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Review Article

Can we estimate crisis death tolls by subtracting total population estimates? A critical review and appraisal

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Abstract

BACKGROUND
In the absence of high-quality data, the death tolls of epidemics, conflicts, and disasters are often estimated using ad hoc methods. One understudied class of methods, which we term the growth rate discontinuity method (GRDM), estimates death tolls by projecting pre-crisis and post-crisis total population estimates using crude growth rates and then subtracting the results. Despite, or perhaps due to, its simplicity, this method is the source of prominent death toll estimates for the Black Death, the 1918 influenza pandemic, the Great Chinese Famine, and the Rwandan genocide, among others.

OBJECTIVE
In this article, we review the influence and validity of GRDM and its applications.

METHODS
Using statistical simulation and comparison with better-validated demographic methods, we assess the accuracy, precision, and biases of this method for estimating mortality in absolute and relative terms.

RESULTS
We find that existing GRDM estimates often misestimate death tolls by large, unpredictable margins. Simulations suggest this is because GRDM requires precision in its inputs to an extent rarely possible in the contexts of interest.

CONCLUSIONS
If there is sufficient data to specify GRDM well, it is probably possible to also use a more reliable method; if there is not sufficient data, GRDM estimates are so sensitive to their assumptions that they cannot be considered informative.

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CONTRIBUTION
These findings question the empirical suitability of existing demographic and econometric work that has used GRDM to analyse mortality crises. They also underscore the need for improved data collection in crisis settings and the utility of qualitative methods in contexts where quantification using better-validated methods is not possible.

1. Introduction

'How many people have died?' is a fundamental question underlying studies of pandemics, conflicts, famines, and disasters. Ascertaining death tolls is a task of great importance to many academic disciplines and practitioners from outside academia because they form an input which contributes to the writing of histories. They are also a means of advocating for both the dead and those still living (Checchi and Roberts 2008). A count of the dead is not the only way to represent mass mortality, nor is it the only way to do so quantitatively (Alburez-Gutierrez 2022; Robins and Greenland 1991), but establishing death tolls that are accurate brings us closer to conveying historical truth and promoting justice. The importance of that truth is emphasized in human rights work, in which estimating an accurate death toll can be a step towards accountability and reconciliation (Asher, Banks, and Scheuren 2008). However, human rights work also emphasizes that producing statistics about mortality crises requires great care and caution because the resulting numbers can be so consequential.

Estimating a death toll is often difficult, especially in the context of crisis. Ascertaining the cause of a single death is often difficult for both empirical (Alter and Carmichael 1996; Broadbent 2013) and political reasons (Gargiulo 2022; Rocco et al. 2021; Soto 2021). Quantifying the total number of deaths due to a single cause, such as a pandemic or conflict, can be even more difficult. Furthermore, even if deaths can be accurately ascribed to a particular cause, some deaths may go undocumented in moments of crisis (Price and Ball 2015). Over time, some records may also be lost. The incompleteness of the data that documents deaths further complicates estimates of crisis mortality, creating additional space for uncertainty and error if not carefully addressed. When the available data are too sparse to estimate mortality using standard demographic tools – such as excess mortality modelling, counterfactual cohort-component methods, multiple systems estimation, or retrospective mortality surveys – scholars and practitioners often estimate crisis death tolls using ad hoc procedures. This article reviews the influence and efficacy of one type of ad hoc method that has been independently invented dozens of times but which lacks a common name. The many variants of this method estimate a death toll by projecting pre-crisis and post-crisis total population estimates and subtracting the resulting discontinuity; for that reason, we name it the 'growth rate discontinuity method' (GRDM).

Ad hoc methods for estimating death tolls play an important role in the demography of crisis contexts. Researchers working on both historical and modern mortality identify the information they have available and then devise methods they think suitable for the important work of accounting for the dead. In the case of the 6th century CE Plague of Justinian, much of the evidence for the death toll comes from closely parsing contemporary written sources (Mordechai and Eisenberg 2019; Sarris 2022). When trying to estimate the pre-Columbian size of indigenous American populations, and therefore the proportion of those populations lost in the following centuries, many ad hoc methods and accompanying non-standard data sources are used. These include extrapolating population sizes from the volume of rubble left by abandoned indigenous settlements (Liebmann et al. 2016), extrapolating them from Aztec and Spanish tax records (Borah and Cook 1969; Zambardino 1980; see also Smith 2014), and extrapolating them by applying exponential decay backwards (Dobyns 1983; Thornton, Miller, and Warren 1991). The estimate that a smallpox epidemic in the 8th century CE killed one-third of the population of Japan results from an extrapolation from defaults on loans of rice (Farris 1985: 66).

In more recent settings, ad hoc methods have been used to examine mortality due to the COVID-19 pandemic in Yemen and Somalia (Koum Besson et al. 2021; Warsame et al. 2021), as well as civilian and military casualties during the Russian invasion of Ukraine (Haque et al. 2022; Meduza and Mediazona 2023). Sometimes, death toll estimates produced by various, often ad hoc methods are added together to produce, for example, composite tolls of the total number of global conflict deaths between 1740 and 1897 (Eckhardt and Köhler 1980) or the total number of global deaths due to the 1918 influenza pandemic (Johnson and Mueller 2002). In other cases, demographic losses are estimated by analogy – for example, by assuming that the "plague" of unknown cause that the Roman Empire began suffering in 165 CE "probably" caused mortality that was proportional to measles outbreaks in 19th century Polynesia (McNeill 1977: 116).

Ad hoc methods like these are created and applied to mortality crises because standard data sources are either limited or missing entirely. The answers to quantitative questions about those crises have important implications for how we construct accounts of the past and how we understand the present, and ad hoc methods can provide crucial information about crises and their impacts that is not possible to glean using standard methods. Due to the nature of the contexts in which these methods are applied, some ad hoc demographic methods are not routinely subjected to detailed scrutiny, and understandably so. When a particular ad hoc calculation is the only possible way to estimate a death toll, there is an urge to accept its result as truth in the absence of any alternative.

However, quantifying a death toll is only a useful exercise if it can be done accurately and with a useful level of precision. This is especially true because quantification is not the only means of description. As historians have lamented in the past, scrutinizing ad hoc methods may lead to the realisation that "the data available cannot lead to a meaningful quantitative result but only to a qualitative assessment" (Zambardino 1980: 7). Moreover, even if there is a commitment to quantifying a death toll, scrutiny is still important. Comparing ad hoc estimates that derive from the same demographic logic allows researchers who have been deploying that logic in isolation to learn from one another. Like all methods, ad hoc procedures also deserve scrutiny because they can be used to support inaccurate narratives about crises. For example, ad hoc methods have led to deep and well-documented misunderstandings about the scale and causes of 19th century famine in British India (see Chattopadhyay 2022; Hall-Matthews 2008), state-sponsored killings in the 20th century (see Dulić 2004; Harff 1996), and violence during the 2013–2020 South Sudanese civil war (see Dawkins 2021). In recent years, scholars have also realized that common ad hoc methods severely underestimated mortality in the Central African Republic in the context of ongoing conflict (Gang et al. 2023) and mortality in Puerto Rico during and after Hurricane Maria in 2017 (Kishore et al. 2018; Santos-Lozada and Howard 2018). In both cases, this meant that sufficient humanitarian relief did not go to communities that needed it.

This article unpacks a set of ad hoc methods that have often been used to estimate historical and contemporary crisis death tolls but that, despite their popularity, appear in no textbook, have no common name, and remain deeply understudied. In particular, we review the use and reliability of seven related models that we collectively term the 'growth rate discontinuity method' (GRDM). Scholars, and especially historians of disease and genocide, have independently invented some form of this method countless times; we have only identified a few dozen instances. It is the source of prominent death toll estimates for the Black Death, the Trail of Tears, the Armenian genocide, the 1918 influenza pandemic, the Great Chinese Famine, the Khmer Rouge regime, and the Rwandan genocide, among many other contexts. GRDM has been independently invented by so many scholars working on data-sparse contexts because its intuitive design implies that it requires little data: each of the seven GRDM variants we identify tries to estimate the scale of a population crisis by simply extrapolating between pre-crisis and post-crisis estimates of the given population's size and attributing any discontinuity to the demographic impact of the crisis.

Like many ad hoc methods, GRDM comes with very large uncertainty bounds. Some scholars who have used the method have explicitly recognised this fact in their work (e.g., Chandra 2013b; Gates 1984; Hilberg 2003; Kleinpenning 2002; Reydams 2021; Whigham and Potthast 1990; van der Eng 2023), and other scholars have critiqued the use of GRDM from outside (e.g., Bijak and Lubman 2016; Blacker 2007; Cribb 2001;

Kateb 2001; Nishimura and Ohkusa 2016; Riffe and Noymer 2017; Staveteig 2007; Tabeau and Zwierzchowski 2013). However, these caveats and critiques have been written in isolation from each other, only looking at one of the seven model variants we identify and only focusing on a single crisis of interest. We synthesize and build on the work of these scholars to offer an extensive review and appraisal of the use of GRDM. We conclude that if there is enough demographic information to specify GRDM well, a more reliable method can be used instead to estimate the death toll in question. In fact, the extreme sensitivity of GRDM to its inputs means that, by itself, a GRDM estimate should not be relied upon as an indication of the true death toll.

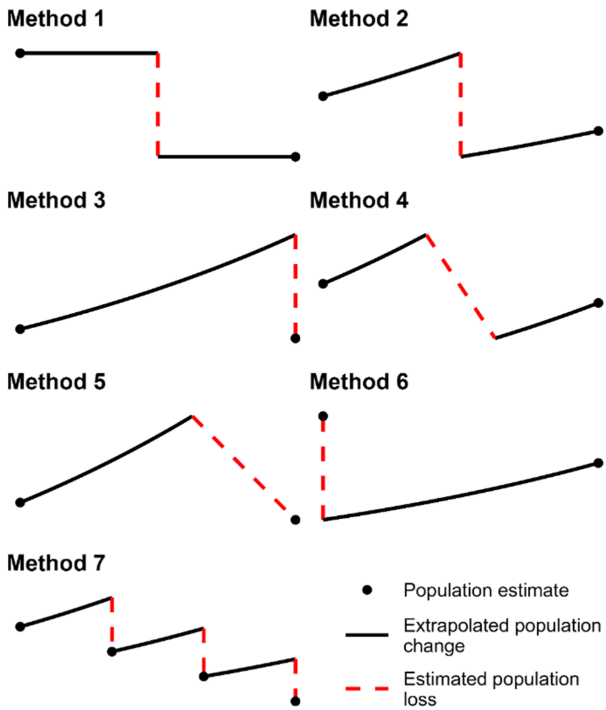
This article proceeds in five parts. In Section 2 we outline the mathematics of GRDM and its many published applications to mortality crises. In Section 3 we demonstrate the sensitivity of GRDM to uncertainty in its parameters and therefore when it should be expected to yield accurate death toll estimates. In Section 4 we review the accuracy of the death tolls that have previously been estimated using GRDM. In Section 5 we consider whether GRDM can yield accurate relative measures of crisis mortality that can, for example, be included in a regression analysis of the causes or effects of that mortality, even if it does not produce accurate death toll estimates in absolute terms. Section 6 concludes.

2. The logic of GRDM

One strategy for identifying a mass death toll is to identify a large population loss. Population decline can only occur through mortality or emigration, and if the size of a population halves in only a few years, it can be assumed that significant excess mortality has occurred. Large emigration flows can contribute to a population loss, but they themselves are often due to mass mortality (e.g., Lardinois 1989; Steele 2019). For example, the fall in the registered population of China between 1959 and 1961 can be attributed to rural people simply emigrating to urban areas (where they then did not obtain household registration) rather than to rural people dying from the famine of the period (Yang 2021), but such efforts are not convincing (see Ashton et al. 1984; Houser, Sands, and Xiao 2009; Ó Gráda 2013). Therefore, a popular method for estimating historical death tolls in data-scarce contexts is to approximate the death toll as the difference between the pre-crisis and post-crisis population.

Figure 1 presents a visual typology of GRDM methods, and this simple method of subtraction is shown in the first panel of the plot. If P_1 is the population size at some time T_{P1} before the crisis of interest and P_2 is the population size at some time T_{P2} after the crisis, a population loss figure (L) can be estimated as $P_1 – P_2$. This will be referred to as Method 1 for estimating L. Then, with B as the estimated number of births occurring in the population between T_{P1} and T_{P2}, M as the number of net migrants into the population in that period, and D_{NC} as the number of deaths in that period that were not caused by the crisis, the death toll of the crisis can be estimated as $D_C = L + B + M - D_{NC}$.

Figure 1: A visual typology of seven GRDM models



In the absence of much demographic information about a population of interest besides longitudinal population sizes, Method 1 has been applied to a large number of important mortality crises. Bijak and Lubman (2016) report that all available estimates for the death toll of the Armenian genocide rely on this type of subtraction exercise. Scholarly disputes about the toll stem solely from scholars relying on different estimates for the pre- and post-genocide Armenian population (including refugees abroad). Method 1 is also the source of the death toll estimate that led to the 1556 Shaanxi earthquake in China being ranked the deadliest earthquake in recorded history (e.g., Ritchie 2018) and to the 8th century CE An Lushan rebellion in China being ranked as the deadliest war in recorded history as a proportion of the global human population (e.g., Pinker 2011: 195).

Other applications of Method 1 to estimate death tolls include the atrocities of the Khmer Rouge in Cambodia and those of Leopold II in the Congo. Table 1 gives a non-exhaustive but extensive list of death tolls estimated using the logic of Method 1, as well as the six other GRDM models we have identified in the literature.

Table 1: Published examples of seven types of GRDM model

Method 1 755–763 CE civil war, China (White 2011; see also Fitzgerald 1936) 1556 earthquake, China (see Wang 2007) 1576 *cocoliztli* epidemic, Mexico (Acuna-Soto et al. 2004) 1779 ethnic cleansing of Iroquois, United States (Koehler 2018) 1885–1908 atrocities, Congo (Morel 1969, 109; Twain 1905: 25) 1904–1908 Herero genocide, Namibia (Whitaker 1985: 9) 1908 earthquake, Italy (Spitzer, Tortorici, and Zimran 2020) 1915–1917 genocide, Armenia (see Bijak and Lubman 2016) 1942–1945 war, Timor-Leste (see Dunn 1983: 26) 1975–1979 mortality under the Khmer Rouge (Vickery 1984: 187) 1975–1979 occupation, Timor-Leste (Hiorth 1985: 61)	**Method 2** 1838–1839 ethnic cleansing of Cherokee, United States (Thornton 1984) 1850–1864 war, China (Cao 2024; Ge, Hou, and Zhang 1999: 109) 1876–1879 famine, China (Ge, Hou, and Zhang 1999: 110) 1918 influenza, British India (Chandra, Kuljanin, and Wray 2012; Tumbe 2020) 1918 influenza, Japan (Chandra 2013a) 1918 influenza, Java (Chandra 2013b) 1918 influenza, Sri Lanka (Chandra and Sarathchandra 2014) 1920s–1930s mortality under Stalin (Lorimer 1946: 135; Rosefielde 1996) 1954–1962 war, Algeria (Ageron 1992; Yacono 1982) 1965–1966 mass killings, Java (e.g., Ash-Shidqi 2021; Chandra 2017a) 1994 Tutsi genocide, Rwanda (Tissot 2020; Verpoorten 2012)
Method 3 1883 eruption, Krakatoa (Reid 2013) 1885–1908 atrocities, Congo (Twain 1905: 25) 1899–1903 war and epidemic, Philippines (Gates 1984; May 1986) 1914–1922 wars, Anatolia (McCarthy 1983: 137) 1914–1922 wars, Soviet Union (Kulischer 1948: 71; Lorimer 1946: 41) 1918 influenza, British India (Davis 1951: 237; Hill 2011) 1920s–1930s mortality under Stalin (Conquest 1986: 301; Dyadkin 1983: 48) 1937–1938 mass killings, Dersim (Turkey) (Deniz 2020) 1941–1965 war and mortality under Tito (Rummel 1998: 169) 1944–1945 famine, Java (e.g., van der Eng 2024) 1947 partition, South Asia (Bharadwaj, Khwaja, and Mian 2008; Hill et al. 2008) 1952–1960 war, Kenya (Elkins 2005: 429) 1975–1979 mortality under the Khmer Rouge (Kiljunen 1984: 44) 1975–1979 occupation, Timor-Leste (Kiernan 2003) 1992–1995 war, Bosnia (Prašo 1996) 1994 Tutsi genocide, Rwanda (Kuperman 2000; Reydams 2021) 1995–1998 famine, North Korea (Lee 2005)	**Method 4** 1864–1870 war, Paraguay (Reber 1988) 1941–1945 war, Soviet Union (Ellman and Maksudov 1994; Sokolov 2014) **Method 5** 1740–1741 famine, Ireland (Dickson, Ó Gráda, and Daultrey 1982: 165) 1845–1852 famine, Ireland (Cousens 1960) 1864–1870 war, Paraguay (Kleinpenning 2002; Whigham and Potthast 1999) 1975–1979 occupation, Timor-Leste (Barbedo de Magalhães 1992: 33) **Method 6** 1347–1348 plague, e.g., Provence (Benedictow 2021: 736) **Method 7** 1959–1961 famine, China (Yao 1999) 1975–1979 occupation, Timor-Leste (Defert 1992: 148)

Method 3 differs from Method 2 in that it projects P_1 forward all the way to TP_2, rather than also projecting backward from P_2 to K_2. Therefore, L is estimated as $K_1 - P_2$. There are two reasons for wanting to use this method. One reason is if the death toll of interest can be practically treated as instantaneous and there exists a good estimate of the population's size immediately after that death toll. For example, in one estimate of the number of Tutsi killed in the Rwandan genocide, Reydams (2021) projects the Tutsi population forward from the 1956 census and then subtracts it from estimates of the number of immediate survivors of the genocide, plus the size of the Tutsi diaspora (see also Kuperman 2000; McDoom 2020). The other reason to use Method 3 is if the crisis is a considerable time before T_{P2} but one wants to estimate the death toll of interest as the counterfactually 'missing' population at T_{P2}. In an instance of popular demography, Mark Twain (1905) claimed that Leopold II's regime killed 10 million people in the Congo on the basis of the population decline in the period (Method 1), which seems to be the origin of the popularly cited figure that 10 million people died (see e.g., Hochschild 1999: 233). But Twain claimed that the Belgian regime could be considered to have killed 15 million people if the number the population would have increased by in the period if not for Belgian rule were taken into account (Method 3).

Table 2: The general equations underlying seven types of GRDM model

Method 1 $L = P_1 - P_2$	**Method 2** $K_1 = P_1 \times R_F^{T_{K1}-T_{P1}}$, $K_2 = P_2 \div R_B^{T_{P2}-T_{K2}}$, $L = K_1 - K_2$, where $T_{K_1} = T_{K_2}$
Method 3 $K_1 = P_1 \times R_F^{T_{K1}-T_{P1}}$, $L = K_1 - P_2$, where $T_{K_1} = T_{P_2}$	**Method 4** Same as Method 2, where $T_{K_1} < T_{K_2}$
Method 5 Same as Method 3, where $T_{K_1} < T_{P_2}$	**Method 6** $K_2 = P_2 \div R_B^{T_{P2}-T_{K2}}$, $L = P_1 - K_2$, where $T_{K_2} = T_{P_1}$
Method 7 $L_i = P_i \times R_{P_i,P_{i+1}} - P_{i+1}$, $L = \sum_{i=1}^{n} L_i$	

Methods 1–3 are the most commonly used forms of GRDM, but we have also identified four other methods that involve estimating a mass death toll based on projecting a population's size and identifying a discontinuity in it. Method 4 works like Method 2 but does not assume that the death toll of interest happened instantaneously. This method has been used to estimate the death toll of the 1864–1870 Paraguayan War (Reber 1988), allegedly one of the most proportionally lethal wars of modern times. Method 5 works like Method 4 but can be applied when a population estimate exists for the period just after the end of the crisis; e.g., the 1851 census of Ireland that roughly coincides with the end of the Potato Famine (Cousens 1960). Method 6 can be applied when a population

estimate for the period just before the crisis exists but the post-crisis population estimate is from a long time after the crisis. Method 7 uses the logic of Method 3 but does so by using the observed population estimates from throughout an extended crisis to estimate a cumulative population loss over time (Yao 1999), or by assuming that the crisis death rate was constant throughout the crisis and therefore iteratively estimating the population change and death toll over time (Defert 1992).

Most of the GRDM estimates we are aware of have been published outside of the field of demography proper and might be considered simplistic by some demographers, but this does not mean that demographers should not engage with these estimates seriously. Many GRDM death toll estimates constitute important statistics in the fields of conflict studies, epidemiology, political science, and regional history, and demographers are well-placed to help scholars in those fields understand these statistics. The COVID-19 pandemic is a case study in how demographers can use their tools and training to improve and, when needed, critique the population-related work undertaken by scholars working in other fields (e.g., Dowd et al. 2020; Gaddy 2021; Meyerowitz-Katz and Kashnitsky 2020). Demographers' engagement with the demographic research conducted in other fields is of great importance (see, e.g., Sheppard and Van Winkle 2020; Sudharsanan et al. 2022; Gaddy, Fortunato, and Sear 2024), as is particularly well-known among conflict demographers (Price and Ball 2014; see also Ball and Price 2014) and demographers engaged with popular narratives around population decline (Sigle 2023; Gietel-Basten 2023). Moreover, GRDM has been used to estimate mass death tolls in 'demography proper', namely in *Demography* (Chandra, Kuljanin, and Wray 2012), *Population Studies* (Cousens 1960; Hill et al. 2008; Chandra 2013b), and *Genus* (Hill 2011). Therefore, this paper aims to guide both demographers and other scholars in the use of GRDM and to encourage future systematic work by demographers to improve the mortality, fertility, and migration research of those working in other fields.

In creating the typology of GRDM applications in Figure 1 and Table 1, we have skimmed over some nuances in the logic used in each cited reference. For example, Davis (1951) and Cousens (1960) only apply GRDM as a means of checking the first-order validity of the mortality estimates they produce using actual death registration. Meanwhile, some applications only focus on subpopulations (e.g., Gates 1984; Hill 2011), and others use a panel regression implementation of GRDM, rather than explicitly using the equations shown in Table 1 (e.g., Chandra 2017a; Tumbe 2020). Several applications fit only roughly into our typology for other reasons (e.g., Benedictow 2021; Rosefielde 1996).

Table 1 also reflects a selective review of the use of GRDM (and GRDM-like) thinking. The lack of a common name for any of the GRDM variants means that a systematic review of the literature was not possible. As we have defined GRDM by its reliance on estimates of a population's total size – rather than estimates of age-specific populations or well-defined population samples – we have excluded work that uses counterfactual intercensal cohort-component techniques (e.g., Spoorenberg and Schwekendiek 2012; Kapend, Bijak, and Hinde 2020) or that follows up on the respondents of pre-crisis household surveys to extrapolate a crisis death toll using Method 1 (e.g., Frankenberg et al. 2011; Kolbe et al. 2010). Nor do we review the use of GRDM logic to estimate population loss (L) without an explicit interest in D_C, such as in research on the demographic impact of the Thirty Years War on Germany (e.g., Friedrichs 1997); or estimate mass emigration as a projection residual, instead of mass mortality (e.g., Ó Gráda and O'Rourke 1997; Rudnytskyi et al. 2015); or estimate changes in self-identification as a projection residual (Shoemaker 1999). We also only review the validity of GRDM in human populations, despite its parallel use by population biologists (e.g., Marburger and Thomas 1965; Pace et al. 2021).

However, by offering a relatively straightforward typology of methods and by roughly mapping a large amount of literature onto it, we have demonstrated that GRDM is used by demographers, historians, and human rights researchers to try to solve a wide range of death toll estimation problems. By giving a name to this set of similar ad hoc methods and by reviewing its uses, we have hopefully made it easier for researchers to talk about these methods and to use them with a knowledge of their history – if they choose to use them. By pointing to the application of GRDM to a large number of disasters and conflicts of great importance, we demonstrate the value of critically examining how sensitive GRDM is to uncertainty in its parameters and how accurate the death tolls produced using it tend to be. We examine these issues of validity in the next three sections of this paper.

3. The sensitivity of GRDM

GRDM has been used to claim a wide range of death tolls for the same event. Before more precise methods were used to quantify the scale of mortality during the 1975–1979 phase of Indonesia's occupation of Timor-Leste (Silva and Ball 2006), GRDM was used to estimate a death toll in that period of less than 95,000 (Hiorth 1985: 61) to up to 345,000 (Defert 1992: 150). The lowest figure equals 14% of the estimated 1974 population of Timor-Leste (International Historical Statistics 2013), while the highest figure equals 53% of the population. In the context of the 1864–1870 Paraguayan war, Reber (1988) uses GRDM to estimate a death toll as low as 9% of the population, while Whigham and Potthast (1999) use it to estimate that up to 69% of the population of Paraguay died. These very large discrepancies suggest that GRDM may estimate death tolls with a large amount of uncertainty.

In this section we explain how GRDM can estimate death toll estimates that differ wildly from the reality. In particular, we discuss three types of bias that can influence a GRDM model: census incompleteness, unobserved intercensal growth rates, and any fertility and migration effects of the crisis of interest. We then show how modest uncertainty with respect to these three factors tends to produce very large amounts of uncertainty in the estimated death toll. There are other factors that affect the accuracy of GRDM estimates. For example, the choice of which GRDM variant (Methods 1–7) to use is not trivial: a model should be chosen that best utilizes the available data, reflects the timing of the crisis of interest with respect to the population estimates available, and minimises uncertainty about the parameters the variant requires. However, the issue of choosing the most appropriate model does then collapse into the issue of assessing the certainty of the census completeness, growth rate, and non-mortality effect estimates. Therefore, we focus primarily on these three issues in the theoretical and simulation work that follows.

3.1 Census incompleteness

Figure 2 simulates how census incompleteness can impact the accuracy of GRDM death toll estimates, using the example of the 1918 influenza pandemic in British India. Several authors have applied GRDM to that context (Chandra, Kuljanin, and Wray 2012; Davis 1951; Hill 2011; Mills 1986; Tumbe 2020), and we are not commenting specifically on their various findings. Instead, we point out how various reasonable assumptions about the coverage of the pre-pandemic 1911 census and the post-pandemic 1921 census lead to the estimation of an unhelpfully wide range of pandemic death toll estimates, using a synthetic example that blends together different published applications of GRDM in this context.[3] In this synthetic example, GRDM estimates a death toll of 20.7 million people as a base case. Then, if it is assumed that the 1911 census was between 90% and 95% complete, and that the 1921 census was between 2% less and 2% more complete than in 1911, GRDM outputs a death toll of between 14.8 million and 30.5 million people. This is a very large margin of error, given that only 50 million people are estimated to have died in the 1918 pandemic worldwide (Johnson and Mueller 2002).

In general, GRDM misestimates the death toll of a crisis if either or both of the pre- and post-crisis estimates of the population's size are inaccurate. If the post-crisis count is

[3] In the base case, we input the 1911 and 1921 census populations of all of British India (i.e., the directly ruled provinces and the princely states that together comprise contemporary India, Pakistan, Bangladesh, and Myanmar) into the equations for Method 2 in Table 2, and then we assume that the unobserved 1911–1918 growth rate equals the observed 1901–1911 rate and the unobserved 1918–1921 rate equals the observed 1921–1931 rate.

more complete than the pre-crisis count the crisis death toll will be underestimated – sometimes as a negative number – while if the converse is true the death toll will be overestimated. Given that GRDM is typically applied in contexts in which detailed demographic data is unavailable, the issues posed by variable census completeness should be of significant concern to researchers wanting to use the method. When detailed demographic data is not available for the population of interest, this may be a sign that its government lacks the administrative capacity to ensure a complete enumeration at census time, and when censuses are incomplete their completeness is often influenced by a milieu of contemporary sociopolitical factors, such that censuses are unlikely to be consistently incomplete over time. Enumeration completeness will also vary across the geographic and social strata of the population, and the crisis of interest may itself have an impact on post-crisis completeness. These factors create particular problems when trying to use GRDM estimates for causal inference.

A review of the literature reveals that census incompleteness is often pervasive and endogenous to crises of interest. This endogeneity can occur because the crisis mortality and the census completeness are influenced by the same social patterns. For example, the 1950 census of the United States was estimated to be 3.5% incomplete nationally but 11.3% incomplete for the country's non-white population (Coale 1955; US Bureau of the Census 1960). The 1870 US census undercounted an estimated 6.6% of its total white population (Hacker 2013), but in a single county in Massachusetts the undercount varied between 10.7% among the wealthier towns and 39.8% among the poorer ones (Ginsberg 1988). The racial and socioeconomic patterns in census completeness such as these are common in historical censuses and create clear problems for estimating the scale and correlates of crisis mortality when relying on GRDM to estimate that mortality.

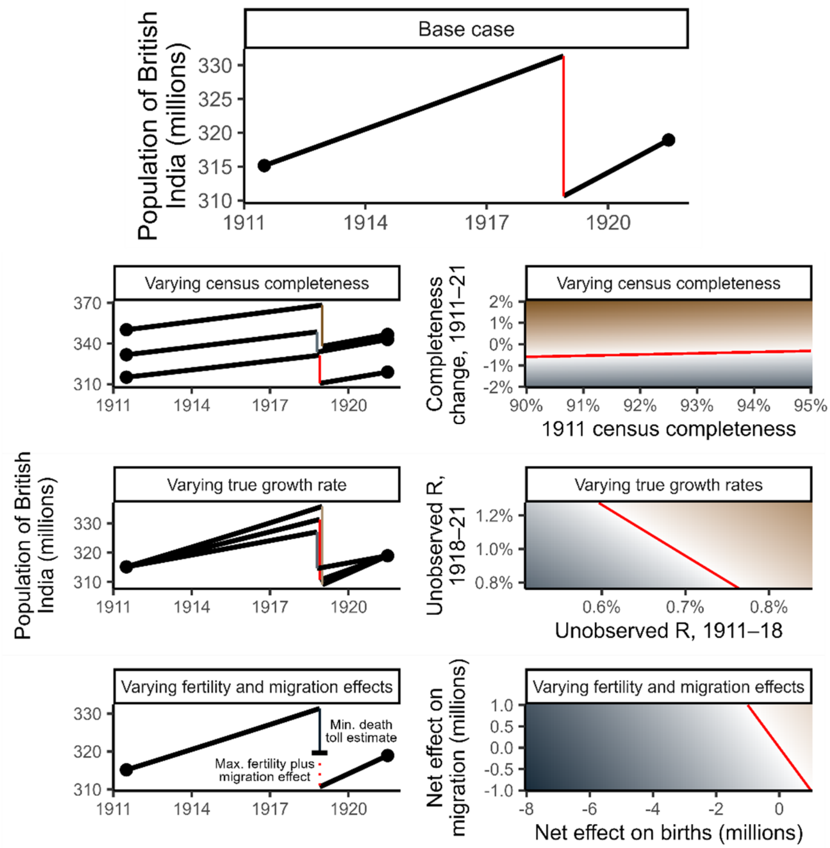
Error and endogeneity can also come about because the circumstances of the crisis of interest directly influenced the pre- or post-crisis census completeness. It was a common claim by early Western sinologists that the An Lushan rebellion killed roughly 70% of the population of 8th century CE China as there was a 70% decline between the pre- and post-war proto-censuses (Method 1) (see e.g., Giles 1915; Wieger 1928: 191), and this and similar GRDM estimates have persisted to the present (Pinker 2011: 195; White 2011). However, the death toll was in fact much smaller and the war simply decimated the capacity of the imperial tax authorities to count the post-war population (Fitzgerald 1936, 1947; Yang 2023). Similarly, the repression of Tutsis that preceded the Rwandan genocide means than the pre-genocide 1991 census greatly underestimated the number of Tutsis in Rwanda (Verpoorten 2005), while in the first census in Bosnia and Herzegovina after the country's 1992–1995 war there seem to have been intentional population overcounts motivated by the same ethnic tensions that caused the war (Hayden 2021; Žíla and Čermák 2021).

Censuses are not impartial observers of the population: the ways in which they are constructed and conducted reflect the biases of those who seek to enumerate (Bouk 2023). In practice, GRDM leans heavily on the assumption that the available population estimates are entirely and consistently complete, but this assumption often neglects the biases and idiosyncrasies in the social processes by which population estimates are generated. Moreover, adjusting population estimates for census incompleteness is not a trivial task. When a census is incomplete, it is only with detailed data from outside of the census – like post-enumeration surveys or detailed mortality and migration data – that demographers can assess how incomplete it actually is. Whenever scholars have needed to apply GRDM, that information is usually lacking, and this also means that they lack the ability to confirm the model assumptions of GRDM. This lack of detailed data means that there is no consensus about the actual extent of census completeness in South Asia around the 1918 pandemic (see Chandrasekhar 1972: 33; Mukerji 1982), but even the fairly narrow range of uncertainty as to the completeness of the 1911 and 1921 census that we allow for in Figure 2 has massive consequences. GRDM is such a sensitive tool that uncertainty about the completeness of two censuses in a single country can have the effect of nearly halving or doubling the global death toll of the 20th century's most deadly pandemic.

3.2 Unobserved growth rates

Figure 2 also simulates the effect that uncertainty regarding intercensal growth rates has on GRDM death tolls. In the case of the 1918 influenza pandemic in British India, scholars have had to estimate the true growth rate of British India's population between the 1911 census and the 1918 pandemic, as well as the true growth rate between the pandemic and the 1921 census. However, intercensal growth rates are difficult to ascertain, as we will discuss. In our simulation, we assume that the true pre- and post-pandemic growth rates were 25% higher or lower (in relative terms) than what we assumed in the base case. Assuming that all other parameters are the same as in the base case (e.g., there is no census under-enumeration), that fairly narrow range of uncertainty in the true intercensal growth rate results in another very wide range of death tolls – between 14.6 million and 26.9 million people.

Figure 2: Simulated results of the effect of parameter uncertainty on the death tolls estimated by GRDM Method 2, using the 1918 influenza pandemic in British India as an example



Many GRDM applications assume that the growth rates within the intercensal period of interest are equal to the observed growth rate(s) in the adjacent intercensal period(s). For example, Verpoorten's (2012) estimate of the Tutsi death toll during the 1994 Rwandan genocide assumes that the growth rate from the 1991 census to the beginning of the genocide was equal to the average growth rate during the baseline period between the 1978 and 1991 censuses. We also make this type of assumption in our base case in Figure 2. The rationale for this assumption is clear, but when it is applied in a strong form – as it often is – it neglects the fact that population growth often varies from period to period. Even with a large amount of demographic input data or well-informed expectations about a population's demographic behaviour, models can fail to predict population trends reasonably accurately (e.g., Gietel-Basten and Sobotka 2021a, 2021b; Gaddy 2021). Moreover, the expectation that population growth will continue at the rate it has in past is not necessarily well-informed, and this can be shown empirically. In the absence of high-quality data, the annual population of a country must be estimated using interpolation, extrapolation, graduation, and other techniques that have the effect of smoothing time series (e.g., Frankema and Jerven 2014; Gerland 2014), but this has the effect of obscuring how variable growth can be over short timespans. Instead, that variability can be gleaned from the high-quality annual population estimates in the Human Mortality Database (HMD).

Using the HMD data from 1751 to 2024, we have tested how well the observed growth rate in each 10-year period observed (e.g., the Netherlands from 1860–1870) predicted the (normally unobserved) growth rate over the following 5 years in the same population (e.g., the Netherlands from 1870–1875). The data allows for 2,773 such comparisons, and the mean absolute difference between the predicted and observed rate was 0.32% growth per year. Compounding that difference over a 10-year intercensal period suggests that growth rate misestimation will routinely cause GRDM to misestimate a death toll by 3% of the starting population, which is a very large margin of error for many mortality crises. In 5% of comparisons the error exceeded 0.90% per year, which would produce an even larger error when estimating a death toll. This analysis of the HMD has limitations (see Figure A-1 and its accompanying notes), but it shows how difficult it is to precisely predict intermittent intercensal growth rates in general.

We also note that the growth rate of a population 'at baseline' can be misestimated. Our analysis of the HMD suggests that it can be misguided to use the growth rate from the intercensal period(s) before or after a crisis to predict the intermittent growth in the same intercensal period as a crisis, but estimating the intermittent growth rate in the surrounding intercensal periods is also not trivial if the population of interest experiences many crises. Chandra, Kuljanin, and Wray (2012) note that using the average growth rate for 1891–1911 to predict the growth rate of British India between 1911–1918 assumes that growth in the immediate pre-pandemic period was somewhat like in the 1890s, even though that period contained highly deadly famines and the early 1910s did not (see Dyson 2018). When they, more reasonably, only use the 1901–1911 period to predict the growth in the early 1910s, their estimate of the death toll of the 1918 pandemic in British India increases by 11% in one model and 49% in the other. This type of problem is also important in other contexts. For example, Thornton (1984) assumes that the Cherokee population grew fairly smoothly between their ethnic cleansing in 1838–1839 and the end of his series of population estimates in 1880. However, a large proportion of the Cherokee population also died during the 1861–1865 American Civil War. Thornton notes this but does not accordingly increase the intermittent growth rate that he calculates for the post-1840 period. Depending on the scale of the losses during the civil war, accounting for them could increase the Trail of Tears death toll that he estimates by 10%–20% (see Figure A-2).

Error in the growth rates applied in a GRDM exercise also compounds exponentially the longer the intercensal interval. This is especially problematic because for some contexts of interest only very infrequent population estimates are available. For example, in Reber's (1988) attempt to estimate the death toll of the 1864–1870 Paraguayan War, she projects forward from a population estimate for 1846 to the start of the war (18 years) and then projects backward from an estimate for 1899 to the end of the war (29 years). In an attempt to ascertain the death toll of the 1850–1864 Taiping Rebellion, Ge, Hou, and Zhang (1999) project forward from 1851 to the end of the war (13 years) and then backward from 1911 to the end of the war (47 years), assuming that the intermittent growth rate throughout the entire 60-year period was equal to the 0.31% annual rate observed between 1820 and 1851. However, Figure 2 shows that uncertainty in the intermittent growth rate estimate that GRDM requires can be very consequential even within a 10-year projection interval.

3.3 Fertility and migration effects of the crisis

Finally, Figure 2 also simulates how a crisis' effect on birth and migration rates can impact GRDM's ability to estimate the death toll of that crisis. If a crisis decreases fertility and net in-migration, the population loss estimate at the time of the crisis will be greater than the crisis' death toll, all else being equal. If the crisis boosts fertility and net in-migration, the discontinuity will be less than the death toll of interest. It is conceptually difficult to formally account for these effects so that the net population-loss estimate that GRDM produces (L) can be converted into a crisis death toll estimate (D_C), and this is rarely done in a rigorous way in the literature.[4]

[4] These effects can be accounted for by either (1) adjusting the assumed growth rate between the crisis and the post-crisis population estimate to reflect the crisis' impact on fertility and migration, or (2) setting the post-crisis growth rate equal to what would have been expected in the absence of the crisis but roughly decomposing L (i.e., the population discontinuity estimated) into a death toll, a net fertility effect of the crisis, and a net migration effect of the crisis. In Section 2 of this paper we assume the former approach when introducing Method 2, so that, for the sake of introductory simplicity, we can say that 'D_C can be taken as directly equal to L… if the instantaneity assumption is reasonable'. However, we adopt the latter approach in Figure 2 in order to hopefully give a wider audience a better intuition of why a crisis' effect on birth and migration rates will affect GRDM's estimate of the crisis' death toll. However, neither of these correction strategies is commonly employed in the literature that uses GRDM. Most GRDM applications are only interested in D_C, but conflate L with D_C without accounting for these fertility and migration effects.

In the case of the 1918 pandemic in British India, it is difficult to estimate both the magnitude and direction of the pandemic's effects on fertility and migration. However, using assumptions that we think are reasonable has a massive effect on the death toll that GRDM estimates.[5] Assuming that all other parameters are the same as in the base case, a plausible range of fertility and migration effects caused by the 1918 pandemic suggests the pandemic killed between 11.7 million and 22.7 million in British India.

One reason that it is important to correct for fertility and migration effects is that mortality crises are often associated with fluctuations in fertility. Mortality can decrease fertility because it kills people who otherwise would have had children (Polizzi and Tilstra 2022); this is especially true of epidemics and conflicts that disproportionately hit reproductive ages (García and Aburto 2019; Jdanov, Glei, and Jasilionis 2010; Viboud et al. 2013). However, on balance, crises can have very heterogeneous associations with birth rates. The 1918 influenza pandemic was associated with a much stronger fertility decline than the pandemic deaths of reproductive-age people alone would predict (Gaddy and Mølbak Ingholt 2024), while the 2004 tsunami in Indonesia was associated with a strong increase in fertility overall (Nobles, Frankenberg, and Thomas 2015). Other mortality crises have no discernible effect on fertility (Svallfors 2022; Floridi, Gargiulo, and Aburto 2023), while some crises have positive effects on fertility in some populations but negative ones in others, like the COVID-19 pandemic (Bailey, Currie, and Schwandt 2023; Cozzani et al. 2023; Sobotka et al. 2023). The fact that excess mortality can strongly dampen, strongly boost, or have no short-term net effect on fertility means that scholars using GRDM need to know about fertility trends in their context of interest, even though such information may be lacking.

Mortality crises can also be associated with migration shocks that bias GRDM estimates of death tolls. Often, the social conditions that cause mass mortality can also drive mass out-migration from a population – sometimes with the out-migration being

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[5] Vital statistics in the period suggest a large reduction in fertility (Dyson 1989; Gaddy and Mølbak Ingholt 2024; Mills 1986), and Hill's (2011) GRDM work concurs, suggesting a deficit of roughly 7 million births around the time of the pandemic. However, there are several reasons to be unsure about this. Vital statistics completeness in part of the post-pandemic period may have been disrupted severely by the Non-Cooperation Movement (Chandrasekhar 1972: 33; see Gaddy and Mølbak Ingholt 2024); indeed, the first detailed study of post-pandemic fertility anywhere in India (in this case, in Chennai) finds only a minor drop in birth rates (Chandra, Sarkar, and Rynjah 2024). Also, GRDM is not a precise method of estimating changes in birth rates, and classical demographic theory does suggest that mortality spikes in pre-transitional populations should cause spikes in fertility (Livi Bacci 2000). Therefore, we allow for between a net birth deficit of 8 million and a net birth surplus of 1 million between the pandemic and the 1921 census, independent of the counterfactual growth rate applied in that period. Understandings of migration in South Asia in this period are even poorer – but we note that there was appreciable international migration in and out of British India in this period (Elahi and Sultana 1985; Jain 2012) and the pandemic seems to have affected lives and livelihoods in British India such that it affected migration decisions (Jha 2023; Donaldson and Keniston 2016). Therefore, we allow for between a net migration deficit of 1 million and a net migration surplus of 1 million in the immediate post-pandemic period.

much greater than the triggering mortality (Steele 2017). These conditions can similarly slow in-migration to a population (Shrestha 2019). On the other hand, mass mortality causing land availability caused mass in-migration to the regions most affected by the Taiping Rebellion and the Black Death (Hao and Xue 2017; Jedwab, Johnson, and Koyama 2022). Overall, the association between mortality crises and migration trends is highly dependent on social context (Alvarado and Massey 2010). However, some GRDM applications have not been conscientious in accounting for migration effects. For example, Wang (2007) argues that the GRDM estimate of the death toll of the 1556 Shaanxi earthquake (830,000 people, or more than 1% of the population of all of contemporary China; see Deng 2004 for population estimates) is so large simply because there was mass emigration from the region the earthquake hit.

3.4 Simulation overview

GRDM can be used to estimate a wide range of death tolls whenever there is a small amount of uncertainty in the values of its parameters. Unfortunately, if a scholar resorts to using GRDM it likely means that they do not have the strong understanding of the census completeness and intercensal birth, death, and migration trends in the period that are required to specify the method. Taking the case of the 1918 influenza pandemic in British India, if all six discussed parameters are varied – the 1911 and 1921 census completeness, the unobserved 1911–1918 and 1918–1921 counterfactual growth rates, and the unobserved net effects of the pandemic on fertility and migration in the 1918–1921 period – within the bounds we consider plausible, GRDM suggests a true death toll between –0.8 million and 39.4 million (not shown). That is an unhelpfully wide interval between no one dying and 12% of the contemporary population dying.

These results demonstrate the importance of simulating the uncertainty bounds that are implicit in GRDM estimates. As we show, this can be done by identifying reasonable bounds of the census completeness and intercensal growth rates in the context of interest and then estimating a range of plausible population loss estimates. Those estimates can then be combined with estimates of the fertility and migration effects of the crisis of interest to produce a death toll estimate. It is unfortunate that few published GRDM estimates have considered the effect that any amount of input uncertainty has on their death toll estimates, with rare exceptions, including Gates (1984), Reber (1988), and Chandra, Kuljanin, and Wray (2012). Simulating the uncertainty of GRDM estimates may be an important next step in the study of the many historical mortality crises listed in Table 1. However, our conclusion is that in most contexts of interest it will not be possible to estimate reasonable (nor helpfully narrow) bounds of the GRDM parameters. Meanwhile, if the data to accurately estimate the census completeness and intercensal growth rates does exist, then it is possible to use a more trusted and informative method of death toll estimation than GRDM.

4. The performance of GRDM for death toll estimation

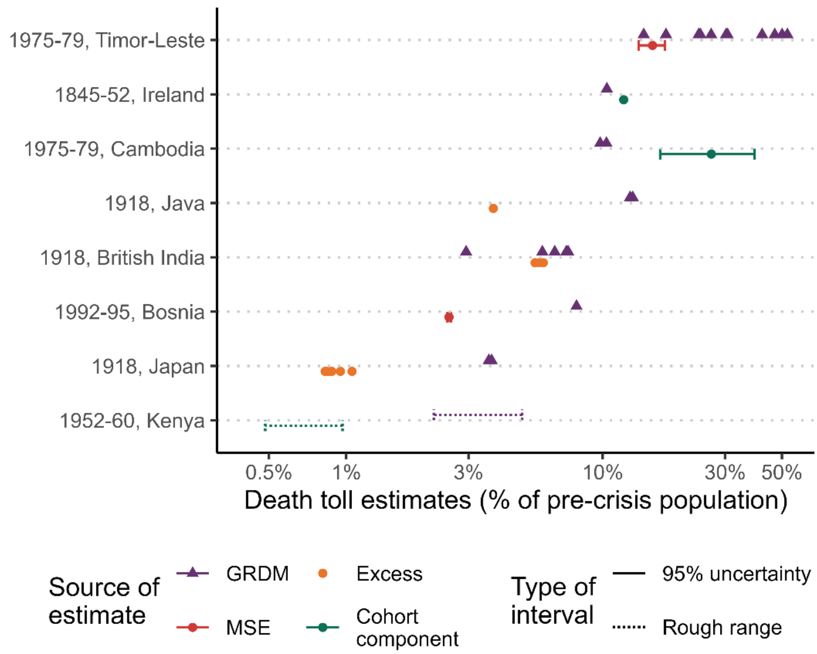
The previous section suggests that GRDM is too sensitive a method to provide a reasonably narrow range of death toll estimates – at least in contexts where the data is not good enough to use a better method. This section examines whether this prediction is borne out by existing literature by comparing published death toll estimates that have been produced using GRDM with published death toll estimates for the same crisis that have been produced using standard demographic techniques.

Our literature review has identified alternative death toll estimates for the same crises, produced using both GRDM and one of three methods from the standard demographic toolkit: (1) excess mortality modelling, (2) intercensal cohort-component techniques, and (3) multiple systems estimation (MSE; also called capture-recapture in some disciplines). Reviewing the mechanics of these three methods is beyond the scope of this paper, but each method is much more widely relied upon as a means of estimating death tolls than GRDM. This is, in part, because they have already been subjected to many independent examinations of their limitations and are informed by a much larger amount of input data than GRDM. Excess mortality models use time series of registered deaths to construct a counterfactual of how many deaths would have occurred in the absence of a crisis, and therefore how many excess deaths are attributable to that crisis (see Wakefield and Knutson 2025). They are the standard technique for estimating epidemic death tolls when information about death registration completeness is available (e.g., Paglino et al. 2023). Cohort-component models use age-specific census counts, model life tables, and assumptions about migration to yield intercensal cohort-specific mortality in excess of that predicted by the model life table (see Preston, Heuveline, and Guillot 2001). They are the standard technique when crisis death registration is poor but census quality is high and the baseline mortality conditions are well understood (e.g., Heuveline 2015). MSE work on mortality crises uses the overlaps between linked lists of victims to statistically infer the whole number of victims, including unobserved cases (see Lum, Price, and Banks 2013). It is the standard technique when civil death registration is poor but deaths are recorded in multiple, overlapping sources (e.g., Brunborg, Lyngstad, and Urdal 2003). In comparison, GRDM is used only in isolated, ad hoc contexts, is being systematically examined for the first time in this article, and is informed by very little input data. The outputs of the three better-validated methods are not beyond criticism and improvement – which we subject them to below – but they are a fair benchmark for assessing GRDM's accuracy and precision.

Figure 3 compares GRDM death toll estimates to the better-validated estimates available for 8 mortality crises. Of these 8 crises, 3 have been analysed using excess mortality methods (the 1918 influenza pandemic in British India, Japan, and Java), 3 have been analysed using cohort-component methods (the 1845–1852 Irish potato famine, the 1952–1960 Mau Mau uprising in Kenya, and the 1975–1979 regime of the Khmer Rouge in Cambodia), and 2 have been analysed using MSE (the 1975–1979 phase of Indonesia's occupation of Timor Leste and the 1992–1995 Bosnian war). The notes below the figure list the references for the GRDM and better-validated exercises in each case. We are not aware of any other mortality crises for which both GRDM and better-validated death toll estimates are available in the literature.

In general, Figure 3 shows that in these cases there is very low and very inconsistent concordance between the GRDM and better-validated estimates. In four contexts (Japan, Bosnia, Java, and Cambodia) a narrow range of GRDM estimates is available, none of which are close to a better-validated value. In one context (Kenya) there is a wide range of GRDM estimates available, none of which are close to a better-validated value. In two contexts (British India and Timor-Leste) there is a wide range of GRDM estimates, only some of which overlap with a better-validated value. Only in the case of the Irish Potato Famine is the sole GRDM estimate (Cousens 1960; 860,000 deaths) fairly concordant with the better-validated estimate (Boyle and Ó Gráda 1986; 1 million deaths). However, the overall low level of concordance between GRDM and better-validated estimates means that if there were no better-validated death toll estimate available for the Potato Famine, we would not know that Cousens' (1960) estimate was fairly accurate. We also would not know that Chandra, Kuljanin, and Wray's (2012) GRDM estimate of the death toll of the 1918 influenza pandemic in British India was accurate but Hill's (2011) GRDM estimate was far too low and Tumbe's (2020) GRDM estimate was somewhat too high. None of the GRDM estimates we cite in Figure 3 come with thoroughly simulated uncertainty bounds, but the poor concordance between them and the available, better-validated estimates suggests that they have very large implicit uncertainty bounds. In the contexts with available, better-validated estimates, it is common for GRDM estimates to be two or three times higher or lower than the better-validated estimate.

Figure 3: Comparison of death toll estimates for 8 mortality crises, produced with GRDM versus better-validated demographic techniques, in terms of the proportion of the pre-crisis population killed



Note: The denominators for the death toll estimates are all for the year before the crisis began.
Source: Death toll estimates: 1845–1852, Ireland (Boyle and Ó Gráda 1986; Cousens 1960: 64); 1918, British India (directly ruled territory only) (Chandra, Kuljanin, and Wray 2012; Davis 1951: 237; Hill 2011: 16, 21; Mills 1986: 39; Murray et al. 2006, adjusted with the registration incompleteness estimate in Hill 2011; Tumbe 2020: 56); 1918, Japan (Chandra 2013a; Hayami 2015; Murray et al. 2006; Ohmi and Suzuki 2018; Richard et al. 2009; Shimada and Urashima 2010); 1918, Java (Chandra 2013b; Gallardo-Albarrán and De Zwart 2021, adjusted with the registration incompleteness estimate in Gardiner 1981: 42); 1952–1960, Kenya (Blacker 2007; Elkins 2005: 429; see also Elkins 2011); 1975–1979, Cambodia (Heuveline 2015; Kiljunen 1984: 44; Vickery 1984: 187); 1975–1979, Timor-Leste (Barbedo de Magalhães 1992: 33; Budiardjo and Liem 1984: 51; Defert 1992: 150; Hiorth 1985: 61; Kiernan 2003; Silva and Ball 2006); 1992–1995, Bosnia (Prašo 1996; Tabeau and Zwierzchowski 2013). Denominators: Nitisastro (1970: 102) (Java), India Office (1922: 204) (directly ruled British India), and International Historical Statistics (2013) (otherwise).

This presents a problem for a swathe of historical and conflict demography, given that there are many mortality crises for which the only apparently credible death toll estimate available comes from GRDM. In many cases, the only indication of a death toll that we have besides GRDM estimates comes from contemporary accounts that are understood to be primarily illustrative in nature, or that may be an accurate description of the death toll in one context but are not appropriate for drawing generalizations. These cases include the 1838–1839 Trail of Tears of the Cherokee (see Thornton 1984) and the

1965–1966 mass killings in Java (see Cribb 1990, 2001; Kammen and McGregor 2012; Roosa 2020). For other crises there is a similar problem: standard demographic methods have been applied to a crisis, but the quality of the data used in them is sufficiently poor or uncertain that those methods cannot be systematically trusted, and so it is unclear whether the available GRDM estimates are accurate. These cases include the 1918 influenza pandemic in Sri Lanka (see Langford and Storey 1992; Murray et al. 2006) and the 1994 genocide of the Tutsi in Rwanda (see Armstrong, Davenport, and Stam 2020; Guichaoua 2020).[6] These are all cases in which the available data does not allow researchers to externally validate the available GRDM death toll estimates.

Some of the discordance between the GRDM estimates and the better-validated estimates in Figure 3 may be attributable to deficiencies in the better-validated work. However, these concerns do not greatly affect the conclusions we draw from Figure 3. The better-validated estimates that come from excess mortality modelling are subject to some uncertainty due to the current lack of consensus as to what is the most accurate way of calculating excess deaths (see Andreasen and Simonsen 2011; Duerst and Schöley 2024; Li et al. 2018; Nepomuceno et al. 2022; Wakefield and Knutson 2025), but that amount of uncertainty is small relative to the difference between the excess mortality and GRDM estimates in Figure 3. We also lack confidence in the better-validated estimate that we offer for the 1918 influenza pandemic in Java, due to the relative crudeness of the figure that we use to adjust for death registration incompleteness in that context. However, the five crises in Figure 3 with available cohort-component and MSE estimates tell much the same story as when we include the contexts with available excess mortality estimates.[7]

Some of the discordance can also be attributed to differences in what the GRDM and better-validated estimates are measuring. A general problem is that many of the GRDM 'death toll' estimates are upper bounds of excess mortality, given that they may be biased upwards by a net negative effect of the given crisis on fertility. However, adjusting the GRDM figures in Figure 3 for fertility deficits does not rehabilitate the track

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[6] Other cases in which we know of no standard demographic methods being applied include the 1850–1864 Taiping Rebellion (see Meyer-Fong 2015) and the 1876–1879 Northern Chinese Famine (see Ó Gráda 2011: 192–193). Other cases in which standard demographic methods have been applied but with highly uncertain results include the 1899–1903 Philippine–American war (see De Bevoise 1995: 13), the 1920s–1930s excess mortality under Stalin (see Anderson and Silver 1985), the 1954–1962 Algerian war of independence (see Locoh, Nizard, and Vallin 1974), and the 1959–1961 Great Chinese Famine (see Ó Gráda 2013).

[7] Some of the discordance in Figure 3 can also be attributed to differences between the denominators used in calculating the better-validated proportions of the pre-crisis population killed for Figure 3 and between the denominators (i.e., K_1) implicit in GRDM. However, the net effect of this is negligible, given that the patterns in Figure 3 remain the same when comparing only the absolute death tolls estimated in each source (see Figure A-3). Additionally, in the case of Timor-Leste, the better-validated estimate we use covers the entire period of Indonesia's occupation (1975–1999), rather than just the period that the GRDM estimates specifically focus on (1975–1979). However, the vast majority of the deaths identified by Silva and Ball (2006) for the longer period occurred just in the period focused on by the GRDM work.

record of GRDM for estimating death tolls. Adjusting for a fertility deficit would increase the discordance between the GRDM and better-validated values for the Irish Potato Famine and the Khmer Rouge, given that, as it stands, the GRDM toll already underestimates the better-validated toll. Meanwhile, adjusting for a fertility deficit in British India in the 1918 pandemic makes Tumbe's (2020) GRDM estimate much more plausible but would make the GRDM estimates by Chandra, Kuljanin, and Wray (2012) much less plausible. Then, in the cases of the 1918 influenza pandemic in Japan (Chandra and Yu 2015), the Mau Mau uprising (Blacker 2007), and the Bosnian war (Staveteig 2011), we know that the post-crisis fertility deficits were not nearly large enough to explain the discordance for those crises in Figure 3.

Instead, most of the discordance between the GRDM and better-validated death toll estimates in Figure 3 must come from inaccuracy in the parameter values that underlie the GRDM work cited. As demonstrated in Section 3, small amounts of uncertainty in the GRDM parameters create large amounts of uncertainty in the death toll of interest. This high sensitivity of GRDM means that many things can go wrong when specifying it – and it is beyond the scope of this paper to dissect the assumptions that underpin each of the GRDM exercises cited in Figure 3 – but the sources of the inaccuracy are fairly clear in two of the cases cited. Blacker (2007) explains that Elkins' (2005) GRDM work overestimates the death toll of the Mau Mau uprising because of changes between the pre- and post-crisis censuses in enumeration completeness, ethnic self-identification, and colonial classification. In the case of Japan in 1918, in which the high quality of the death registration available means that excess mortality methods will work very well to estimate the pandemic's mortality (Morita 1963; Riffe and Noymer 2017; Takase 1991; see also Johansson and Mosk 1987), we observe that the discrepancy between Chandra (2013a) and the available excess mortality work can be explained precisely by the change in how Japan's population was estimated around the time of the pandemic.[8] It is telling that in each of these cases, the key problem seems to be GRDM's assumption that censuses are complete and are stable in their enumeration practices.

Like the simulations in Figure 2, the real-world examples in Figure 3 suggest that GRDM is unreliable because of its extreme sensitivity to its inputs, and a GRDM death toll can only be relied on if another demographic method can be used to verify it.

[8] Prior to 1920, de facto population estimates came from de jure household registration adjusted for estimates of long-term and short-term migration, while from 1920 onwards they came from a de facto census (see Taeuber 1958). The discrepancy between the GRDM population loss estimated in Chandra (2013a) and the excess mortality estimate in Hayami (2015) can be explained away entirely if the 1920 post-pandemic census was complete but the pre-pandemic population estimate that Chandra (2013a) uses (the end-of-year 1913 type B de facto estimate) was roughly a 1.4% overcount. Indeed, comparing the population estimates that Chandra (2013a) uses for 1913 and 1920 to the current, official estimates for what Japan's population was at those points in time suggests that the latter was highly accurate, while the former was a 1.7% overcount (Ministry of Health, Labour and Welfare 2023).

5. Can GRDM capture the relative spread of crisis mortality?

Sections 3 and 4 have suggested that GRDM is not a useful method for estimating the size of death tolls in absolute terms – i.e., for answering whether an epidemic killed 10,000 or 100,000 people in Population A. However, this does not necessarily mean that GRDM cannot be used to estimate excess mortality in relative terms – i.e., for answering whether an epidemic probably killed a greater proportion of Population A than Population B. Since excess mortality has a causal effect on population growth, GRDM may be able to reliably pick up a signal of the relative scale of that mortality. Therefore, in this final analytical section we examine whether GRDM death toll estimates tend to capture the relative spread of crisis mortality well, such that it can at least serve as a proxy for the variation in real, unobserved death tolls.

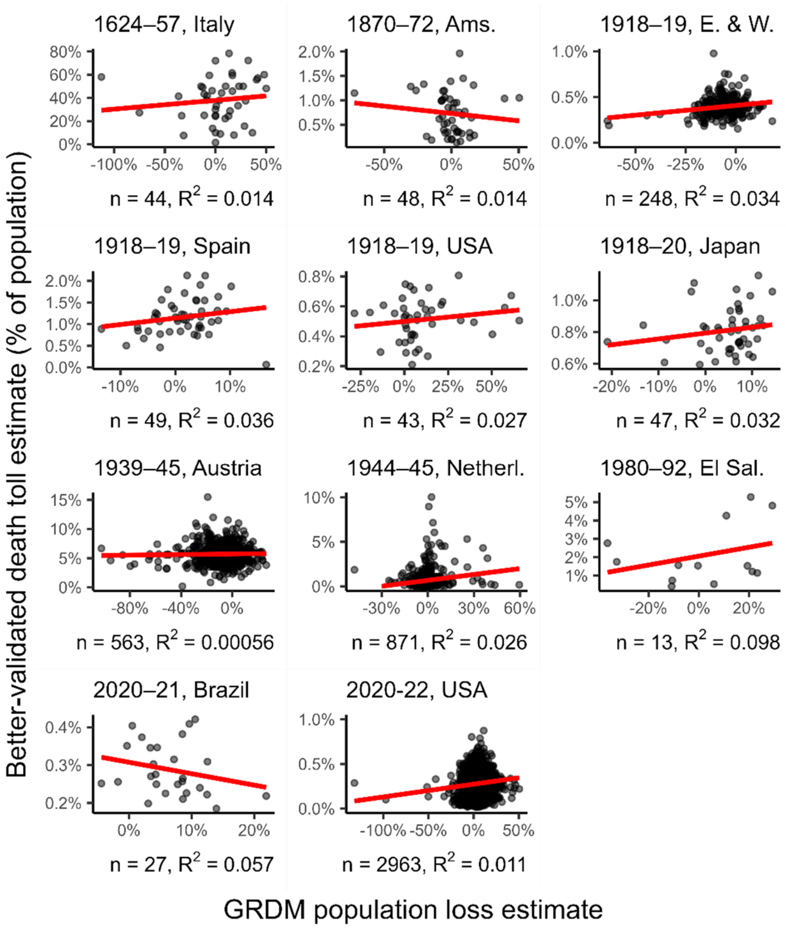
This is an important question to ask because it is a common practice to use GRDM outputs in this way in econometric work. In particular, the population loss (L) estimated by GRDM is used as a proxy for crisis mortality within a regression framework in order to estimate the community-level determinants of who was most likely to die in that crisis, or, to estimate the community-level consequences of that crisis. For example, Verpoorten (2012) uses GRDM to test the neo-Malthusian hypothesis that land scarcity predicted violence in the Rwandan genocide, and Chandra (2017a) uses GRDM to estimate patterns of violence during the mass killings in Java in 1965–1966 (see also Ash-Shidqi 2021; Chandra 2017b, 2019a, 2019b; Chandra and Zhang 2023; Winward and Chandra 2023). The use of GRDM outputs as a regression proxy has also played a major role in the literature on the population change caused by the 1918 influenza pandemic in South Asia and the subcontinent's partition in 1947 (see Bharadwaj, Khwaja, and Mian 2008, 2015; Bharadwaj and Quirolo 2016; Jha and Wilkinson 2012; Tumbe 2020; Xu 2023: Appendix C).

In order to test whether GRDM outputs are good proxies for ground-truth mortality, we have collected subnational better-validated mortality estimates for 11 mortality crises. These crises are from varying sociodemographic and historical contexts, and they have high-quality mortality estimates available at varying levels of geographic granularity. For each of these crises we have identified better-validated subnational mortality estimates in the literature, matched them to subnational population estimates, applied a GRDM model, and then compared the resulting GRDM discontinuity outputs to the available better-validated mortality estimates. Specifically, we look at plague mortality across cities in Italy in 1624–1657 (Method 1); smallpox mortality across neighbourhoods in Amsterdam in 1870–1872 (Method 2); influenza mortality across county boroughs, metropolitan boroughs, urban districts, and rural districts in England and Wales in 1918–1919 (Method 1); influenza mortality across provinces in Spain in 1918–1919 (Method 2); influenza mortality across cities in the United States in 1918–1919 (Method 2); influenza mortality across prefectures in Japan in 1918–1920 (Method 2); conflict mortality among soldiers across municipalities in Austria in 1939–1945 (Method 6); famine mortality across municipalities in the Netherlands in 1944–1945 (Method 1); conflict mortality across departments in El Salvador in 1980–1992 (Method 5); state-level COVID-19 mortality in Brazil in 2020–2021 (Method 5); and county-level COVID-19 mortality in the United States in 2020–2022 (Method 5).

Figure 4 shows how well GRDM outputs serve as a proxy for the better-validated death toll estimates available in 11 crisis contexts. The figure compares whether communities with larger GRDM population loss estimates also had larger better-validated death tolls, and how tight the relationship between those two variables is. For example, in the case of the United States in 1918–1919, we compare the excess pneumonia and influenza death rates estimated by Markel et al. (2007) for 43 cities to a GRDM exercise that estimates a population discontinuity for end-of-year 1918 by extrapolating between the 1900–1940 census populations for each city. In the case of the United States in 2020–2022, we compare the excess all-cause death rates estimated by Paglino et al. (2023) for 2,963 counties to a GRDM exercise that estimates the discontinuity between projected population values for the beginning of the pandemic and the officially estimated populations for mid-year 2022. In both of these cases, communities with larger population loss estimates did have larger death tolls on average – this is shown by the positive associations in Figure 4 – but there is also a large amount of variance in this relationship. In the 1918–1919 case, the GRDM outputs only capture 2.7% of the variance in the better-validated death rates (R^2), and in the 2020–2022 case they only capture 1.1% of that variance.

GRDM outputs have similarly low predictive values in all the case studies we examine. The R^2 values across all 11 cases only range between 0.056% and 9.8%, and in 2 of the 11 cases the association between the GRDM outputs and better-validated death tolls is not even in the right direction. In Amsterdam in 1870–1872 and in Brazil in 2020–2021, subpopulations for which GRDM predicted a relatively large death toll in reality had a relatively small death toll. This means that GRDM outputs are an extremely poor proxy for ground truth when estimating the determinants or consequences of mortality, and the statistical associations found may even be of the wrong sign. GRDM's fit of the better-validated data is very poor even when population estimates from relatively shortly before and after the crisis are used (e.g., 1918–1920 in Japan and 1944–1945 in the Netherlands).

Figure 4: The associations between GRDM estimates and the subnational death tolls estimated for 11 mortality crises using standard demographic methods



Note: The sign convention for the population loss is that a positive value implies a reduction in the population at the time of the crisis, while a negative value implies an increase in the population.
Source: 1624–1657, Italy (Alfani and Percoco 2019; Malanima 2005); 1870–1872, Amsterdam (Muurling, Riswick, and Buzasi 2023); 1918–1919, England and Wales (Johnson 2001a, 2001b; Nomis 2022); 1918–1919, Spain (Chowell et al. 2014; Instituto Nacional de Estadística, 2004); 1918–1919, US (Gibson 1998; Markel et al. 2007); 1918–1920, Japan (Hayami 2015; Japan Statistical Association 1987); 1939–1945, Austria (Eder 2022); 1944–1945, Netherlands (Ekamper et al. 2020); 1980–1992, El Salvador (Centro Centroamericano de Población 2008; Hoover Green and Ball 2019); 2020–2021, Brazil (IBGE 2019, 2023; Robles Colonia et al. 2023); 2020–2022, US (Manson et al. 2023; Paglino et al. 2023; US Census Bureau 2024).

GRDM is such a poor fit for the relative spread of excess mortality for the same reasons that it is described to be a poor estimator of mortality in Sections 3 and 4 of this paper. In the subnational estimation case, the biases presented by unobserved intercensal migration rates are particularly concerning. Washington D.C. and Nashville, Tennessee both saw an estimated 0.61% of their population die at the peak of the 1918–1919 influenza pandemic, but variable migration rates mean that GRDM predicts very divergent pandemic death tolls for the two cities. This is because Washington's population boomed between 1910 and 1920, growing 32% in total compared to an average of 15% per decade in the two decades on either side, while Nashville's population stagnated, growing just 7% in total compared to 33% on average in the surrounding decades. In the case of 17th century Italy, divergent migration rates mean that even though San Servo and Cagliari both saw roughly 60% of their populations die from plague in 1656–1657, the former's population fell by half between 1600 and 1700, while the latter's population more than doubled.

Even if a strong association is found between GRDM outputs and a suspected cause or consequence of mortality, this may solely be a data artifact. This is because the sources of bias described in Section 3 may not be orthogonal to the variable of interest. For example, if the interest is in the association between relative death tolls (as proxied by GRDM outputs) and some demographic, economic, or political variable, but that variable is associated with one of the parameters of GRDM, the estimated association between that variable and the proxied death toll may be entirely spurious. Population groups that are relatively poorly counted in the post-crisis census will appear to have had a relatively high death toll even if they did not actually die at higher rates, and the post- or pre-census completeness may be associated with the variable of interest, independent of the crisis. Communities that are estimated to have had relatively high intercensal growth rates, e.g., because their growth between the two censuses before the crisis was high, will also appear to have suffered badly in the crisis, all else being equal. The ratio between the net fertility and migration response to the crisis of interest and the mortality response may also vary across populations in a way that is confounded with the variable of interest. Since GRDM tends to capture true death rates poorly, small amounts of these biases can easily skew its outputs significantly.

The mortality crises we consider in Figure 4 are not necessarily representative of all crises to which scholars might want to apply GRDM, but they do present a cautionary tale. Like in Figure 3, the results suggest that we cannot trust that GRDM estimates are a good proxy for reality without confirming that fact with standard demographic analysis, at which point researchers can and should use the output of that more-standard analysis. The fit between the GRDM and better-validated estimates in Figure 4 does increase markedly if certain outliers are dropped – for example, the R^2 in the case of Spain in 1918–1919 increases from 0.04 to 0.17 if the Canary Islands are omitted – but if we do not have access to higher-quality mortality estimates we cannot assess which GRDM estimates are the outliers.

Therefore, we conclude that GRDM tends to be a highly unreliable method for assessing both the absolute size of death tolls and their relative size across local units of analysis. In particular, in a regression setting, GRDM may often be a biased indicator; this is because the factors that bias GRDM are bound up with the social, political, and economic contexts that prevail both before and after the crisis of interest. As a result, GRDM's measurement error will often be correlated with the variable of interest, making it difficult to estimate the variable's true association with crisis mortality.

6. Conclusion

Knowing the size of a crisis death toll is an important task in demography, economic and social history, epidemiology, conflict studies, and disaster studies, among other fields. Outside of academia, knowing a death toll can improve a human rights or humanitarian organization's ability to seek resources and justice in the face of tragedy. However, death tolls are sometimes estimated with a large amount of inaccuracy or imprecision. The class of statistical methods that we term GRDM, which crudely estimate death tolls by projecting pre- and post-crisis total population estimates and then calculating any resulting population discontinuity, produce estimates with very large amounts of imprecision and often with large amounts of inaccuracy. This is especially problematic because the contexts in which GRDM is resorted to are the exact ones in which the basic demographic parameters required as inputs to GRDM are not known with much certainty.

In effect, GRDM is a method in want of a proof of concept. After reviewing dozens of published applications of GRDM, the only cases in which a GRDM death toll estimate tracks an externally better-validated estimate are Cousens' (1960) work on the Irish Potato Famine, Chandra, Kuljanin, and Wray's (2012) work on the 1918 influenza in British India, and Hiorth (1985) and Kiernan's (2003) work on the occupation of Timor-Leste. Moreover, in the 1918 British India case, GRDM death toll estimates exist that use similar data and assumptions to Chandra, Kuljanin, and Wray (2012) which are 50% lower (Hill 2011) or 25% higher (Tumbe 2020) than the better-validated death tolls in that case, while in the case of Timor-Leste there are GRDM estimates that are up to 235% higher than the better-validated work (Defert 1992). Future analysis may reveal a well-justified set of use cases for GRDM, but this first systematic attempt to identify contexts in which GRDM works well has not identified them. We come to these conclusions based on simulation work (Section 3), comparisons between published GRDM death toll estimates and better-validated work for the same crises (Section 4), and comparisons of how well GRDM outputs tend to capture the relative spread of better-validated death tolls in crisis contexts (Section 5).

Scholars have used GRDM because they want to understand crisis mortality in contexts in which it is difficult to do so, but in those contexts, GRDM estimates come with very large uncertainty bounds. In Section 3 we have shown one approach to estimating a range of plausible GRDM death tolls from a technical point of view, using plausible variation in input parameters. However, a practical concern is that the uncertainty implicit in GRDM estimates might always be so large as to mean that it may not be possible to draw reliable insights into the scale, causes, or consequences of mortality from GRDM work alone. In contexts in which both GRDM and better-validated death toll estimates are available in the literature, scholars should assess the reasons why those estimates may diverge and therefore assess which estimates are likely to better reflect reality. In cases in which only a GRDM death toll estimate is available, scholars should focus their efforts on gathering the data that can allow them to use standard demographic techniques for death toll estimation or that will allow them to develop new reliable methods.

In the absence of such data, we encourage scholars to describe and study mortality crises qualitatively. Quantitative analysis does have advantages over qualitative analysis: accurate statistics about mortality crises allow for advocating for the dead and still-living in ways that accurate qualitative description cannot. However, even in a complete absence of statistics, witnesses of disease and conflict can and often do provide detailed qualitative accounts of the scale, causes, and consequences of those crises' mortality. There are many historical mortality crises and some contemporary ones for which the most objectively accurate information available is qualitative, not quantitative. We question how many academic and activist objectives can be achieved by applying ad hoc demographic methods to data of very uncertain quality, as opposed to using the qualitative accounts available from the same context. Some claims can only be made using numbers, but when a death toll estimate is wildly inaccurate or imprecise, as is often the case with GRDM, it can negatively affect the desired aim in terms of both scholarship and justice.

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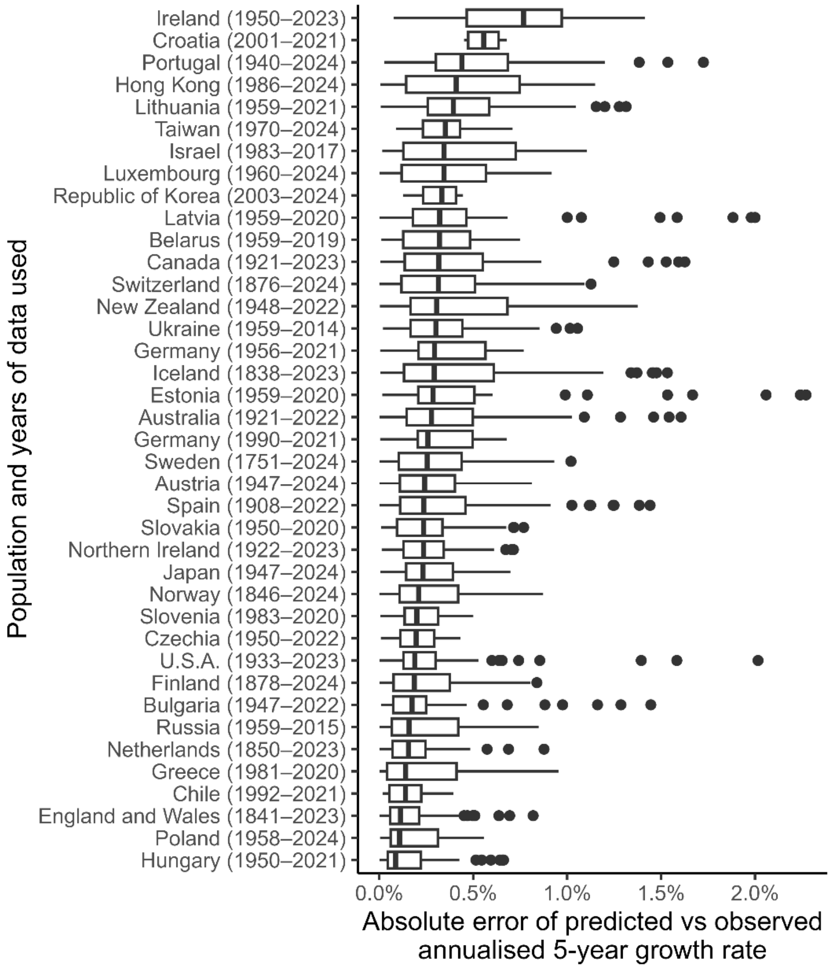
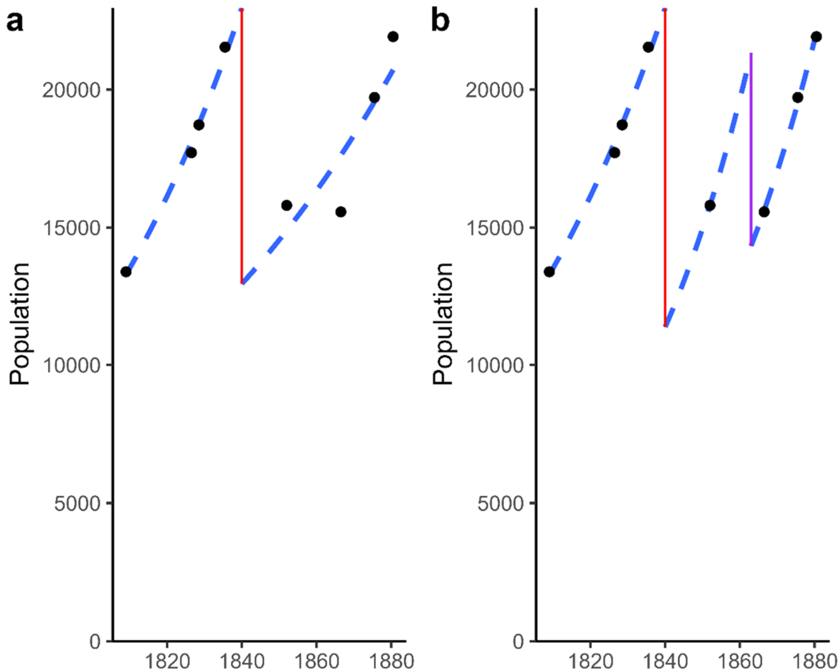
Supplementary figures

Figure A-1: Absolute differences between the annualized growth rate in a population between year *t* and *t*+10 and between year *t*+10 and *t*+15 in the Human Mortality Database (2025)



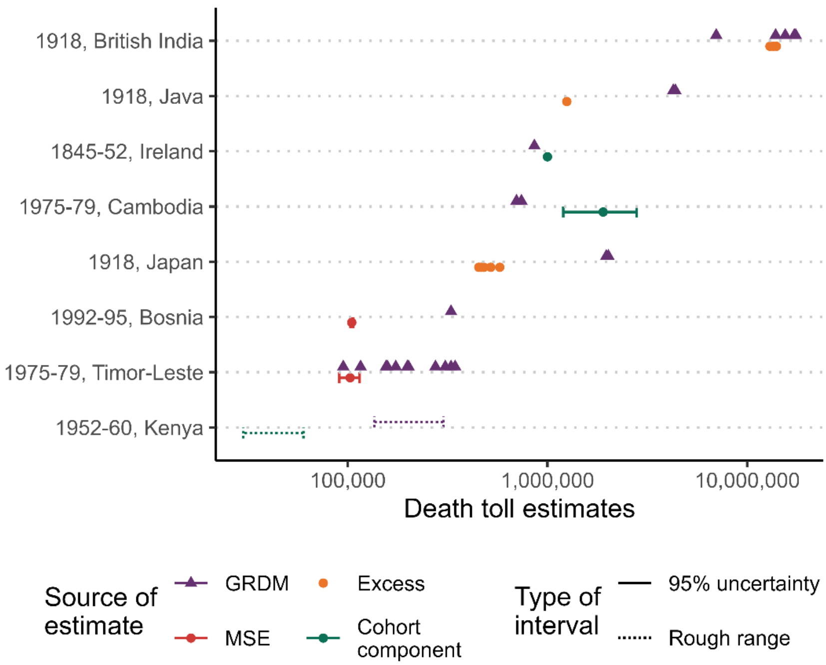
Note: The HMD focuses disproportionately on the histories of countries that are currently high-income, but its key advantage in this case is that its annual population estimates result from comparatively large amounts of high-quality data. We calculated the difference between observed and expected growth rates (as described in the text) for all 40 distinct national populations with no major changes in their definitions over time, using the HMD as available in February 2025. The years included in the analysis for each population are shown in the figure.

Figure A-2: Replication of the Cherokee death toll estimate during the Trail of Tears in Thornton (1984) (panel a), and a modification of the estimate accounting for a hypothetical death toll of 7,000 suffered by the Cherokee during the American Civil War (panel b)



Note: There does not seem to be a better-validated death toll estimate available for the Cherokee death toll during the American Civil War, but we have taken the figure of roughly 7,000 deaths from Mooney (1975, 149) simply to illustrate this methodology problem.

Figure A-3: Comparison of death toll estimates for 8 mortality crises produced with GRDM versus better-validated demographic techniques and data in terms of the absolute number of people killed



Source: See the notes below Figure 3 for the death toll sources.