Methods to Estimate Mortality Curves in Small Areas: an Application to Municipality Data in Brazil

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Abstract

We estimate life expectancy at birth at municipal level in Brazil using different methodologies: parametric, non-parametric and frailty correlated models. Life expectancy at birth is a widely used indicator to compare levels of mortality and health status among populations. However, producing life tables in small areas is limited by the quality of data, especially in the case of Brazilian municipalities, where there are random variations related to small numbers. We find that direct estimation over-estimate life expectancy at birth in Brazilian municipalities and it is necessary a combination of statistical models with formal demography models to obtain proper estimates of life expectancy.

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Introduction

Knowing the exact level and structure of mortality is essential for government agencies to set up their health policies. In face of the millennium goals, more studies on this field are becoming necessary, especially when the population of interest is small. Such studies are important because they aid researchers investigating the environmental and behavioral aspects of diseases, the access to health care, and better understanding the socioeconomic determinants of mortality and morbidity in these areas (Ferguson et al.,2004).

In developing countries, mortality estimates, as well as the knowledge of the levels and trends of mortality are limited by the quality of data. The most common problems faced in these countries are the incomplete coverage of the vital registration systems and the errors in age declaration for both population and death counts. In recent years, the collection of data for death counts has improved, but there are still limitations for studying mortality in several parts of the world. In Brazil, for example, mortality estimates and the knowledge of levels and trends of mortality are very limited (Lima and Queiroz, 2011; França, et. al, 2012; 2008; Paes, 1999, 2005; Gomes and Turra, 2009). Brazil is characterized by regular levels of coverage of death counts, but with large variation across regions (Paes, 2005; Luy 2010, Setel et.al, 2007; The PLoS, 2010).The most common problems are the incomplete coverage of the vital registration systems, the errors in age declaration for both population and death counts, and the lack of information on causes of deaths. These limitations are even more striking in small areas of the country, such as municipalities or counties (Cavalini, et.al, 2007; França, et.al, 2008; Paes, 2007).

The inability to produce proper estimates of mortality, especially in small areas, hinders the development of public health policies and does not advance the understanding of the health transition in the country. On the one hand, a lot is known about the variations of infant and child mortality in Brazil (Souza, Hill and Dal Poz, 2010; Castro and Simões, 2009), but, on the other hand, very little is known about spatiotemporal trends in adult and old-age mortality levels in Brazil, and overall mortality schedule. We argue that producing proper estimates of adult and old age mortality for small areas in Brazil is relevant in this context as recent and future changes in life expectancy are most probably going to be explained by variations at the age of death of adults and the elderly, since there is a clear trend in convergence in the levels of infant and child mortality (Souza, Hill and Dal Poz, 2010).

Although the search for better estimates of rates in small areas gained ground in the research agenda of many demographers even with large samples and censuses, vital rates estimates in small areas are still very limited and incipient. This often happens due to the problem of few events recorded in the denominator and/or numerator of the measures of interest. This instability is even worse when sub-national groups are disaggregated by age and sex (Assunção et al. 2005). Bernadinelli and Montomoli (1992) argue that, in small populations, the estimated rates generally have extreme values, often dominated by sampling noise which less reflect the true risks. Assunção et al. (2005) also argues that for a large number of small areas, one can observe a large variability in the estimated rates that do not reflect the true level of heterogeneity of the geographic location. Therefore, estimates of vital rates in small areas present a great challenge for demographers, but several authors argue that a variety of statistical methods exist to adequately address the volatility of these estimates (for example Ferguson, 2004).In studies estimating fertility rates in Brazil, Assunção et al. (2005) showed how Empirical Bayes was effective in the case of Brazilian municipalities. Therefore, estimates of vital rates in small areas present a great challenge for demographers, but several authors argue that a variety of statistical methods exist to adequately address the volatility of these estimates (for example Ferguson, 2004).

In this context, we aim to estimate life tables at municipality level in Brazil, based on parametric, non-parametric and correlated frailty models. The second objective is to compare estimated mortality (by each of the applied methods)with life tables constructed from observed data in the small areas. The case of Brazil is interesting because, in addition to the limitations of small-area data (scarce information, zero cases), several regions of the country face also problems with the registration of death counts. This means that an age group with zero deaths could be related to the non-occurrence or the non-registration of the event. An alternative option, would be to estimate mortality patterns by using information on infant and child mortality, as well as model life tables. However, this can be applied only to census years, while model life tables might not reflect the current mortality conditions in the country.

In this paper, we present results of different parametric fittings based on the Poisson and the Negative Binomial distribution for each city in the states of Maranhão and São Paulo. The choice of these states is determined by the contrast in the quality of mortality data and in the level of economic development: while São Paulo is considered the most developed region in the country and one that has a high-quality vital record system, Maranhão is the poorest state in socio-economic terms and has the worst vital registration system in the country.

Methodology and Data

We make extensive use of mortality data from 2000 and 2010 provided by the Ministry of Health, that includes death counts at the level of municipalities, the smallest administrative units of the country. The population counts are available from the Brazilian population census from 2000 and 2010. In this paper, we produce estimates using municipal data from Maranhão, a less developed state in the Northeast, and São Paulo, a more developed region with better data quality.

1. Parametric methods for mortality estimation

First, we estimate mortality curves according to different parametric specifications. These models are used to fit the data when zero or few events are observed, which is the case in many age groups and municipalities. In addition to that, the models can smooth mortality functions for all municipalities in the period.

To test these methods, we focus on two regions of the country: the Federal State of Maranhão, comprised of 217 municipalities, and the State of São Paulo, containing 645 municipalities. The choice of these two states is not random. Maranhão is well known for the worst quality of mortality data in the country while São Paulo presents better death count information. (Lima and Queiroz, 2014).

Five models are estimated: three with a Poisson and two with a Negative Binomial specification[5]. The first model is a simple Poisson model specified as $E_i e^{\beta x_i{}^T} + \varepsilon_i$ (1), where E_i is the exposure or risk population, $x_i{}^T$ is the covariate profile of that municipality and β is a vector of regression coefficients. As covariate in the model, we have the age groups at which the deaths occur. Thus, the assumption behind these parametric models is that the death counts are age-dependent.

The second model we apply is the zero-inflated Poisson (ZIP) model. It is a statistical model based on a zero-inflated probability distribution, i.e. a distribution that allows for frequent zero-valued observations (Lambert, 1992). This model is used to count data that have an excess of zeroes (Lambert, 1992; Hall, 2000), a pattern observed in many municipalities of this study. Note that, the excess of zeros in some localities can indicate two things: either 1) the events really did not occur, or 2) there is a sub-registration of death counts.

The ZIP model uses two components that generate two zero processes. The first process is a binary distribution that generates structural zeros. The second process is a Poisson distribution that generates counts, some of which may be zero. Thus, it assumes that 1) excess zeros are generated by a separate process from the count values and 2) the excess zeros can be modeled independently, by a Poisson model and a logit model for predicting the excess of zeros (Lambert, 1992; Hall, 2000).

The third model is a Hierarchical Poisson model, specified as $E_i e^{\beta_{oj} + \sum_k \beta_{kj} X_{kj} + \varepsilon_{ij}}$ (2), where E_i indicates the exposure population in each municipality, as *i* indexes the individuals (unit 1) and *j* indexes the level 2, in this case the municipalities. The β_0 indicates the intercept that varies between the units at level two, in other words, this is a random term. The other coefficients are fix terms in the equation. The random term is defined as $\beta_{0j} = \gamma_{00} + u_{0j}\ and\ \beta_{kj} = \gamma_{k0}, K \neq 0$.

The two Negative Binomial models are described by a discrete probability distribution of the number of successes in a sequence of independent and identically distributed Bernoulli trials before a specified non-random number of failures occurs (Hilbe, 2011). Negative binomial regression can be used for over-dispersed count data, i.e. when the conditional variance exceeds the conditional mean (Hilbe, 2011). It can be considered as a generalization of the Poisson regression since it has the same mean structure as

[5]The zero-inflated Negative Binomial model did not converge in certain cases. Thus, we decide to show only the results of the estimated models.

the Poisson regression and an extra parameter to model over-dispersion. If the conditional distribution of the outcome variable is over-dispersed, the confidence intervals for the Negative binomial regression are likely to be narrower in comparison to those from a Poisson regression model (Hilbe, 2011).

In sum, in this paper, we propose a combination of methods to produce estimates of the levels and structure of mortality for small areas in Brazil. The models are estimated separately for males and females in the census years of 2000 and 2010, but for simplicity we will show only the results for males in 2000.

2. Evaluation of mortality under-registration of death counts

In the case that the second condition (presented above) is valid, it is necessary to analyze the mortality data for under-registration of death counts. In other words, the excess of non-events not registered in certain ages can be attributed to the fact that the event occurred, but it was not correctly recorded. In this case, we analyze the completeness of death counts based on formal demographic methods.

Several methods based on equations of population dynamics have been developed to evaluate the coverage of reported deaths relative to the population. The death distribution methods (DDM) are commonly used to estimate adult mortality in a non-stable population (Timeaus, 1991; Hill et al, 2005). There are four major approaches: the General Growth Balance (GGB) Methods (Hill, 1987), the Synthetic Extinct Generation (SEG) method (Benneth & Horiuchi, 1981), the Adjusted Synthetic Extinct Generation (SEG-adj) method (Hill, You & Choi, 2009), and the Synthetic Extinct Generation plus delta (Dorrington, 2011). The death distribution methods make four strong assumptions: the population is closed to migration, the completeness of the recording of deaths is constant by age, the completeness of recording of the population is constant by age, and the ages of the living and the dead are reported without error.

Preliminary results

a) Structure of mortality

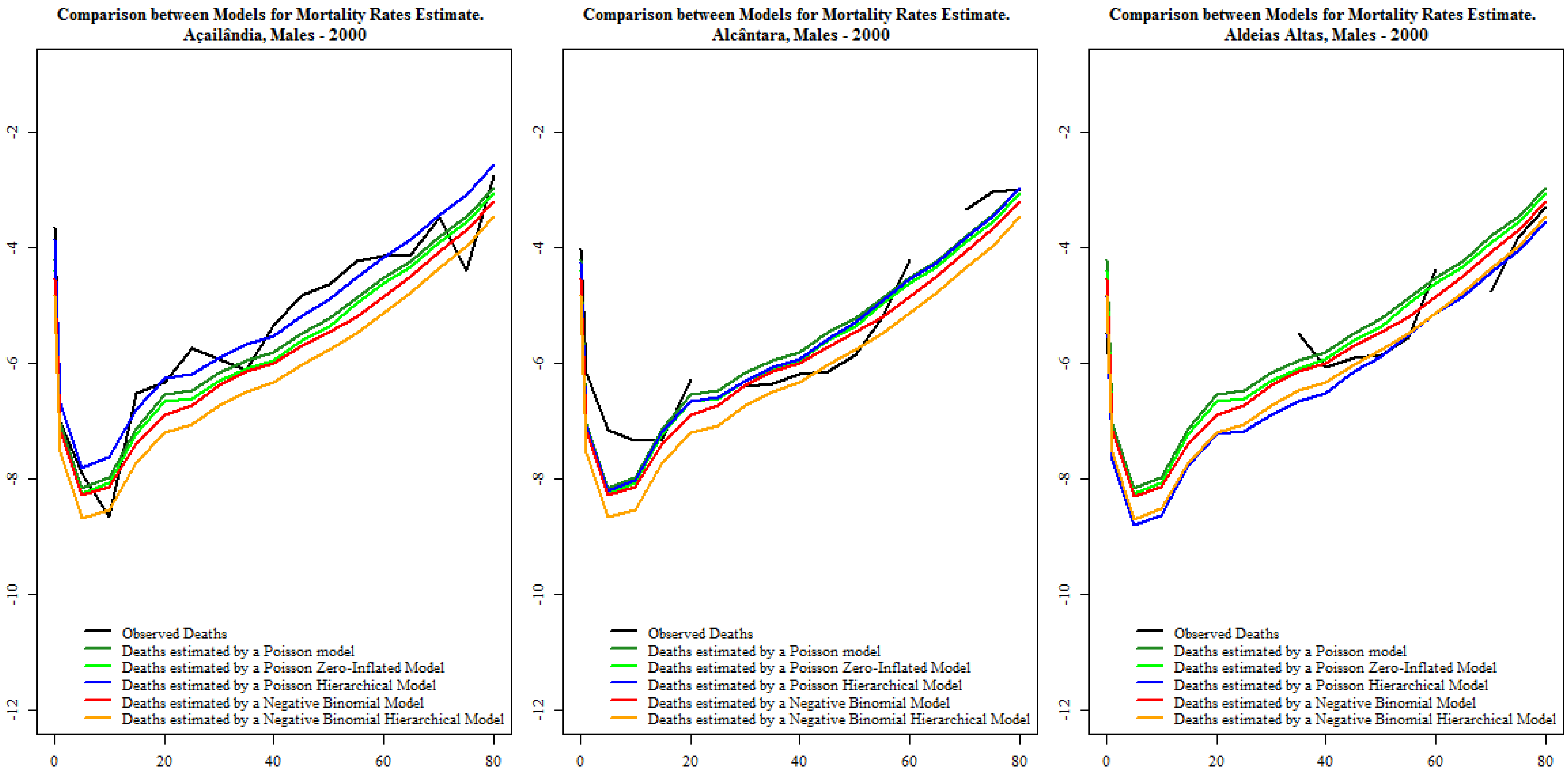
Figures 1 and 2 present the mortality curves for selected municipalities from the two States in study. Results indicate that many municipalities have a series of zero cases of death in some age groups and very unstable mortality structure, as the case of the municipalities Açailândia, Alcântara, Aldeias Altas, Alto Alegre do Pindaré, Zé Doca, Adamantina, Águas de Santa Bárbara, Altinópolis and Valinhos. We argue that this unstable mortality structure can result in untrustworthy measures of mortality, such as life expectancy and probabilities of death. The estimates using different methods are able to produce complete and smooth curves, however, a question that remains is which model gives reliable estimates of mortality in those small areas, and if those estimates are reasonable given the knowledge about the evolution of mortality in the country.

The curves estimated by the models do not vary in terms of structure, but they present different mortality levels, and visually (in some cases) the Poisson Hierarchical model (blue curve) is the one with closest distance[6] from the observed values, cases of São Luís, Adamantina and São Paulo. In addition to that, this model is the only one where we can identify variation in the mortality levels. Table 1 shows estimates of life expectancy at birth for several cities.

In general, the models do not fit infant and child mortality very well. This is a relevant point, we are working on different set of adjustments that will be presented in the final version of the paper. For example, we can observe the cases of Açailândia, Alcântara, Campinas and Valinhos. For this reason, we also evaluate the quality of the estimates generated by the 45q15(adult mortality). But, most important they are very useful to smooth mortality functions allowing to estimate life tables. In most cases, one cannot use observed data to perform any type of analysis.

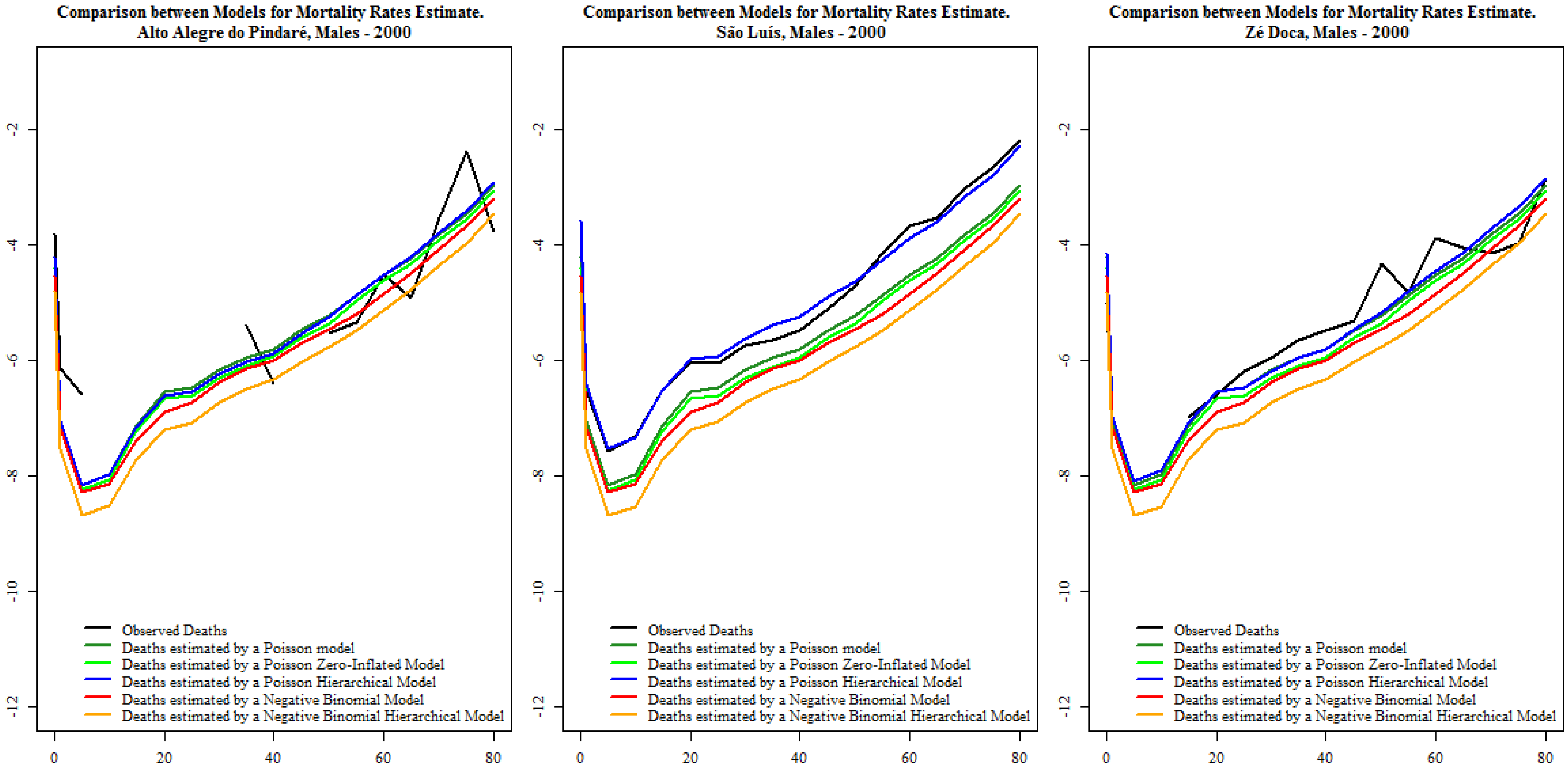
[6]The distances between observed and fitted curves was also estimated based on root mean square error (RMSE), which is a frequently used measure of the differences between values (sample and population values) predicted by a model or an estimator and the values actually observed.

Figure 1: Parametric models to estimate mortality curve in municipalities of State of Maranhão, Brazil, Males – 2000.



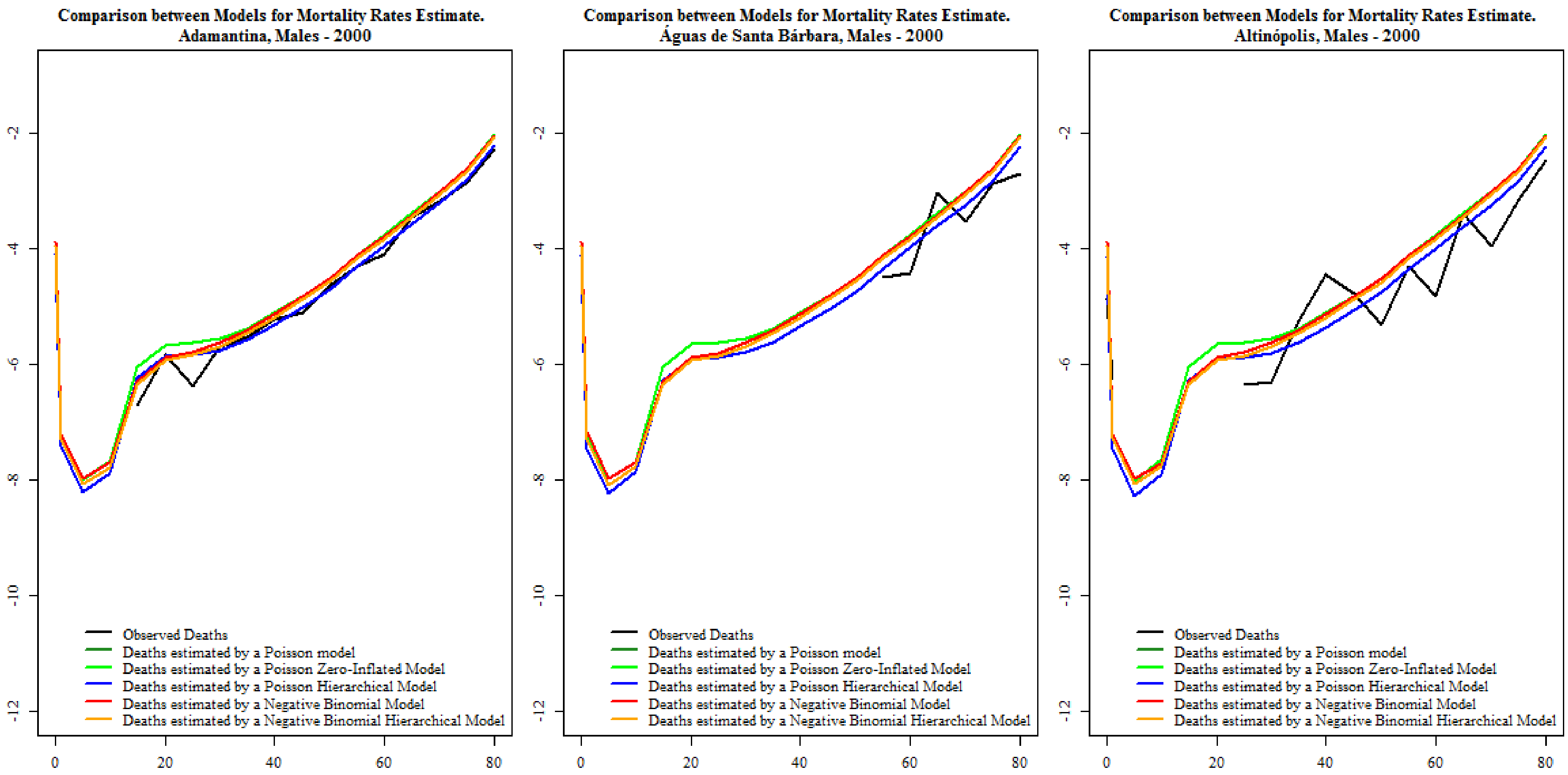
Sources: Census and DATASUS, 2000.

Continuation.Figure 1: Parametric models to estimate mortality curve in municipalities of State of Maranhão, Brazil, Males – 2000.



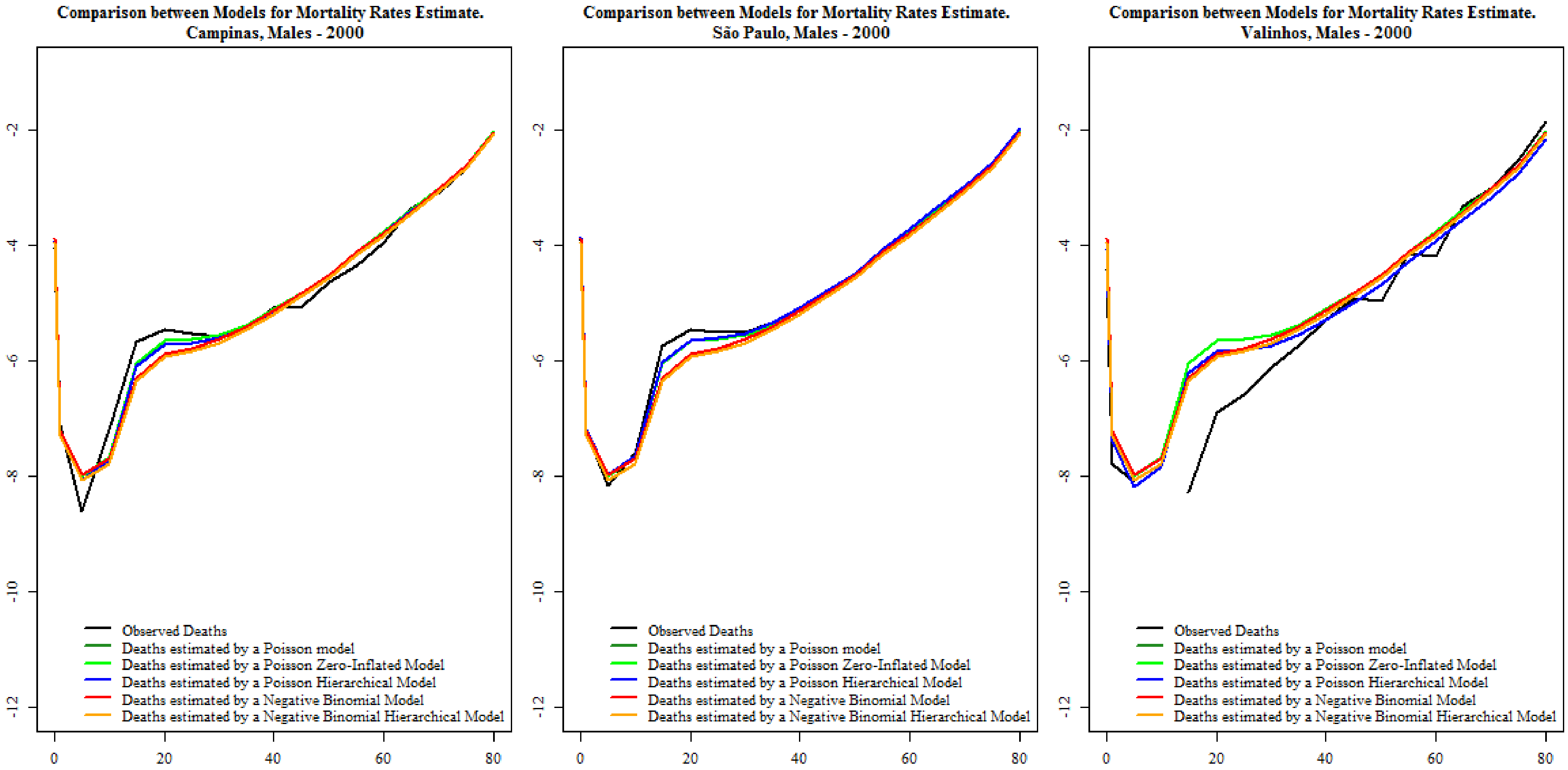
Sources: Census and DATASUS, 2000.

Figure 2: Parametric models to estimate mortality curve in municipalities of State of São Paulo, Brazil, Males – 2000.



Sources: Census and DATASUS, 2000.

Continuation. Figure 2: Parametric models to estimate mortality curve in municipalities of State of São Paulo, Brazil, Males – 2000.



Sources: Census and DATASUS, 2000.

b) Levels of mortality

In this section, we evaluate the mortality levels produced by the models, taking into account the observed life expectancies as standard just for comparison. First, we observe that Negative Binomial hierarchical model overestimate as well as underestimate mortality levels in almost all areas. The same is observed with life expectancies estimated by a simple Negative Binomial model.

Although, in both States, Poisson distribution seems to fit better the data. Furthermore, except for Campinas (in Sao Paulo), a simple as a zero-inflated Poisson model, we do not identify variation in levels of mortality, this means that the Poisson Hierarchical probably generate better estimates of the mortality levels in the least-populated areas.

Despite that, we are still observing unreliable results of life expectancy, as we verify in Aldeias Altas, where we have indicator of males living in mean 101 years after their birth. This could also indicate that the excess of zeros in the data might be related with under-registration of death counts. For that reason is important to evaluate the quality of mortality data for under-registration using Death Distribution Methods.

Table 1: Life Expectancy estimated according to different model specifications

Municipalities of Maranhão	Observed data	Poisson model	Poisson zero-inflated model	Poisson hierarchical model	Negative Binomial model	Negative Binomial hierarchical model
Açailândia	76.2	82.5	85.4	74.6	89.3	98.1
Alcântara	82.9	82.5	85.4	83.3	89.3	98.1
AldeiasAltas	95.6	82.5	85.4	101.2	89.3	98.1
Alto Alegre do Pindaré	91.1	82.5	85.4	82.2	89.2	98.1
São Luís	68.8	82.5	85.4	69.2	89.3	98.1
ZéDoca	80.2	82.5	85.4	80.6	89.3	98.1
Municipalities of São Paulo	**Observed data**	**Poisson model**	**Poisson zero-inflated model**	**Poisson hierarchical model**	**Negative Binomial model**	**Negative Binomial hierarchical model**
Adamantina	71.9	67.3	67.3	70.6	68.0	68.8
Águas de Santa Bárbara	81.2	67.3	67.3	71.2	68.0	68.8
Altinópolis	74.3	67.3	67.3	71.3	68.0	68.8
Campinas	67.9	68.0	67.3	68.0	68.0	68.8
São Paulo	66.7	67.3	67.3	66.8	68.0	68.8
Valinhos	70.9	67.3	67.3	70.1	68.0	68.8

Source: Census data and Datasus, 2000.

c) Levels of mortality after correction of death completeness

After correcting the levels of under-registration of death counts[7], we re-estimate the life expectancy for the 12 municipalities selected (Table 2). The results indicate a significant reduction in mortality levels after we taken into account the degree of completeness of death counts. In the case of Aldeis Altas the life expectancy reduced in 16 years. The same picture is observed in other municipalities of Maranhão.

Figure 3 also show results of adult mortality for all municipalities in São Paulo and Maranhão. Since the data in São Paulo have higher quality, we need a smaller correction for under-registration of death counts and smoothing, we find that levels of adult mortality observed and correcting are very similar. This result is relevant for our discussion, because it shows that methods seem to work properly in the different scenarios we proposed.

Table 2: Life Expectancy estimated according to Poisson Hierarchical model

Municipalities of Maranhão	Observed data	Poisson hierarchical model	Poisson hierarchical model and correction for mortality under-registration all ages
Açailândia	76.2	74.6	72.7
Alcântara	82.9	83.3	66.3
AldeiasAltas	95.6	101.2	79.6
Alto Alegre do Pindaré	91.1	82.2	74.9
São Luís	68.8	69.2	69.2
ZéDoca	80.2	80.6	74.4
Municipalities of São Paulo	**Observed data**	**Poisson hierarchical model**	**Poisson hierarchical model and correction for mortality under-registration all ages**
Adamantina	71.9	70.6	69.9
Águas de Santa Bárbara	81.2	71.2	70.6
Altinópolis	74.3	71.3	71.0
Campinas	67.9	68.0	68.0
São Paulo	66.7	66.8	66.5
Valinhos	70.9	70.1	67.9

Source: Population Census (IBGE) and Datasus, 2000.

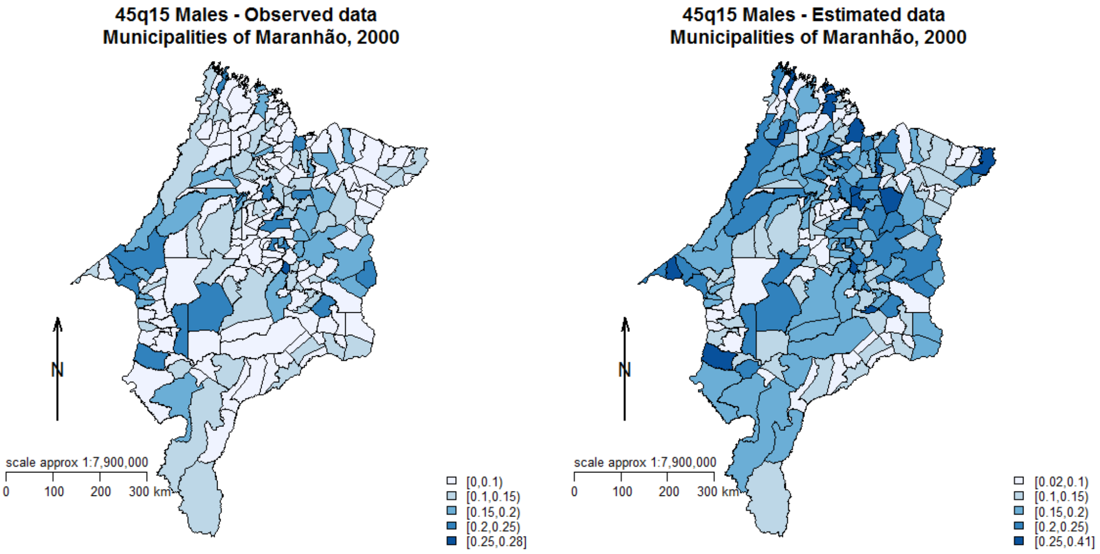
[7]We estimate the completeness of death counts coverage using Death Distribution Methods. In general, the estimates are used to adjust adult mortality levels. In this paper, we use the same adjustment factor for the whole mortality curve, including infant, child and old-age. In the final version, we aim to produce different adjustment factors for each age segment.

Table 3: Adult probability of death from ages 15 to 60 (45q15)

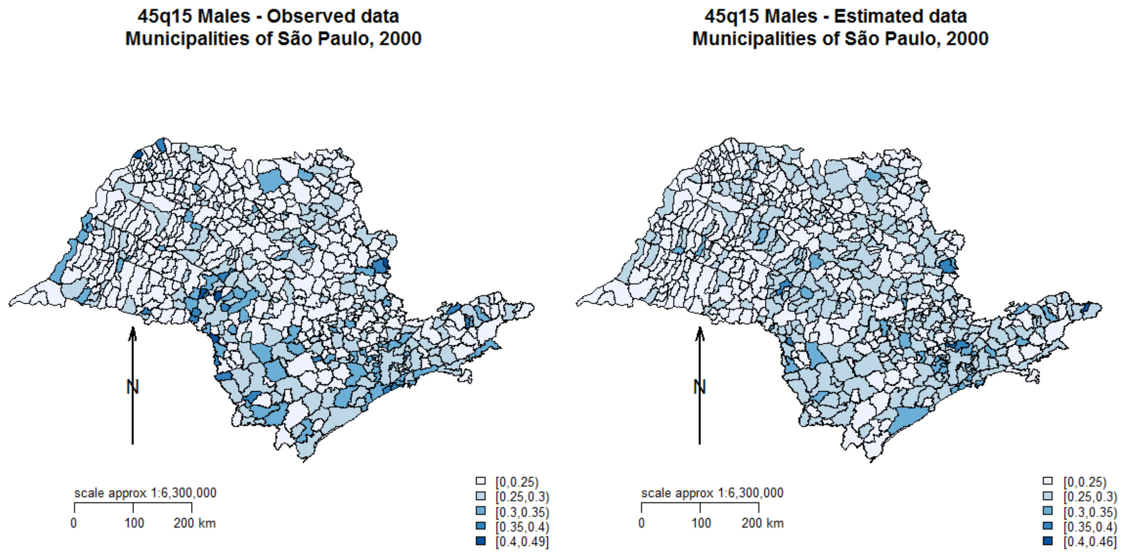
Municipalities of Maranhão	Observed data	Poisson hierarchical model	Poisson hierarchical model and correction for mortality under-registration all ages
Açailândia	0.22	0.18	0.19
Alcântara	0.09	0.12	0.26
AldeiasAltas	0.08	0.07	0.14
Alto Alegre do Pindaré	0.08	0.13	0.17
São Luís	0.21	0.23	0.23
ZéDoca	0.18	0.14	0.18
Municipalities of São Paulo	**Observed data**	**Poisson hierarchical model**	**Poisson hierarchical model and correction for mortality under-registration all ages**
Adamantina	0.21	0.21	0.22
Águas de Santa Bárbara	0.05	0.21	0.22
Altinópolis	0.21	0.21	0.21
Campinas	0.24	0.25	0.25
São Paulo	0.26	0.26	0.26
Valinhos	0.19	0.22	0.22

Source: Population Census (IBGE) and Datasus, 2000.

Figure 3: Spatial distribution of adult mortality (45q15), Municipalities of Maranhão e São Paulo, 2000.



Continuation. Figure 3: Spatial distribution of adult mortality (45q15), Municipalities of Maranhão e São Paulo, 2000.



Source: Population Census (IBGE) and Datasus, 2000.

Preliminary conclusions and future steps

The results indicate that there is a major deficiency in the basic mortality data and population in small areas, which makes direct use of these sources problematic. Main limitations are the random variation due to small numbers in death counts by age and under-registration of death counts. Therefore, direct estimates of mortality levels in small areas could then produce results that are not robust, in other words, very high life expectancies at birth. In addition, application of demographic methods also appears to be limited, for the most localities, due to limitations of basic assumptions of the models.

In this paper, we attempt to test alternative parametric and non-parametric methods to estimate mortality curves by age in different municipalities of two states in Brazil, as an example. The proposed solutions, however, only solve the problems of zeros and unsmoothed rates. In most cases, we find that methods could be used to adult mortality, but not for infant and child mortality rates. The second stage of our analysis uses Death Distribution Methods to evaluate the quality of mortality data. We apply a combination of DDM methods and find that in most cases the generated mortality curves were reflecting the under-registration of death counts that are still common in the Brazilian scenario.

The adjustments are larger for Maranhão, which is known for the low quality of mortality data (Lima and Queiroz 2014). In the case of São Paulo, higher quality data, the proposed methods provide proper adjustments in the mortality curve and it is not necessary large adjustments due to under-registration of death counts.

The results generated by this form of estimation in two steps appear to be robust and appropriate. Estimates in two stages were so robust that they reduced the over-registration of deaths in some cases and improved adult mortality estimates in some areas, where data are less reliable.

Tests with non-parametric regressions and Local regression (see Leone, 2013) models have also been performed, but we did not obtained satisfactory results. The smoothing appears to distort much the mortality distribution in some municipalities and, in many cases, the estimates predict negative numbers of death counts at certain ages groups.

As further steps, we will pursue to estimate frailty correlated models. These frailty models have been used for modeling dependence in multivariate time-to-event data (Clayton, 1978; Oakes, 1982; Yashin et al., 1995; Hougaard, 2000; Wienke et al., 2002). The dependence usually arises because individuals in the same group (or family) are related to each other, or because of multiple recurrence of an event for the same person (Vaupel, 1979). In our study, the dependence will be stated as the neighborhood structure of the municipalities. The main idea is to create spatial clusters, based on many socio and economic characteristics of theses municipalities and apply these frailty models in order to estimate survival functions. We assume that these clusters present better information.

Alternatively, we will also try to improve the parametric methods by including more covariates (see Ahmed and Hill, 2011) in the second level of the Poisson hierarchical model. We believe that this will increase the prediction power of the model estimates. Furthermore, a goodness-of-fit test (see Lenart and Missov, 2014) will also be applied in order to see if it is possible to fit a Gompertz distribution in the adult and later ages.

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