Empirical Bayes Estimation of Small Area Adult Mortality Risk in Addis Ababa, Ethiopia

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Abstract

In sub-Saharan Africa, analysis of neighborhood health differentials has been inhibited by the paucity of data as well as quality concerns. This paper takes advantage of near-complete mortality data collected in Addis Ababa via ongoing burial surveillance in order to explore the relationship between AIDS mortality and selected neighborhood characteristics. We make use of Bayes' Theorem to generate smoothed age- and sex-specific probabilities of death by district between the ages of 15 and 59, distinguishing between AIDS and non-AIDS mortality using estimates based on lay diagnosis. Results (may) show the degree of unexplained variance in AIDS-attributable mortality to be significantly higher than for mortality due to other causes after accounting for selected socioeconomic determinants. Since death due to AIDS in Addis Ababa is highly correlated with HIV illness due to the lack of available treatment, the results provide useful insight into the spatial characteristics of urban HIV transmission.

1 Introduction

The availability of geographically coded health and population data, together with advances in computing and statistical methods, have allowed serious exploration of small-area health statistics in recent years. Such spatial analyses have investigated behavioral or environmental aspects of disease, access to health care, and the social and economic determinants of morbidity and mortality. While the estimation of rates in geographic areas with small population sizes does pose special challenges, a variety of statistical methods exist that adequately address volatility in rates. In sub-Saharan Africa, however, such analyses of mortality differentials have been inhibited by a paucity of data on adult mortality as well as concerns over quality [1].

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In Ethiopia, as throughout most of Africa, the public health community has relied on indirect estimations of mortality based on data sources such as hospital records or household surveys. Indirect estimation has been further complicated in many settings by the HIV/AIDS epidemic and its unprecedented demographic consequences. In Ethiopia, the first case of AIDS was reported in 1986[2]. By 1997, HIV-1 (predominantly subtype C) seroprevalence in the capital city of Addis Ababa was estimated to be 10-27% among pregnant women and 47-59% among prostitutes [3],[4],[5]. In 2001, the government estimated HIV prevalence to be 6.6% for the country as a whole (over 3 million people) and 15.6% among the roughly 2.6 million residents of Addis Ababa [6],[7]. Despite indications of declining HIV prevalence in successive cohorts of pregnant women attending antenatal care in the late 1990s [8], an estimated 60-70% of adult deaths in 2001 were attributed to AIDS [9],[10].

This analysis takes advantage of near-complete mortality data currently being collected in Addis Ababa through ongoing surveillance of burial sites initiated by the Ethiopia-Netherlands AIDS Research Project [11],[5] and currently funded by the AIDS Foundation in Amsterdam. We combine this data with population forecasts to generate age- and sex-specific mortality rates for adults (ages 15-59) for 304 districts using an empirical Bayes approach to smooth random variability due to limited exposure. Empirical Bayes estimation of small area rates combines a prior distribution (based on age- and sex-specific rates for Addis Ababa as a whole) with area-specific rates resulting in posterior estimates with decreased standard errors. Finally, we analyze the relationship between several determinants of mortality with the posterior estimates of the probability of dying between ages 15 and 59 and investigate their degree of correlation with estimates of HIV prevalence based on lay diagnosis. Further analysis will demonstrate that these results are largely insensitive to the error and assumptions associated with the population forecasts.

2 Data

2.1 Estimates of Population

Estimates of the age- and sex-specific populations by small area for Addis Ababa are derived from the most recent national census conducted in 1994. Addis Ababa was estimated to have roughly 2.1 million inhabitants in the 1994 Census. Table 1 shows summary statistics of selected social and economic characteristics of these districts. In projecting the populations to the year 2002 (the midpoint of the mortality data) we make use of survivorship data derived from demographic sites forming part of INDEPTH, a growing network of community-based field stations in Asia and sub-Saharan Africa which collect population-based health and demographic data [12]. Mortality data for the small areas within Addis Ababa have been acquired through ongoing burial surveillance. The surveillance system covers all municipal cemeteries except one, where such data on the deceased is unknown (accounting for roughly 15% of total deaths). The information recorded in the surveillance includes basic socio-demographic background characteristics as well as the lay diagnosis of the cause of death. This information is provided by the relatives of the deceased while fulfilling the administrative requirements at the cemetery prior to burial. Since May 2002, additional information is collected on the birthplace of the deceased, his/her ethnicity, religion and marital status. Araya and colleagues elaborate a method for monitoring AIDS mortality in Addis Ababa based on the lay diagnoses information collected through this surveillance[9].

[TABLE 1: Social and Demographic Characteristics of Areas]

2.2 Surveillance of Burial Sites

The most apparent bias in the burial registration data is the underreporting of infant deaths [13], and this is one of the primary reasons that we limit the focus of this study to adults. Another evident weakness of the data concerns the burial of anonymous bodies at the Baytewar cemetery. Baytewar is a municipal cemetery where corpses are buried of individuals without close relatives or friends willing to facilitate a funeral service ("baytewar" is an Ethiopian Amharic word signifying someone who is lonely or socially isolated). In 2001, the Baytewar cemetery alone accommodated 14% of the deceased. The majority of its burials are of unidentified individuals (61.5%) for whom we often lack the most essential demographic background information, and these are mostly comprised of infants[1]. These and other issues regarding the organization and coverage of the burial surveillance are discussed in more detail in Sanders et al.[13], Araya et al.[9], and Reniers et al.[10]. For the purposes of the present study it is sufficient to note that the crude death rate derived from the first three months of these surveillance data (CDR=7.8) is close to that implied by the official medium variant population projections (CDR=7.6), suggesting that the burial surveillance is nearly exhaustive. It should be mentioned, however, that the official population projections do not account for the impact of AIDS, such that the actual crude death rate could be up to twice this level. Irrespective of its magnitude, it is assumed that the degree of underreporting is more or less constant across districts and thus has a minimal effect on the posterior relative risks. The age at death is unknown in approximately 6% of the individuals in the dataset, and males constitute approximately 70% of this subgroup.

3 Methods

3.1 Population Projection

As the most recent population census in Ethiopia took place in October of 1994, it is necessary to project these estimates forward to the year 2002. We specify the population vector N for sex x and district i at time t to be the function:

$$\mathbf{N}_{xi(t+1)} = \mathbf{N}_{xit}\mathbf{A}_{xit}+\mathbf{I}_{xi}-\mathbf{E}_{xi} \tag{1}$$

[1]Neonates and infants that die before the naming ceremony (40 days for boys and 80 days for girls) often end up in Baytewar cemetery.

where $\mathbf{A}$ is a Leslie matrix containing age-specific probabilities of survival along its subdiagonal[14], $\mathbf{I}$ is the number of annual immigrants, and $\mathbf{E}$ is the number of annual emigrants. We estimate the annual number of immigrants to each district from the 1994 census data using Poisson regression where the expected number of immigrants based on the age, sex and area of destination of those immigrants who report having arrived in their current district of residence within the year prior to the 1994 census:

$$\hat{\mathbf{I}}_{xij} = \beta_1(\mathbf{I}_{Age})+\beta_2(\mathbf{I}_{Sex})+\beta_3(\mathbf{I}_{Area}) + \varepsilon \tag{2}$$

While information on whether or not an individual has immigrated into the their current district of residence (and, if so, how recently) is available in the census, such district-level information on emigration is lacking. The only information available on emigration are CSA estimates of net emigration of individuals from Addis Ababa by age and sex, and so we apportion these emigrants among the districts according to population size. This is a common problem confronted by small area studies and the effect of neglecting migration can be potentially significant[15]. Polissar (1980) and Kliewer (1992) have quantified the effects of neglecting migration on the estimated relative risks for a number of cancer sites and disease latency periods using estimates of age-dependent migration flows in the United States. In general, the bias increases with latency time, decreases with age (older people move less frequently) and decreases at higher levels of spatial aggregation (migration is over small distances). The scale of the bias varies strongly by disease latency period, migration rate, geographical scale, and true underlying relative risk [16][17].

A common phenomenon observed in data from vital registration and household surveys is the tendency to misreport one's age. The resulting age-heaping at the population level reflects normative influences as well as poor memory and simple ignorance. In the census data for Addis Ababa, we observe heaping at those adult ages which are multiples of five, as well as at age 18. In order to minimize distortions in the population projections, we fit a succession of third-degree polynomials to the reported population, expressed as numbers of persons under ages $a + 3$, $a + 8$, $a + 13$, and $a + 18$, where a is a multiple of five. We then compute the values of these polynomials over their central ranges in order to obtain a smoothed single-year age distribution [18].

An additional challenge faced in projecting population estimates for Addis Ababa results from the acceleration in AIDS-related mortality over the period 1994-2002. We estimate sex-specific survivorship probabilities for each year during the period with the aid an adult mortality schedule selected from among the INDEPTH model life tables for sub-Saharan Africa [12]. In order to account for the substantial effect of AIDS on both the level and distribution of mortality by age and sex, we project the population to 2002 using the INDEPTH life table, and then use the projections to calculate p_x for the year 2002 using the burial surveillance data. We specify the annual survivorship probabilities for the interim period as the linear interpolation of the survivorship probabilities observed in the 1994 AIDS-free mortality schedule and those observed in 2002 based on burial surveillance.

3.2 Estimation of Relative Risk

The Poisson distribution arises naturally in the study of data taking the form of counts and is frequently used in epidemiology for modeling disease incidence. If a data point y follows the Poisson distribution with rate θ, then the probability distribution of a single observation y is

$$p(y|\theta) = \frac{\theta^y e^{-\theta}}{y!}, \text{ for } y = 0, 1, 2, ... \tag{3}$$

We assume that the rates of adult mortality in Addis Ababa are independent across areas such that the number of deaths y for sex x in area i is an observation on an independent Poisson random variable with an expected mean value m_{xi}. The relative risk is the observed count divided by the estimated expected value, m_{xi} multiplied by 100:

$$\mathrm{RR}_{x\mathrm{i}} = 100 * \frac{y_{xi}}{\hat{u}_{xi}} \tag{4}$$

Insofar as many of the areas within Addis Ababa have small population sizes, the observed count data are not sufficient for general comparisons of mortality risk. As a result, a number of researchers have proposed Bayesian methods in order to produce a measure of risk which takes estimation precision into account [19],[20],[21],[22],[23]. Early applications to the modeling of disease risk have been presented by Clayton and Kalder [24] as well as Manton and colleagues [25], and a comprehensive review can be found in Clayton and Bernardinelli [26]. Bayesian statistics is concerned with estimation where prior knowledge or beliefs about parameters of interest are considered as well as observed data when estimating their values. An unconditional prior probability distribution for values of a parameter of interest is converted to a posterior distribution for the values of that parameter using data actually observed. Bayes theorem derives a posterior distribution by combining the likelihood for the data with the prior distribution. The posterior distribution is then used to derive an estimate for the parameter and a standard error. Empirical Bayesian estimation refers to the case when the prior distribution is based on certain global aspects of the data. In this case, information on the risk of adult mortality in Addis Ababa as a whole.

Assume the true but unknown rate for each area is θ_{xi} and the observed rate is r_{xi}, where

$$r_{xi} = \frac{y_{xi}}{n_{xi}} \tag{5}$$

The non-Bayesian best estimate of θ_{xi} is r_{xi}. Suppose, however, that we have a prior probability distribution for each area θ_{xi} with mean γ_{xi} and variance ϕ_{xi}. The best Bayes estimate of θ_{xi} is then the result of the combination of these prior distributions with the observed rates:

$$\hat{\theta}_{xi} = w_{xi} r_{xi} + (1 - w_{xi}) \gamma_{xi} \tag{6}$$

this is referred to as a shrinkage estimate, where

$$\hat{w}_{xi} = \frac{\phi_{xi}}{(\phi_{xi} + \gamma_{xi}/n_{xi})} \tag{7}$$

w_{xi} is essentially an area-specific weighting factor which is a function of the population at risk and the variance of the prior distribution. As w_{xi} approaches 1, weight shifts to the observed rate, while as it approaches 0, weight shifts toward the prior mean. We assume that the prior means and variance are the same for all areas and follow a gamma distribution. The gamma distribution has two parameters ν and α, where the mean is equal to υ/α, and the variance is equal to ν/α^2. We now have:

$$\gamma_x = \frac{\nu_x}{\alpha_x}, \text{ and } \phi_x = \frac{\nu_x}{\alpha_x^2} \tag{8}$$

We estimate γ_x by calculating the global mean of the observed rates and ϕ_x by the weighted sample variance of the observed rates around the mean:

$$\hat{\gamma}_x = \frac{\sum y_{xi}}{\sum n_{xi}}, \text{ and } \hat{\phi}_x = \frac{\sum n_{xi}(r_{xi} - \hat{\gamma}_x)^2}{\sum n_{xi}} - \frac{\hat{\gamma}_x}{\bar{n}_x} \tag{9}$$

where $\bar{n}$ is the average population across all areas. Those areas that have larger populations will be adjusted less than those that have smaller populations.

The Bayes estimates of the rates are then:

$$\hat{\theta}_{xi} = \hat{\gamma}_x + \frac{\hat{\phi}_x(r_{xi} - \hat{\gamma}_x)}{(\hat{\phi}_x + \hat{\gamma}_x/n_{xi})} \tag{10}$$

4 Results

Figures 1-4 show the raw probability of dying between ages 15 and 59 (${}_{45}q_{15}$) for each of the 302 areas in Addis Ababa for males and females. Rates of ${}_{45}q_{15}$ for the city as a whole are 0.356 for females and 0.418 for males. Figure 5 shows the shrinkage estimates (w_{xi}) where low values (light colors) indicate that due to the small population size of the area, there is little information content in the raw estimate such that the posterior estimate is determined largely by the prior estimate. As the figure shows, the areas which have the smallest population sizes and thus highest degrees of stochastic error in their raw mortality rates tend to be those areas in the geographic center of the city.

Figures 6-9 show the smoothed estimates of absolute and relative ${}_{45}q_{15}$ by sex for the areas. The range of observed values of both ${}_{45}q_{15}$ and relative risk are considerably smaller for both males and females, however the smoothing technique has standardized the estimates with respect to the uncertainty associated with small exposure, such that the rates are now comparable across areas. As expected given the geographic distribution of the shrinkage estimates in Figure 5, we observe the largest differences in relative risk among the more centrally located areas of Addis Ababa. Using area-level data available for individuals and households from the 1994 Census, we will now investigate the relationship between these smoothed estimates of risk of dying with certain socioeconomic determinants of mortality.

The average household size has been declining steadily in Addis Ababa in recent decades. This may be partly due to a change in government policy allowing the renting of privately owned houses leading to breakup of extended families. In 1994, single person households comprised 11.1% of the total households and accommodated 2.2% of the total population. Figure 10 shows the distribution of median household size across areas, and shows a relationship between number of individuals in the household with distance from the geographic center of the city.

According to the 1994 Census, the majority (82%) of residents are Orthodox Christian. Next to Orthodox are Muslims with 12.7 percent, followed by Protestants and Catholics comprising an additional five percent. There is considerable ethnic variation within these religious classifications. Figure 11 shows the percentage of households reporting Orthodox religion, and we observe a substantial degree of neighborhood segregation by this variable.

Figure 12 shows the percentage of adults who are considered economically active by area. The economically active population comprises all persons aged ten years and over who were engaged in productive activity for at least one day during the seven days prior to the census day for urban areas and during most of the previous twelve months for rural areas (certain areas of Addis Ababa are designated as rural areas). Prostitutes who are partly engaged in productive activities during the reference period, such as preparing and selling of drinks or serving as waitresses in hotels, bars and restaurants are considered as economically active individuals.

We observe a relatively high degree of neighborhood segregation based median years of education by area (Figure 13). We also observe a high degree of correlation between median years of schooling and median household wealth (Figure 14). Median household wealth is estimated using a principal components analysis approach which takes into consideration a group of indicator variables regarding assets, household characteristics such as number of rooms and wall material, as well as access to services such as electricity, water and sanitation. Table 2 shows the degree of correlation between these socioeconomic variables and the smoothed estimates of ${}_{45}q_{15}$ and relative risk. We are currently implementing a random-effects model to estimate the magnitude of the variance in our smoothed estimates of ${}_{45}q_{15}$ after taking the above determinants into account, and will use these results to validate estimates of AIDS-attributable mortality based on lay diagnosis (see Figure 15)[10].

Figure 1: Male Raw Probability of Dying Between the Ages of 15 and 59 by Area, Addis Ababa, 2002

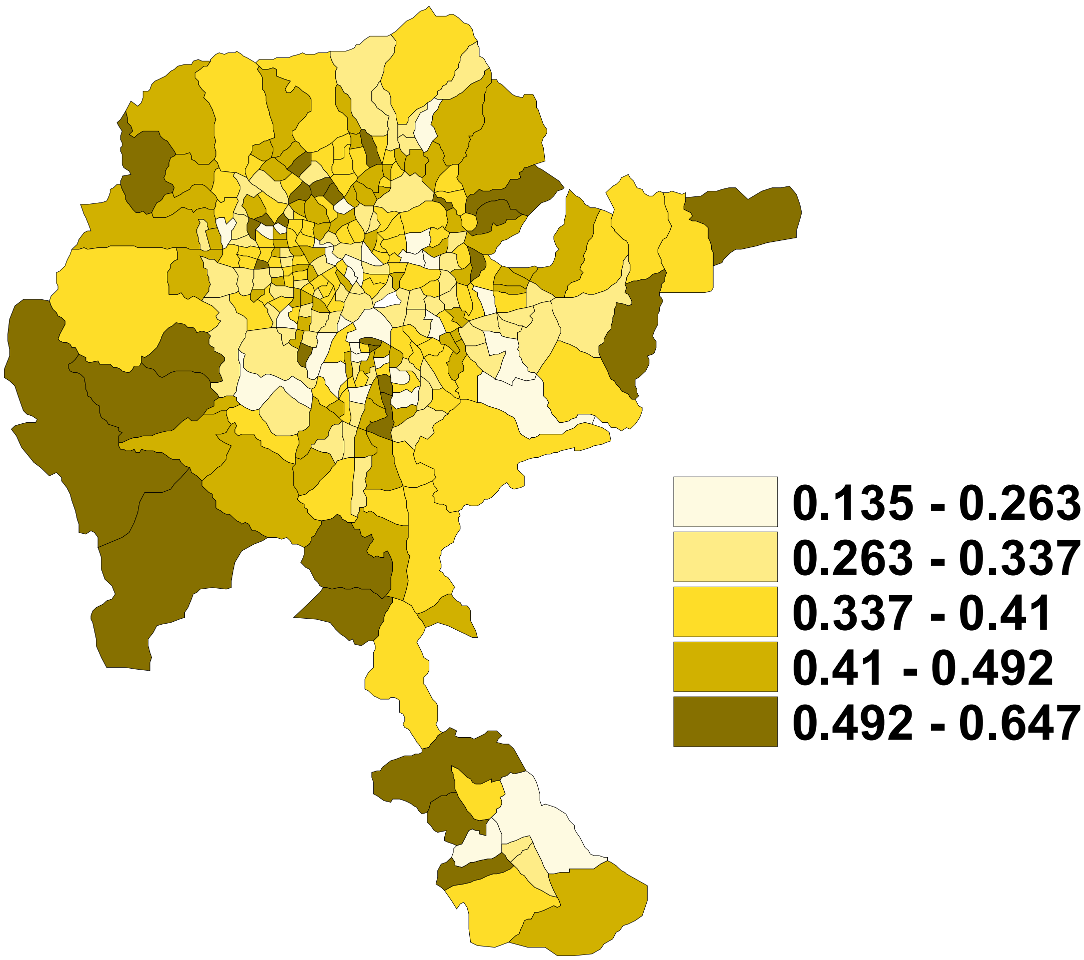


Table 2: Correlation of Selected Socioeconomic Variables with Mortality Indicators

Mortality Indicator (Both Sexes)	Med. School	% Econ. Active	% Orthodox	Wealth	HH Size
% Mortality AIDS-Attributable	0.01	-0.12	0.21	-0.22	-0.09
Posterior Relative ${}_{45}q_{15}$	-0.23	-0.23	0.18	-0.32	-0.12

5 Discussion

In this paper we utilize an empirical Bayes procedure for the estimation of area-specific relative risks of adult mortality for subsequent exploration and analysis. The method involves estimation of the parameters of a random process that is assumed to generate the relative risks, and calculation of posterior expectations as the estimates of individual relative risks.

Figure 2: Male Raw Relative Risk of Dying Between the Ages of 15 and 59 by Area, Addis Ababa, 2002

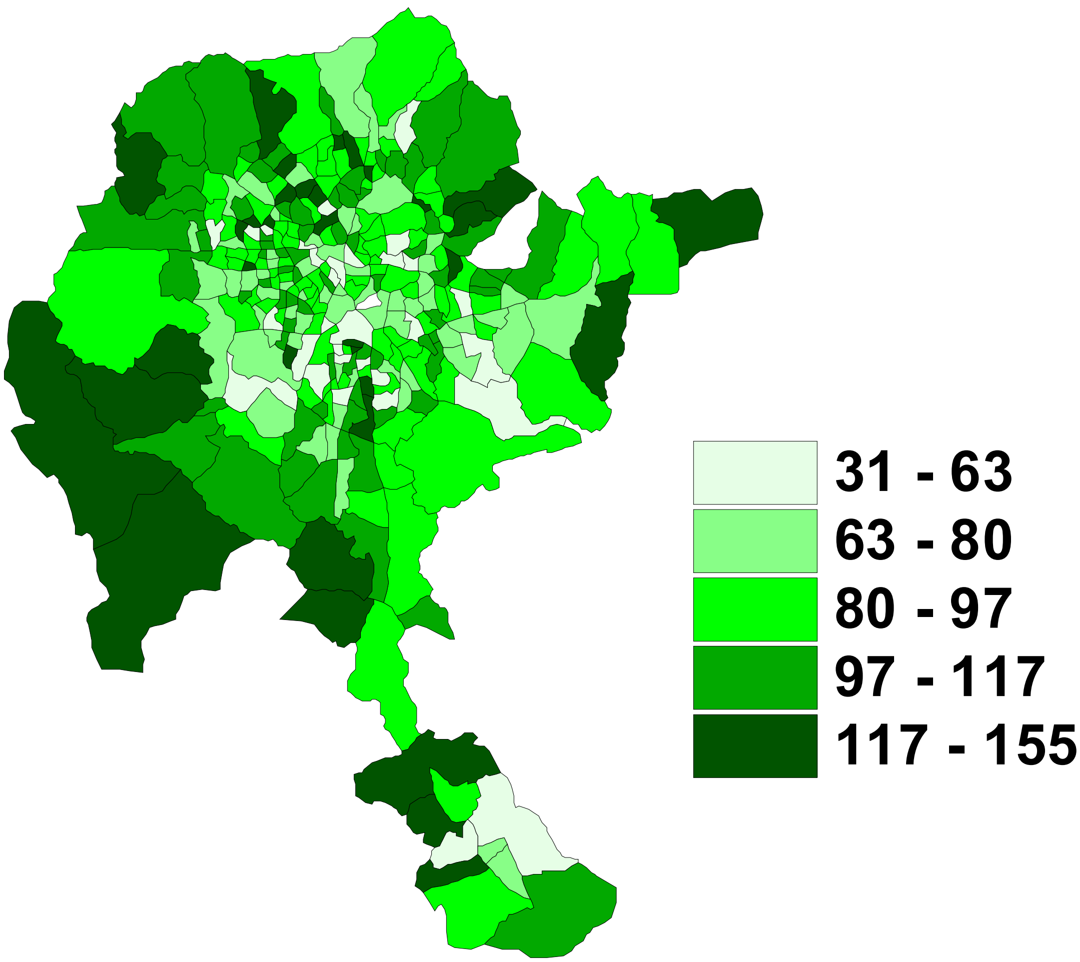


Figure 3: Female Raw Probability of Dying Between the Ages of 15 and 59 by Area, Addis Ababa, 2002

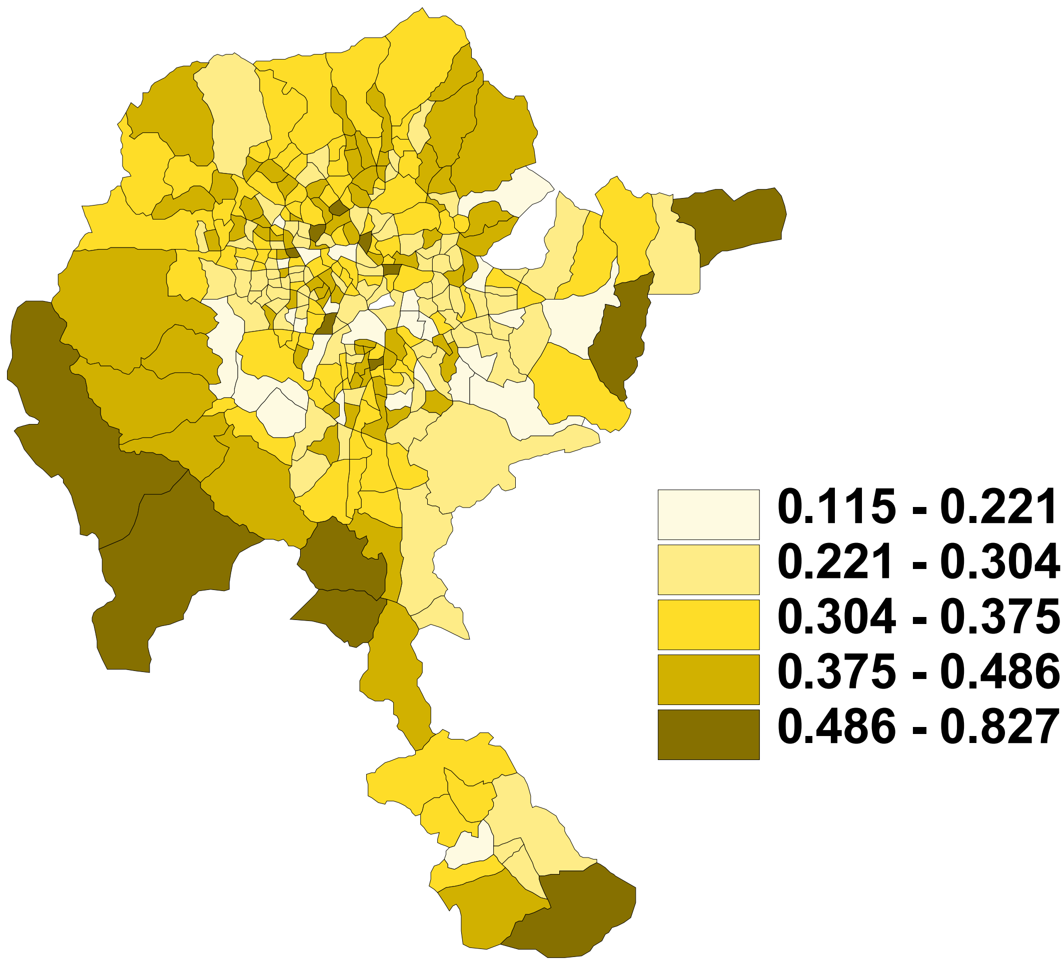


Figure 4: Female Raw Relative Risk of Dying Between the Ages of 15 and 59 by Area, Addis Ababa, 2002

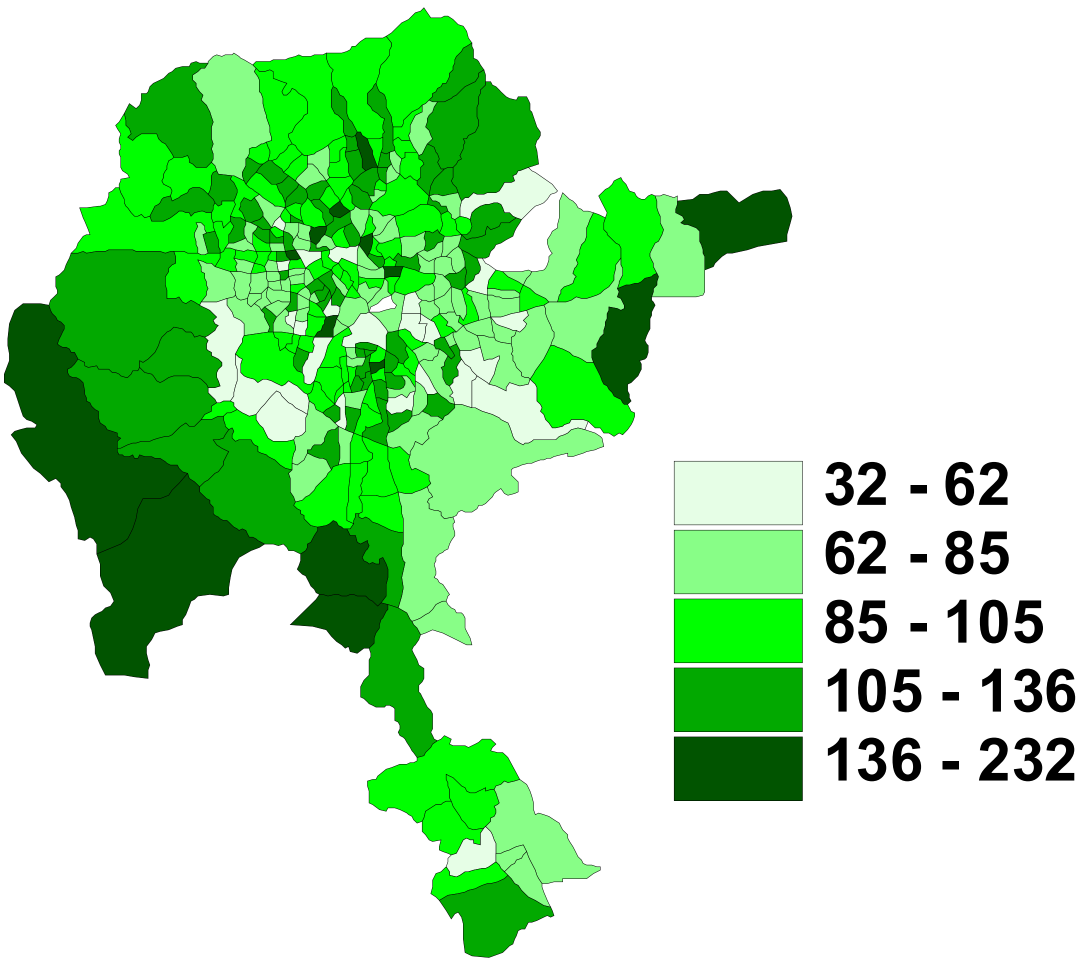


Figure 5: Shrinkage Estimates by Area (Males), Addis Ababa, 2002

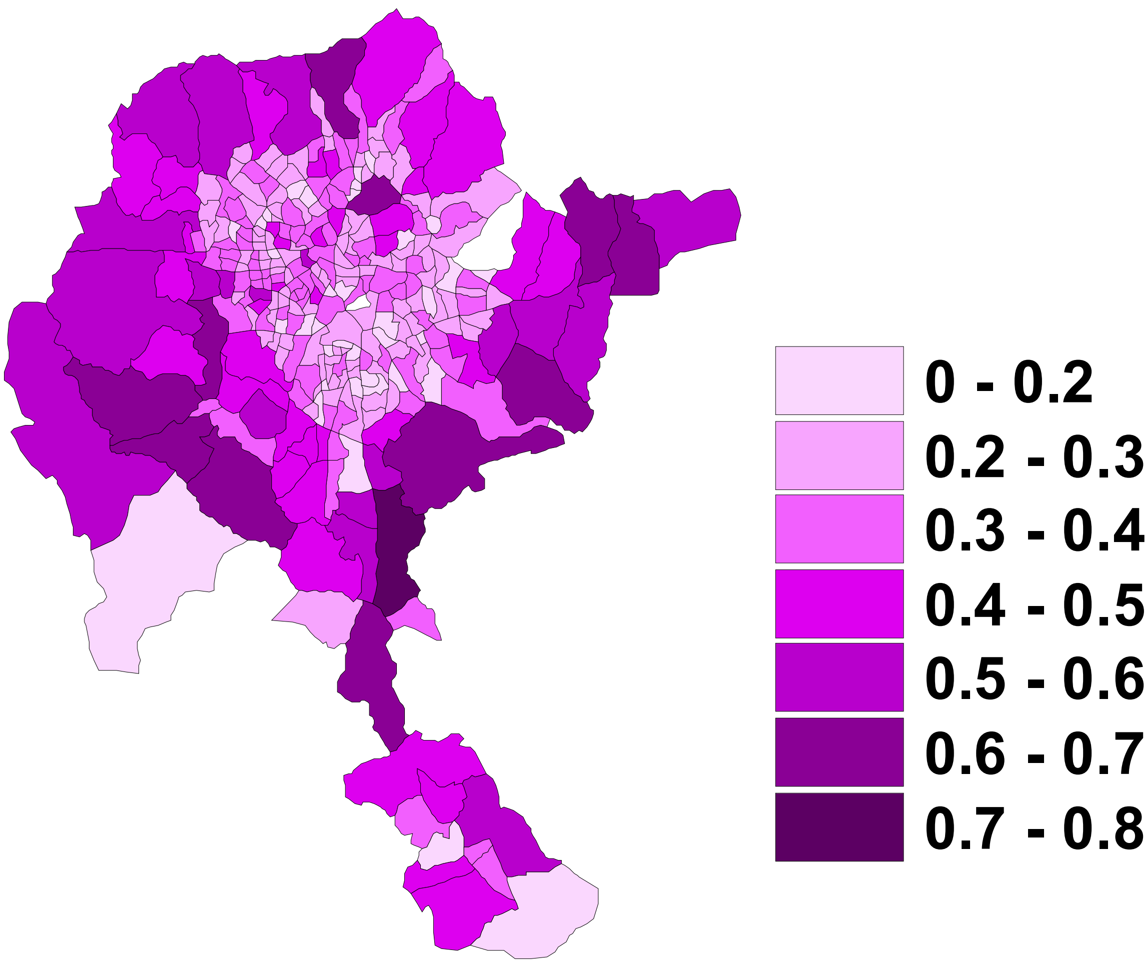


Figure 6: Male Smoothed Probability of Dying Between the Ages of 15 and 59 by Area, Addis Ababa, 2002

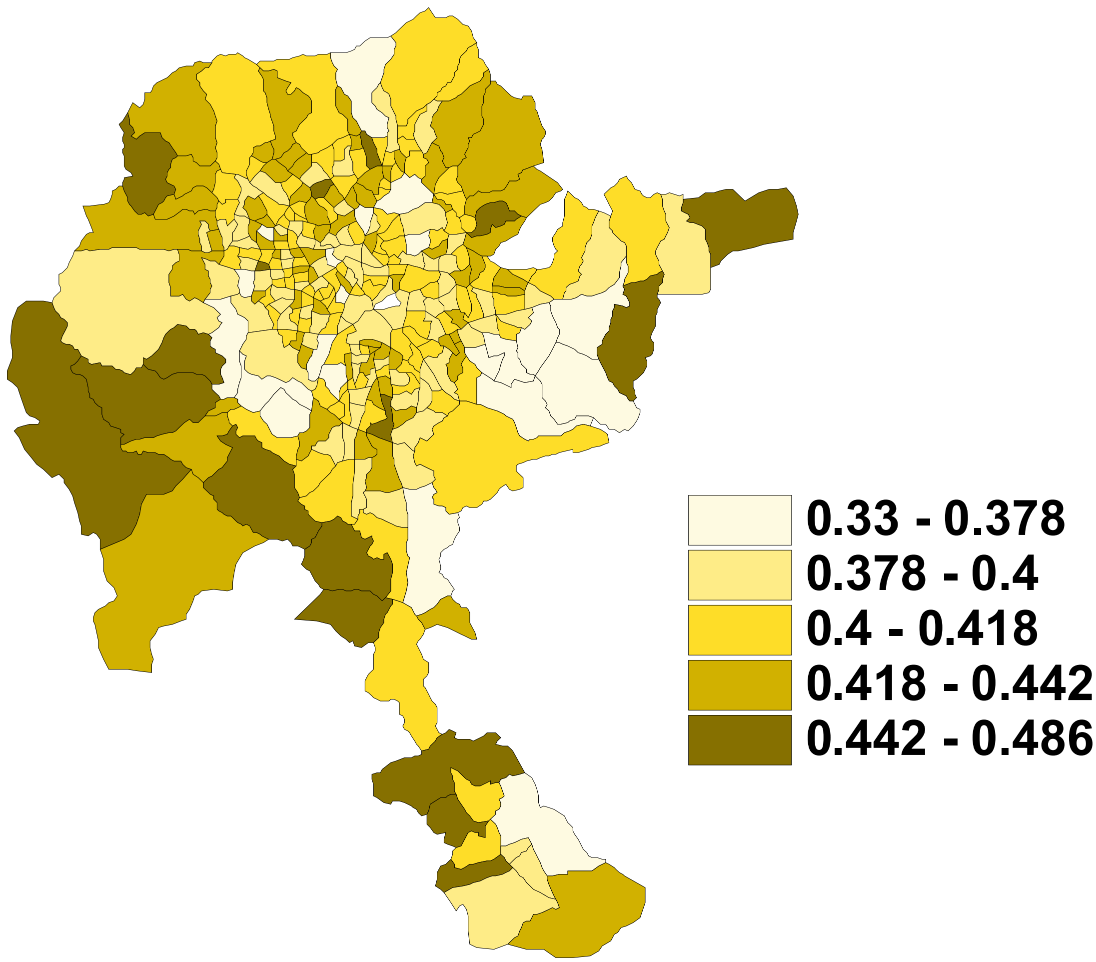


Figure 7: Male Smoothed Relative Risk of Dying Between the Ages of 15 and 59 by Area, Addis Ababa, 2002

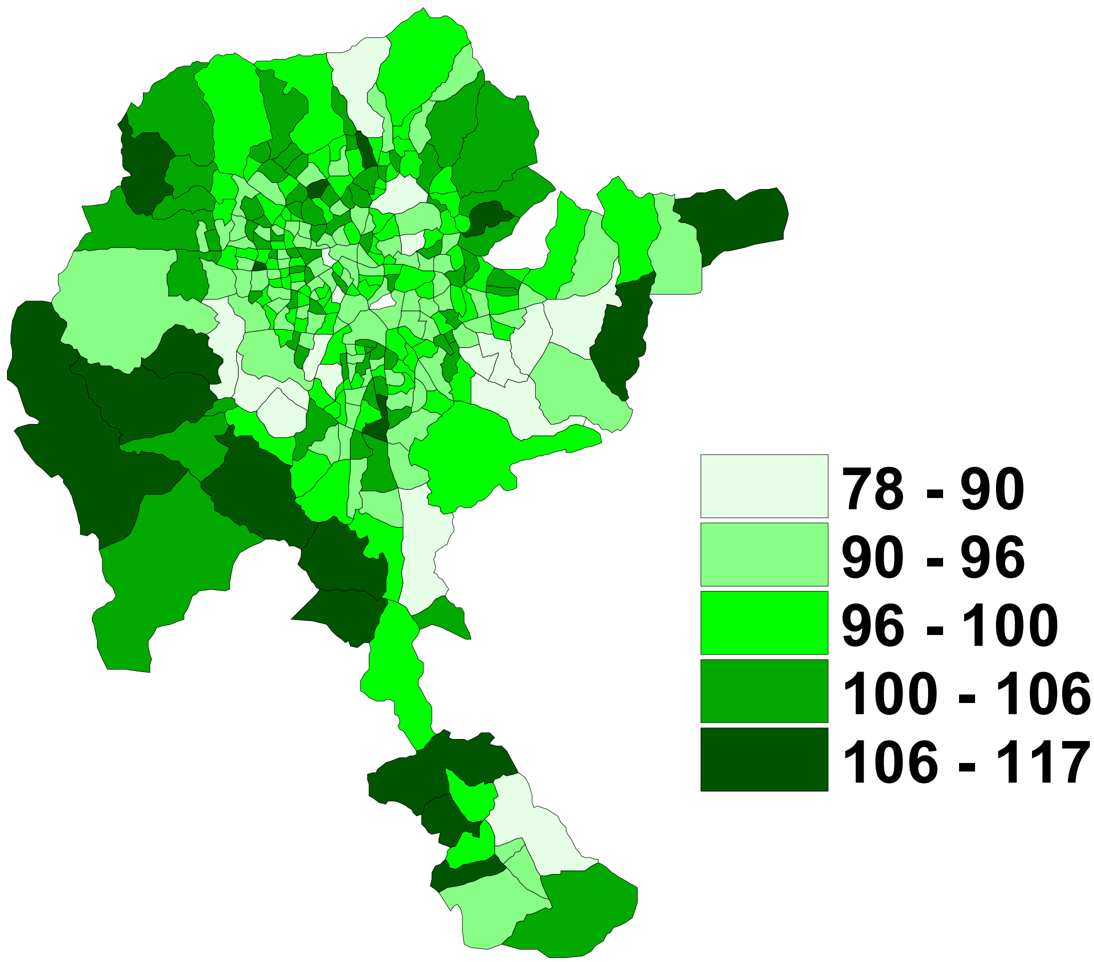


Figure 8: Female Smoothed Probability of Dying Between the Ages of 15 and 59 by Area, Addis Ababa, 2002

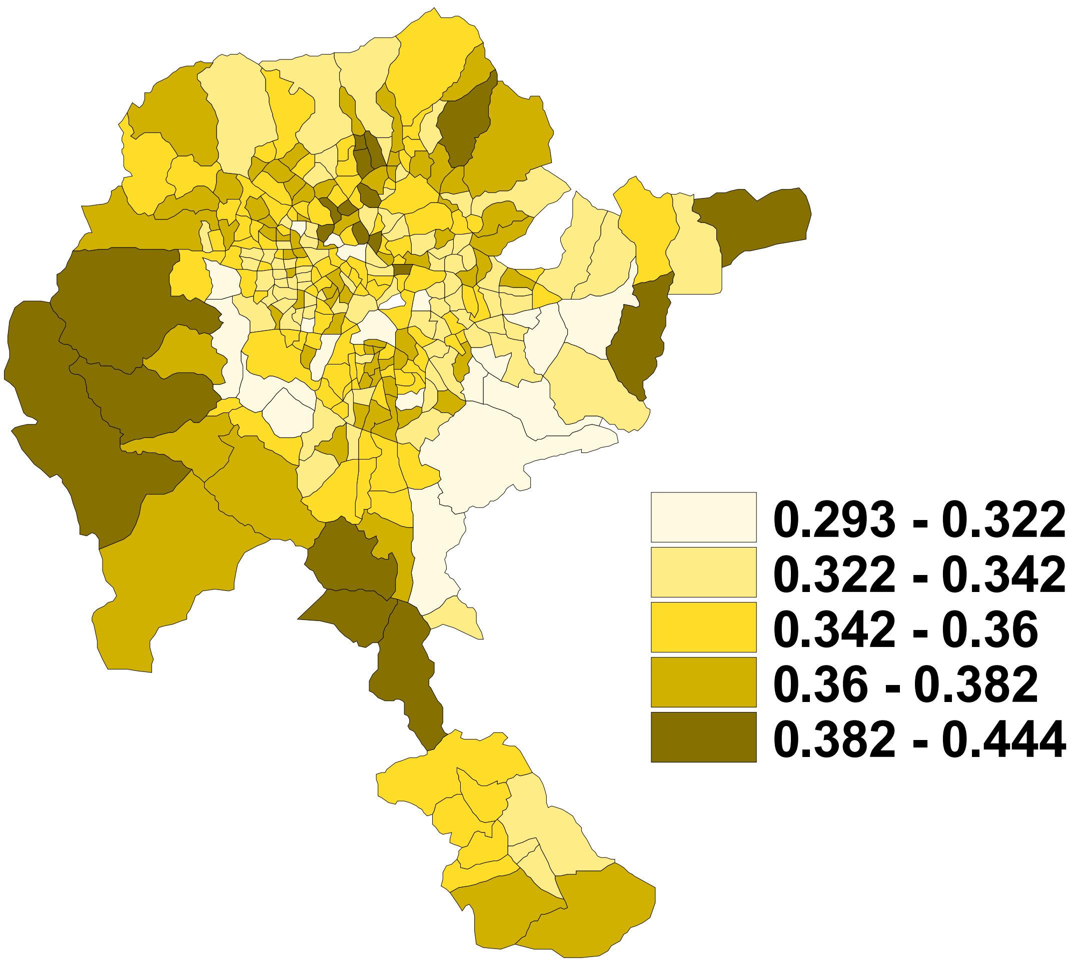


Figure 9: Female Smoothed Relative Risk of Dying Between the Ages of 15 and 59 by Area, Addis Ababa, 2002

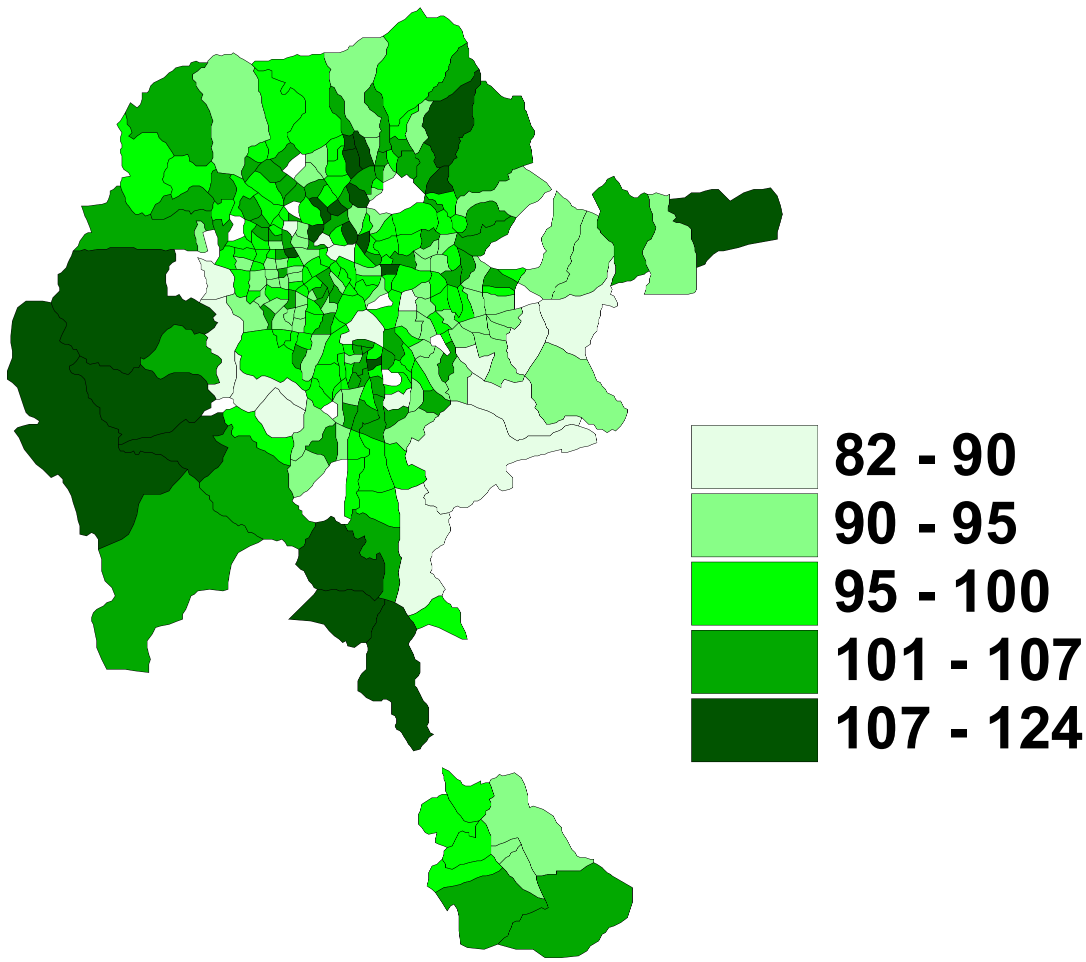


Figure 10: Median Household Size by Area, Addis Ababa 1994 Census

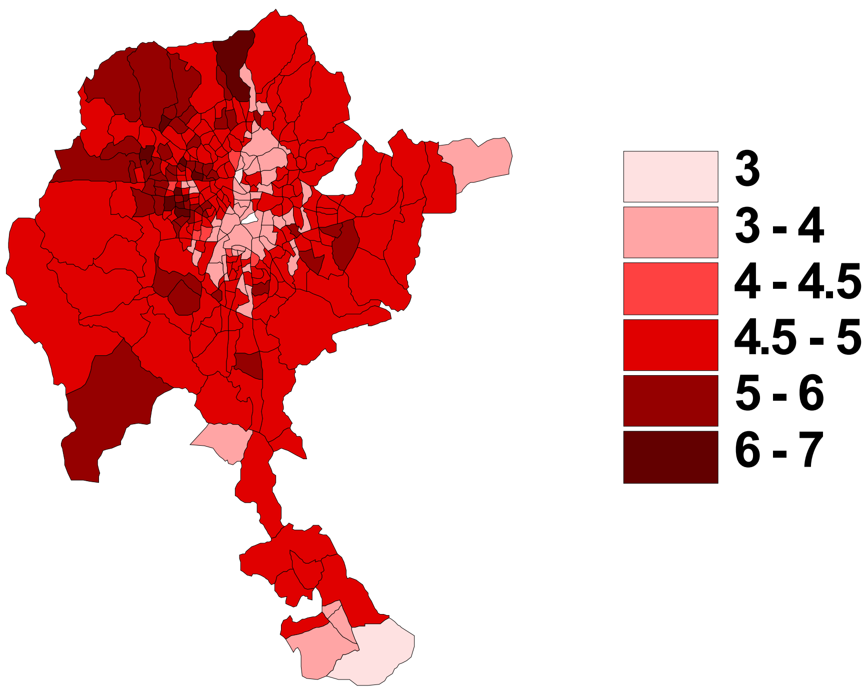


Figure 11: Percentage of Households Reporting Orthodox Religion, Addis Ababa, 1994 Census

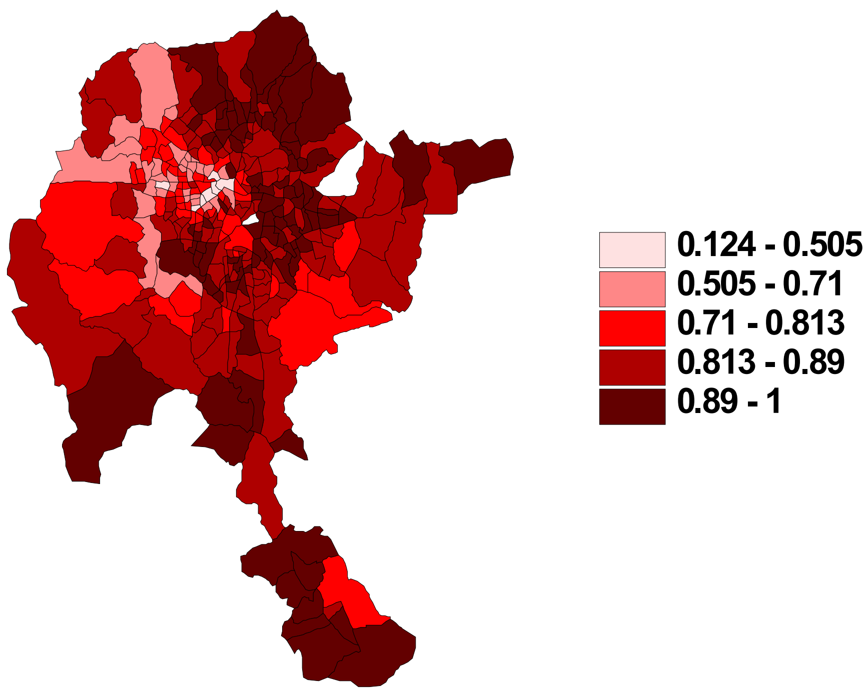


Figure 12: Percentage of Adults Designated as "Economically Active", Addis Ababa, 1994 Census

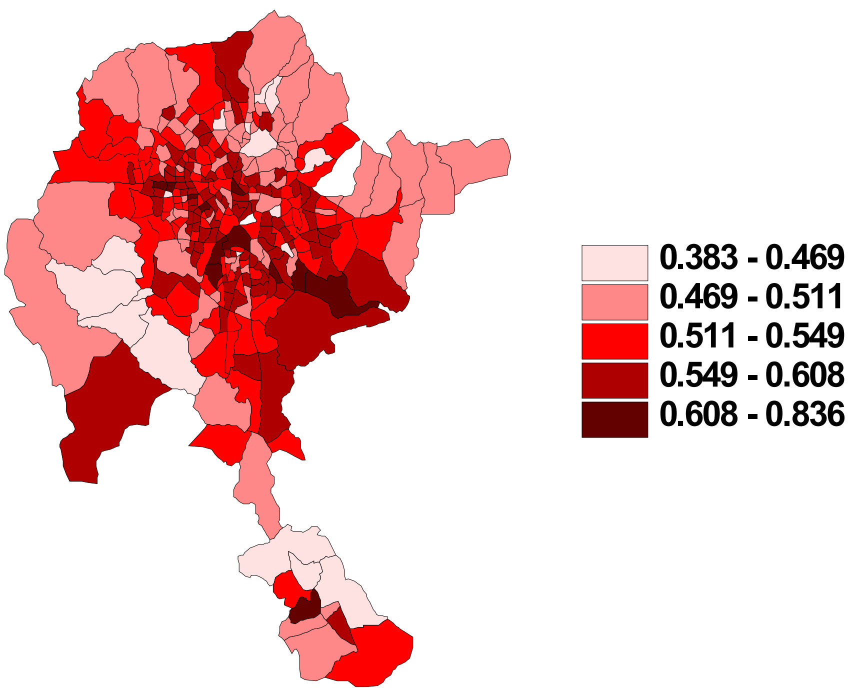


Figure 13: Median Years of Schooling by Area, Addis Ababa, 1994 Census

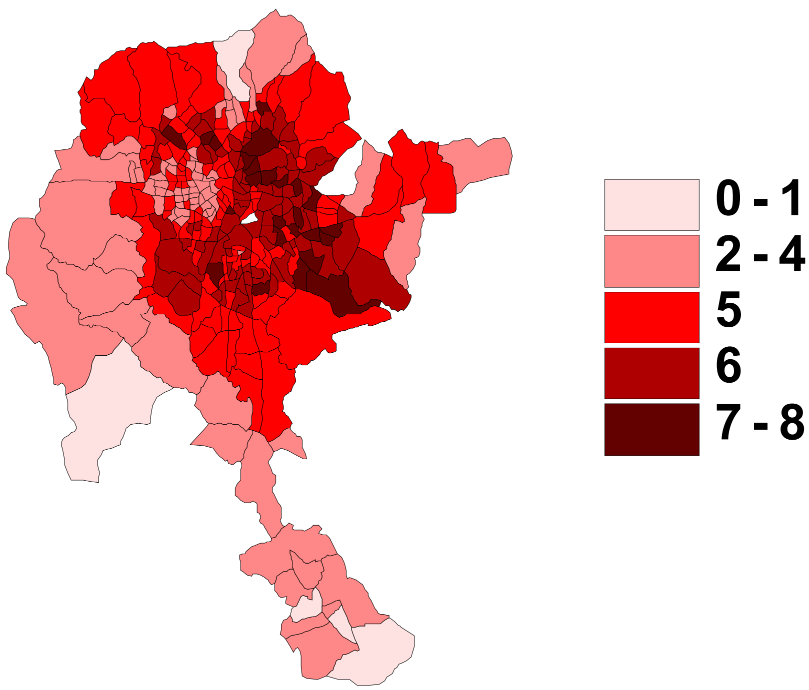


Figure 14: Median Estimated Household Wealth by Area, Addis Ababa, 1994 Census

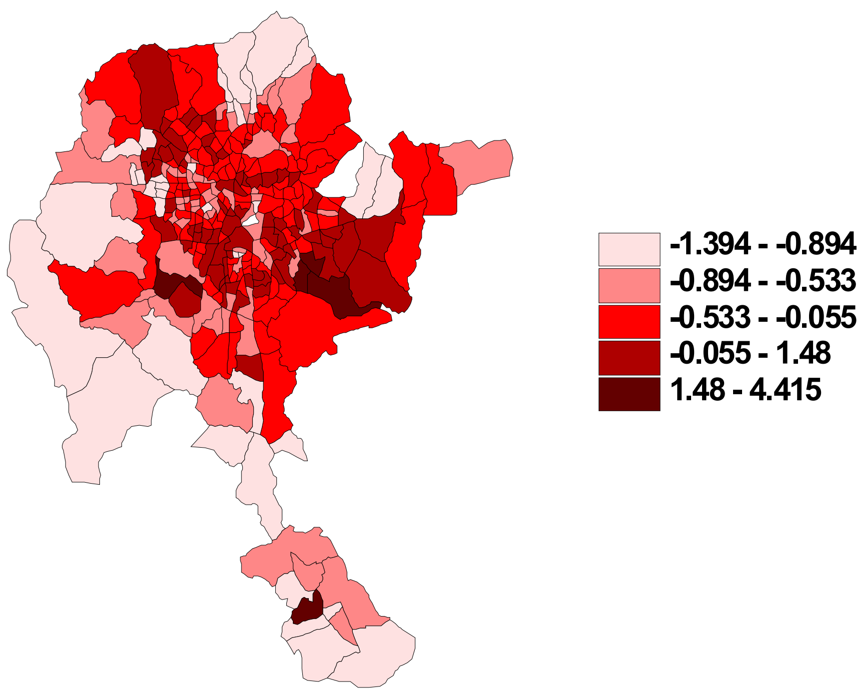
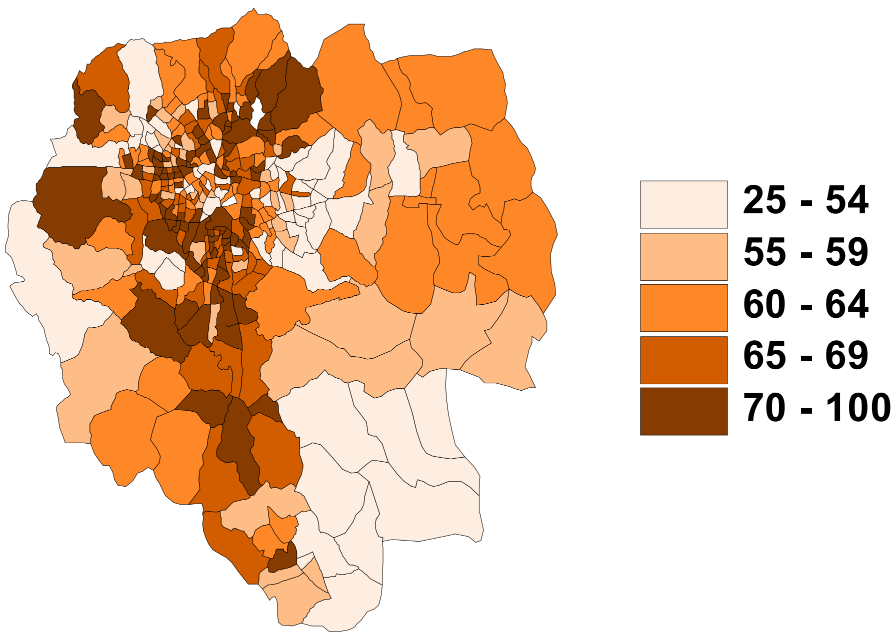


Figure 15: Percentage of Total Mortality Attributable to AIDS by Area, Addis Ababa, 2002



In contrast to other methods of smoothing, the extent of smoothing is totally determined by the data. While our uncorrelated mixture model does no more than provide a set of risk estimates which take into account relative precision, it has the advantage of being based on relatively few assumptions while enabling descriptive analysis of mortality patterns. which will allow formulation of more specific hypotheses which can be tested with more structured spatial models at a later stage.

Of particular interest is the difference in relative adult mortality risk by sex that we observe in certain areas. These may be related to sex differences in the transmission of HIV and will warrant further investigation after additional data checks. Survey research conducted in Addis Ababa in 1995 indicated a high general knowledge of AIDS; most respondents (86%) were familiar with the disease and the majority of these had accurate perceptions of its etiology. Practicing a single sexual partner relationship and using condom were regarded as ways of preventing AIDS by 80% and 53% of the respondents, respectively [27]. In a recent study of HIV prevalence among male army recruits, Abebe and colleagues find a significantly lower risk of infection among Muslim recruits relative to Orthodox Christians [28]. Other research has shown that 99% of the women in Addis Ababa know about AIDS and about 80% could cite at least two programmatically important ways to avoid HIV infection.

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