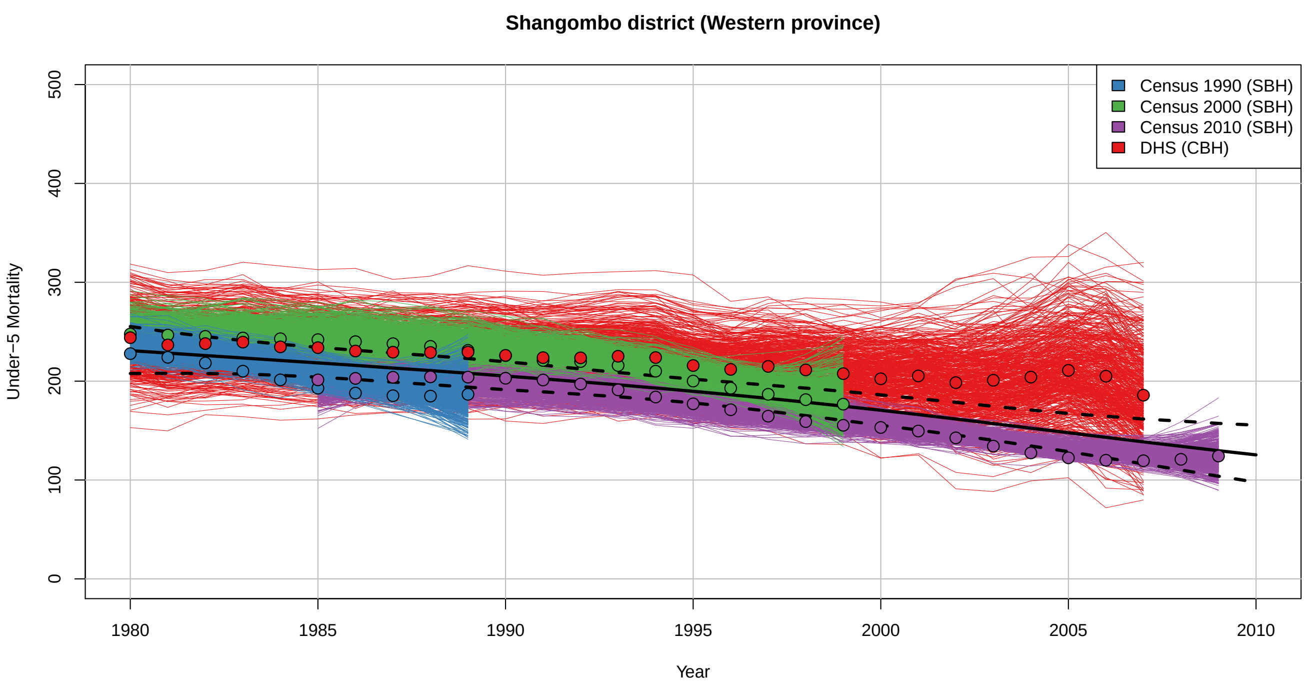

Figure A.80: Under-5 mortality estimates with uncertainty, Shangombo district (Western province)