

Population projections for U.S. counties by age, sex, and race controlled to the Shared Socioeconomic Pathways *

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Small area and subnational population projections are important for understanding long-term demographic changes. I provide county-level population projections by age, sex, and race in five-year intervals for the period 2015-2100 for all U.S. counties. Using historic U.S. census data in temporally rectified county boundaries and race groups for the period 1990-2015, I calculate cohort-change ratios (CCRs) and cohort-change differences (CCDs) for eighteen five-year age groups (0-85+), two sex groups (Male and Female), and four race groups (White NH, Black NH, Other NH, Hispanic) in for all U.S. counties. I then project these CCRs/CCDs using a Bayesian structural time series as inputs into Leslie matrix population projection models and control the projections to the Shared Socioeconomic Pathways. My ex-post facto evaluations demonstrate confidence in the accuracy of the projections. These data have numerous potential uses and can serve as inputs for addressing questions involving sub-national demographic change in the United States.

Keywords: Population projections; subnational; demographic change; cohort-change ratios

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BACKGROUND & SUMMARY

Population projections have a long history in the social and physical sciences as a means of examining demographic change, planning for the future, and to inform decision making in a variety of applications ^{1,2,3,4,5,6,7}. Scholars typically produce detailed population projections for countries ^{6,8}, but growing demand for small-area demographic analysis, especially as it relates to climate change, highlights the importance of subnational projections ^{9,10,11,12,13,14}.

Despite the growing demand for subnational population projections, relatively few subnational population projections in the United States exist. County-level population projections are typically only available through the gray-literature (such as through the Federal and State Cooperative for Population Projections) or through for-profit companies and oftentimes only comprise several states rather than the whole United States. These projections, while incredibly useful, tend to employ a variety of methods, input data, time horizons, and demographic groupings making a inter-state and

*The data and code that supports this analysis are available at https://github.com/mathewhauer/county_projections_official.

inter-projection comparisons difficult. Other research has turned to gridded-population projections for subnational analysis¹⁴. Such data are useful, but lack demographic details by age, sex, or race and utilize geographies uncommon to other United States statistical reporting. The lack of rigorous small-area population projections by detailed demographic subgroups has hampered our understanding of subnational demographic change in the United States.

The Cohort-component method for population projection, the typical demographic projection methodology, requires oftentimes difficult, if not impossible, to obtain data on each population component process (fertility, mortality, and migration), and this data limitation generally limits population projections to the nation scale^{6,8}. Using a parsimonious cohort-component alternative¹⁵, I overcome the data issues associated with a typical cohort-component projection to produce a set of U.S. county-level population projections by detailed demographic characteristics (18 age groups, 2 sex groups, and 4 race groups) controlled to the five Shared Socioeconomic Pathways (SSPs)⁸ and make both the *R* code and subsequent population projections available for dissemination to a wide audience. These projections can be used to understand small-area demographic change in the United States.

The Hamilton-Perry method^{16,17} is a simple, parsimonious technique for producing population projections directly from multiple age-sex distributions through the use of cohort-change ratios (CCRs)¹⁵ and is a common alternative to cohort-component. The minimal data requirements to produce CCRs and the ability to implement CCRs in Leslie matrix projection methods¹⁸ make CCRs attractive in the production of small-area demographic projections. However, CCRs suffer from two major disadvantages over the use of cohort-component: 1) short-term rapid population growth can create impossibly explosive growth in long-range projections due to the nature of compound growth and 2) small cell sizes can create impossibly large CCRs with very small numeric change (ie 2 persons -> 4 persons yield a doubling each period).

I use an alternative to CCRs, which I call cohort-change differences (CCDs), that create linear rather than exponential growth in a blended model where county-race groups projected to grow utilize CCDs while county-race groups projected to decline utilize CCRs. Blended linear/exponential demographic projections tend to outperform both linear and exponential models, respectively¹⁹. This technique has all of the advantages of CCRs by remaining just as simple and parsimonious with minimal data requirements while producing projected populations without impossibly ex-

plosive growth. I use a variant of a Bayesian structural time series called an Unobserved Component Model (UCM) for forecasting equally spaced univariate time series data²⁰ to project the CCRs/CCDs. UCMs decompose a time series into components such as trends, seasons, cycles, and regression effects and are designed to capture the features of the series that explain and predict its behavior and are similar to dynamic models in Bayesian time series forecasting²¹. All individual CCRs/CCDs (CCR_{asrc}) over all series are modeled ($n=336744$) in individual UCMs that populate the Leslie matrices for projection. The resultant projected age structures are then controlled to the five SSPs⁸.

Out-of-sample validation reveals errors on par with or better than cohort-component population projection models undertaken at the national and sub-national scale^{22,19,23,24,25,26,27,28,29,30,31}.

METHODS

The cohort-component method is the most accepted methodology to produce population projections^{1,32}. The method makes use of all three population component processes (fertility, mortality, and migration) and applies them across varying population cohorts to arrive at a future population.

Equation 1 outlines the basic structure of a cohort-component model.

$$P_{t+1} = P_t + B_t - D_t + M_{t,in} - M_{t,out} \quad (1)$$

Where P_t is the population at time t , B_t is the births at time t , D_t is the deaths at time t , and $M_{t,in/out}$ refers to in- or out-migration at time t .

Cohort-component requires data on each component process disaggregated by the dimensionality of the population to be projected. To produce detailed projections by age, sex, and race, detailed data by age, sex, and race for each component of change must be available. Certain elements of these data can be difficult to obtain for complete national coverage of sub-national geographies. There is no comprehensive data set of both in- and out-migration estimates by age, sex, and race for all U.S. counties. Birth and death data are typically obtained through the National Center of Health Statistics (NCHS) vital events registration databases³³. Birth data, however, are only available for counties with populations greater than 100k and Death data are only available for cells with more than 10 deaths³⁴. These limitations surrounding fertility, mortality, and migration

render a universal county-level population projection difficult, if not impossible, to complete using publicly available data sets using a traditional cohort-component model.

An alternative to cohort-component is the Hamilton-Perry method^{17,15}, which uses cohort-change ratios (CCRs) in place of components to project populations. The basic CCR equation is found in [Equation 2](#).

$$CCR_t = \frac{{}_nP_{x,t}}{{}_nP_{x-y,t-1}} \quad (2)$$

$${}_nP_{x+t} = CCR_t \cdot {}nP_{x-y,t} \quad (3)$$

Where ${}_nP_{x,t}$ is the population aged x to $x+n$ in time t and ${}_nP_{x-y,t}$ is the population aged x to $x+y$ in time t where y refers to the time difference between time periods. These CCRs are calculated for each age group a , for each sex group s , for each race group r , in each time period t , in county c . Thus to find the population of ten to fourteen year olds (${}_5P_{10}$) in five years ($t+1$), we multiply the ratio of the population aged 10-14 in time t (${}_5P_{10,t}$) to the population aged 5-9 five-years prior in time $t-1$ (${}_5P_{10-5,t-1}$) to the population aged 0-4 in time t (${}_5P_{10-5,t}$). ie, if we have 100 5-9 year olds five years ago and we now have 125 10-14 year olds and 90 5-9 year olds, we can expect the number of 10-14 year olds in 5 years to be ($125/100 \cdot 90 = 112.5$).

CCRs offer several advantages and disadvantages over the use of a cohort-component model. CCRs are considerably more parsimonious than cohort-component. Calculation of CCRs for use in population projections requires data as minimal as an age-sex distributions at two time periods – data ubiquitous across multiple scales, countries, and time periods. However, this parsimony comes at a relatively steep price: CCRs can lead to impossibly explosive growth in 1) long-range projections due to the natural compounding of the ratios and 2) in small cell sizes with impossibly large CCRs due to a small numeric change in population. Consider the growth presently occurring in McKenzie County, North Dakota (FIPS=38053) driven by the Shale oil boom. In 2010 McKenzie had a population of 6,360 that had ballooned to 12,792 by 2015, according to the Vintage 2016 population estimates from the US Census Bureau, with a CCR for the 20-24 year old population of 2.46 (416 to 1,027). Implementing a 50-year population projection using that CCR would create a projected population that is approximately 8,000 times larger (2.46^{10}) – clearly an improbable

number given the small, rural nature of its population – yielding a potential population of approximately 8,000,000. Kalawao County, Hawaii (FIPS= 15005) has 2017 estimated population of just 88 persons. Numeric change in any given age-group could lead to impossibly large CCRs in a county as sparsely populated as Kalawao County.

Cohort Change Differences

The implementation of CCRs naturally implies a multiplicative model, typically utilizing Leslie matrices. It is possible, however, to implement an **additive** model by using the *difference* in population rather than the *ratio* of population.

$$\begin{aligned} CCD_t &= {}_n P_{x,t} - {}_n P_{x-y,t-1} \\ {}_n P_{x+t} &= CCD_t + {}_n P_{x-y,t} \end{aligned} \tag{4}$$

Where ${}_n P_{x,t}$ is the population aged x to $x+n$ in time t and ${}_n P_{x-y,t}$ is the population aged x to $x+y$ in time t where y refers to the time difference between time periods. These CCDs are calculated for each age group a , for each sex group s , for each race group r , in each time period t , in county c . Thus to find the population of ten to fourteen year olds (${}_5 P_{10}$) in five years ($t+1$), we add the difference of the population aged 10-14 in time t (${}_5 P_{10,t}$) to the population aged 5-9 five-years prior in time $t-1$ (${}_5 P_{10-5,t-1}$) to the population aged 0-4 in time t (${}_5 P_{10-5,t}$). ie, if we have 100 5-9 year olds five years ago and we now have 125 10-14 year olds and 90 5-9 year olds, we can expect the number of 10-14 year olds in 5 years to be ($125-100 + 90 = 115$).

CCDs are just as parsimonious as CCRs but have the additional advantage of producing linear growth rather than exponential growth. Using the same example as McKenzie County, ND, a numeric change of 611 persons in the 20-24 year age group (416 to 1,027) yields a potential population change of just approximately 6,000 persons rather than 8,000,000 (when using a CCR) – much more realistic growth. However, for areas experiencing population declines, CCDs have the potential of creating impossible negative populations through linear decline. A blended approach, using CCDs in areas projected to increase and CCRs in areas projected to decrease creates more utility in the projections, preventing impossible negative populations and explosive population growth, and pre-

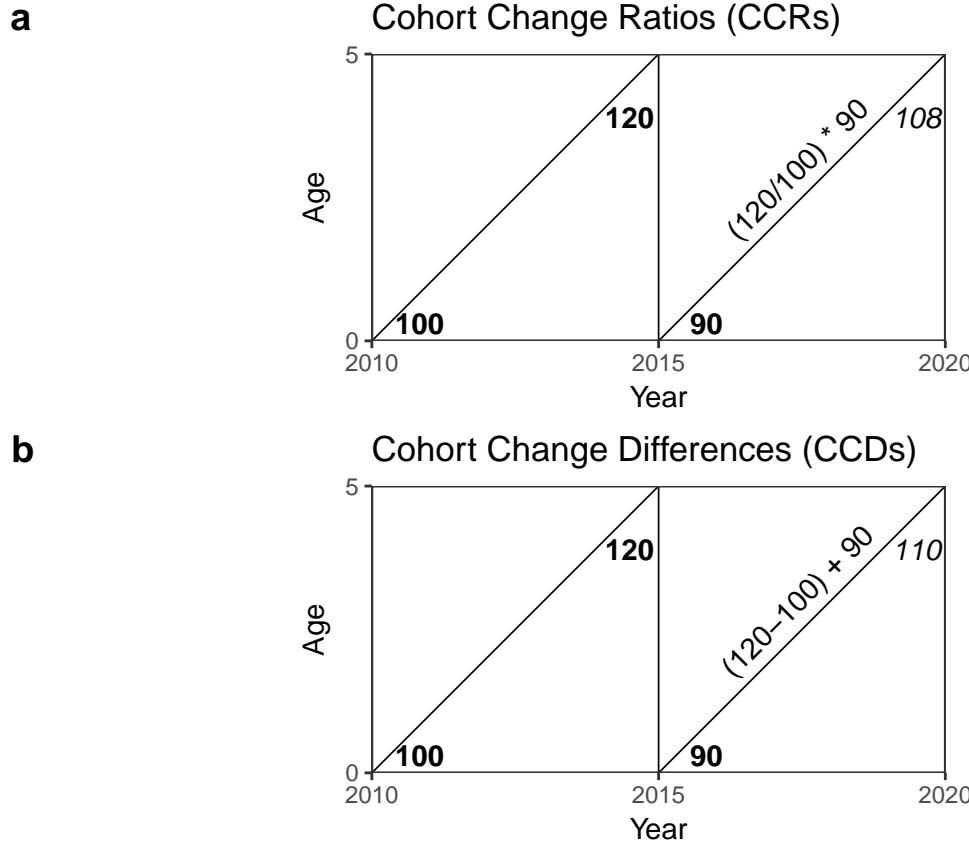


Figure 1: **Lexis Diagrams for CCRs and CCDs.** (a) demonstrates the general framework for Cohort-change ratios and (b) the general framework for cohort-change differences. The observed populations are in bold while the projected populations are italicized.

vious research has shown blended linear/exponential population projections outperform both linear and exponential models, respectively¹⁹.

Projecting CCRs and CCDs

To account for possible changes in CCRs/CCDs, I employ the use of an Unobserved Components Model (UCM) for forecasting equally spaced univariate time series data²⁰. UCMs decompose a time series into components such as trends, seasons, cycles, and regression effects and are designed to capture the features of the series that explain and predict its behavior. UCMs are similar to dynamic models in Bayesian time series forecasting²¹. All projections were undertaken in **R** using the RUCM package.

The basic structural model (BSM) is the sum of its stochastic components. Here I use an irregular, level, and a random error component and it can be described as:

$$\begin{aligned} y_t &= \mu_t + \sum_{j=1}^m \beta_j x_{jt} + \epsilon_t \\ \epsilon_t &\sim i.i.d. N(0, \theta_\epsilon^2) \end{aligned} \quad (5)$$

Each of the model components are modeled separately with the random error ϵ_t modeled as a sequence of independent, identically distributed zero-mean Gaussian random variables. $\sum_{j=1}^m \beta_j x_{jt}$ provides the contribution of the autoregressive component.

The level component is defined as:

$$\begin{aligned} \mu_t &= \mu_{t-1} + \xi_t \\ \xi_t &\sim i.i.d. N(0, \theta_\xi^2) \end{aligned} \quad (6)$$

These equations specify a trend where the level μ_t vary over time, governed by the variance of the disturbance term ξ_t in their equations. Here all individual CCRs/CCDs (CCR_{asrc}) over all series are modeled ($n=336744$) in individual UCMs.

The projected CCRs and CCDs are then input into Leslie matrices to create projected populations³⁵.

[Equation 7](#) describes the Leslie matrices for CCRs and [Equation 8](#) describes the Leslie matrices for CCDs.

$$\begin{bmatrix} n_0 \\ n_1 \\ \vdots \\ n_{18} \end{bmatrix}_{t+1} = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 & 0 \\ CCR_0 & 0 & 0 & \dots & 0 & 0 \\ 0 & CCR_1 & 0 & \dots & 0 & 0 \\ 0 & 0 & CCR_2 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 & 0 \\ 0 & 0 & 0 & \dots & CCR_{16} & CCR_{17} \end{bmatrix} \begin{bmatrix} n_0 \\ n_1 \\ \vdots \\ n_{17} \end{bmatrix}_t \quad (7)$$

$$\mathbf{T} = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 & 0 \\ CCD_0 & 0 & 0 & \dots & 0 & 0 \\ 0 & CCD_1 & 0 & \dots & 0 & 0 \\ 0 & 0 & CCD_2 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 & 0 \\ 0 & 0 & 0 & \dots & CCD_{16} & CCD_{17} \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & \dots & 0 & 0 \\ n_0 & 0 & 0 & \dots & 0 & 0 \\ 0 & n_1 & 0 & \dots & 0 & 0 \\ 0 & 0 & n_2 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 & 0 \\ 0 & 0 & 0 & \dots & n_{16} & n_{17} \end{bmatrix} \quad (8)$$

$$\begin{bmatrix} n_0 \\ n_1 \\ \vdots \\ n_{18} \end{bmatrix}_{t+1} = \begin{bmatrix} \sum \mathbf{T}_{1j} \\ \sum \mathbf{T}_{2j} \\ \vdots \\ \sum \mathbf{T}_{17j} \end{bmatrix}$$

[Equation 7](#) and [Equation 8](#) both require special consideration for two specific age groups: the populations aged 0-4 (${}_5P_0$) and the population comprising the open-ended interval (${}_\infty P_{85}$; CCR_{17} and CCD_{17}). The populations aged 0-4 (${}_5P_0$) and 85+ (${}_\infty P_{85}$) must have special consideration since the preceding/proceeding age groups do not exist for these age groups.

To project 0-4 year olds, I use the child-woman ratio (CWR)

$$CWR_t = \frac{{}_5P_{0,t}}{45W_{15,t}} \quad (9)$$

$${}_nP_{x+t} = CWR_t \cdot {}_{45}W_{15,t+1}$$

Where ${}_{45}W_{15}$ is the population of women in child-bearing ages 15-50. I use the state/race-specific CWRs for member counties.

The population aged 0-4 in time $t + 1$ are projected by applying a 1.05 sex ratio at birth (SRB) to the projected children born of women of childbearing age [15, 50) in time $t + 1$.

To calculate the CCR/CCD for the open-ended age group,

$$\infty CCR_{85,t} = \frac{\infty P_{85,t}}{\infty P_{85-y,t-1}} \quad (10)$$

$$\infty P_{85+t} = \infty CCR_{85,t} \cdot \infty P_{85-y,t}$$

$$\infty CCD_{85,t} = \infty P_{85,t} - \infty P_{85-y,t-1} \quad (11)$$

$$\infty P_{85+t} = \infty CCD_{85,t} + \infty P_{85-y,t}$$

If a given race/county combination is projected to increase, I use CCDs and if a given race/county combination is projected to decline, I use CCRs.

Group quarters

Extra consideration must be paid to the Group quarters (GQ) population in each county. GQ is defined a place where people live in a group living arrangement. Prisons, college dormitories, nursing homes, and military barracks are some examples of GQ. I also include those without permanent living facilities (i.e., the homeless population) in my estimate of GQ. Unlike the resident population, the typical demographic structure of a GQ oftentimes remains constant and the underlying populations are not exposed to typical demographic processes in the same manner as the resident population. College dormitory populations do not age, are almost always between the ages of 18 and 22, and fertility rates among college students are very low, for instance. Rather than demographic processes that change GQ populations, change is often the result of local, state, and federal policymaking resulting in a new prison, a military base reordering, a new college dormitory, etc. These structural changes are difficult to predict without detailed knowledge of local decision making. For this reason, I hold GQ constant throughout the projection horizon.

I calculate GQ as the difference between the occupied household population and the total population in each age.sex/race/county group from Summary File 1 of the 2000 Decennial Census for the out-of-sample validation and from Summary File 1 of the 2010 Decennial Census for the population projections. This difference is the Group quarters population.

All *resident* populations are projected in this modeling scheme such that the populations at launch year are equal to the total population minus the group quarters population. Group quarters populations at time t are then added back into the projected resident population at time $t + 1$.

Miscellaneous

In the event a UCM contained NA or infinite values or produced covariance matrices with values larger than 10,000,000, the projections were set to 0. Upper and Lower bounds of failed UCMs were set to 0. Any infinite, NA, or NAN CCR, CCD, or CWR was set to 0. In the event the projections still produced negative populations, they were also set to 0.

DATA

Data used to project the populations consist of a single primary data source: the National Vital Statistics System (NVSS) U.S. Census Populations with Bridged Race Categories data set¹. These data harmonize racial classifications across disparate time periods to allow population estimates to be sufficiently comparable across space and time. All county boundaries are generally rectified as well. The National Center for Health Statistics bridge the 31 race categories used in Census 2000 and 2010 with the four race categories used in the 1977 Office of Management and Budget standards.

There are two primary bridged-race data sets. The first covers the time period 1969-2016 and utilizes three race groups: White, Black, and Other. The second covers the time period 1990-2016 and uses four race groups (White, Black, American Indian/Alaska Native, and Asian/Pacific Islander) as well as two origin groups (Hispanic and Non-Hispanic). Due to small cell sizes, I convert the eight possible race classifications in the 1990-2016 bridged-race data to just four race groups (White NH, Black NH, Hispanic, and Other NH). Out-of-sample validation makes use of the three race group data set covering 1969-2016 while the actual population projections use the 1990-2016 data.

In the Technical Validation, only the continental United States is considered. Counties in Alaska and Hawaii were aggregated to their respective states in the 1969-2016 NVSS bridged race data. Several counties were created after 2000 (most notably is Broomfield County, Colorado). I only consider counties that existed prior to 2000 that are contained in the NVSS data.

¹Data can be downloaded here: <https://seer.cancer.gov/popdata/download.html>

Projection Controls

As shown below, any set of population projections are likely to produce higher than expected projections (see [Table 1](#)). To prevent runaway population growth, I control the projected output to the Shared Socioeconomic Pathways (SSPs)⁸. The SSPs are socio-economic scenarios that derive emissions scenarios coupled with climate policies. They are designed to evaluate both climate change impacts and adaptation measures in harmony with the Representative Concentration Pathways (RCPs) for emission scenarios. Scholars have downscaled the SSPs to gridded population projections¹⁴, while these projections are incredibly useful, they lack detailed demographic characteristics.

The five SSPs are colloquially named SSP1 (Sustainability), SSP2 (Middle of the Road), SSP3 (Regional Rivalry), SSP4 (Inequality), and SSP5 (Fossil-fueled Development)³⁶. These five SSPs cover potential futures involving various growth policies, fossil-fuel usage, mitigation policies, adaptation policies, and population change³⁷.

Each SSP contains projected population information in five-year increments for 5-year age groups (0-100+) and two sex groups (Male and Female) for the period 2020-2100 and I truncate the open-ended interval from 100+ to 85+ to be consistent with NVSS population estimates. I control my projected age/sex/race/county projections to the the SSPs by using

$$P_t = \frac{p_{asrc}}{p_{as}} \cdot P_{as,SSP} \quad (12)$$

where p_{asrc} refers to the age/sex/race/county specific population projected as outlined above, p_{as} refers to the age/sex specific population projection, and $P_{as,SSP}$ refers to the age/sex specific population projection for each SSP. This control allows preservation of the the underlying age structures, race projections, and sex ratios, while allowing the projections consistency with the SSPs.

Code availability

All *R* code used to reproduce this analysis are available at https://github.com/mathewhauer/country_projections_official.

TECHNICAL VALIDATION

To evaluate the projection accuracy, I use the base period 1969-2000 to project the population for eighteen age groups, two sexes, three races (White, Black, Other), and 3134 counties for the projection period 2000-2015. I utilize an ex-post facto analysis at periods 2005, 2010, and 2015 using a pure CCD model, a pure CCR model, and blended model (CCR/CCD). The CCR/CCD model utilizes CCDs if a county is projected to grow and CCRs if it is projected to decline. Blended models have been shown to outperform both purely linear or purely exponential models in simple extrapolation approaches to population projections¹⁹.

In keeping with demographic tradition^{22,1,26}, I evaluate the projections using three primary statistics. To determine the overall accuracy of the projections, I use Absolute Percent Errors (APE) and to determine the bias of the projections I use the Algebraic Percent Error (ALPE). In some places I have substituted a Symmetric Absolute Percent Error (SAPE)³⁸.

Equations 14 – 15 describe the equations used to evaluate errors. P_i refers to the projected value and A_i refers to the actual, observed value.

$$APE = \left| \frac{P_i}{A_i} \right| \quad (13)$$

$$ALPE = \frac{P_i}{A_i} \quad (14)$$

$$SAPE = \frac{|(P_i - A_i)|}{(P_i + A_i)} \quad (15)$$

Overall Errors

Table 1 reports the overall errors for the sum of the population for the whole US. Overall the pure CCD model outperformed the purely CCR model, suggesting CCDs in this model could produce more accurate results compared to CCRs. It should also be noted that all model variants (CCD, CCR, and CCR/CCD) have a tendency to over-project the overall population in the United States.

Table 1: Evaluation of overall total errors for the entire United States.

TYPE	YEAR	POPULATION	PRED	APE
CCD	2005	292,555,450	297,506,030	1.69%
CCD	2010	306,397,813	314,468,603	2.63%
CCD	2015	317,731,270	331,782,317	4.42%
CCD/CCR	2005	292,555,450	297,516,880	1.70%
CCD/CCR	2010	306,397,813	314,541,133	2.66%
CCD/CCR	2015	317,731,270	332,018,899	4.50%
CCR	2005	292,555,450	299,051,653	2.22%
CCR	2010	306,397,813	320,893,789	4.73%
CCR	2015	317,731,270	355,964,884	12.03%

Table 2 reports the overall errors for the sum of the population in each of the counties. Here we can see that for the average county, the CCD and CCR/CCR models produce similar APEs but the CCR/CCR model tends to produce slightly lower APEs when compared to the purely CCD model. In all cases, the errors associated with the CCR model are greater than the CCD or CCR/CCR varieties.

Table 2: Evaluation of overall errors for each county.

TYPE	n	EVAL	2005	2010	2015
CCD	3134	Median APE	2.5306%	5.091%	8.500%
CCD/CCR	3134	Median APE	2.5306%	5.118%	8.196%
CCR	3134	Median APE	2.5513%	5.450%	8.999%
CCD	3134	Median ALPE	1.212%	1.707%	3.908%
CCD/CCR	3134	Median ALPE	1.136%	1.605%	3.896%
CCR	3134	Median ALPE	1.064%	1.720%	4.685%

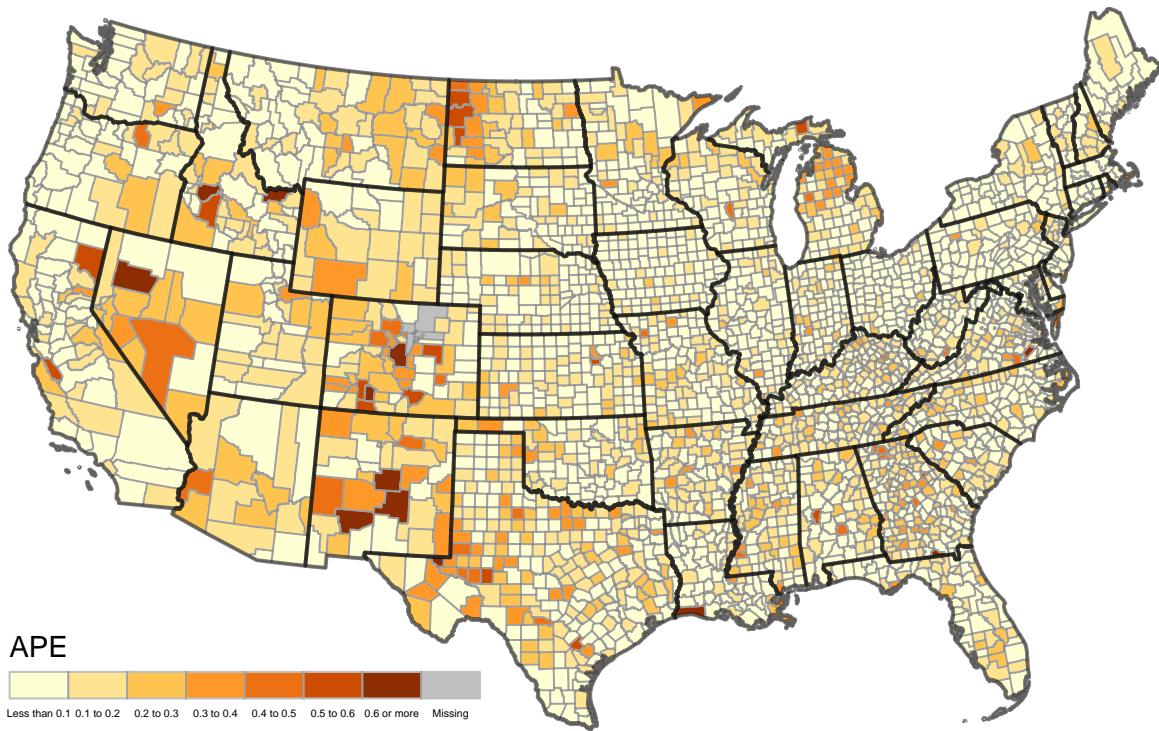


Figure 2: Map of county errors of the total population in 2015 using the CCR/CCD model. Here I show the geographic distribution of absolute percent errors. Most states and counties have low error rates of the total population with isolated pockets of large errors. The missing counties in Colorado are due to geographic boundary changes associated with the creation of Broomfield County in 2001.

Figure 2 shows the absolute percent errors associated with the total population for the CCR/CCD model in U.S. counties in 2015. Most states and counties see relatively low errors with the median APE of just 8.2% by 2015, however some isolated pockets of high errors do exist randomly distributed throughout the United States, specifically in the Western half of the United States in states such as Colorado and New Mexico.

Age Structure Error

Table 3 reports the overall errors for age groups at the county level. All three models produce similar APEs. For any given county, the average error is approximately 11% with the blended

CCD/CCR model producing the lowest errors. Similar to the overall errors, the bias tends to be for over-projection of age groups as all of the ALPEs are positive.

Table 3: **Evaluation of Age Group Errors.**

TYPE	n	EVAL	2005	2010	2015
CCD	56412	Median APE	5.202%	8.077%	11.634%
CCD/CCR	56412	Median APE	5.075%	7.694%	10.819%
CCR	56412	Median APE	5.140%	7.971%	11.574%
CCD	56412	Median ALPE	0.973%	1.041%	3.286%
CCD/CCR	56412	Median ALPE	0.950%	1.011%	3.056%
CCR	56412	Median ALPE	0.792%	0.629%	2.292%

[Figure 3](#) shows projected age structures in nine samples counties across three county types – college counties, suburban counties, and retirement counties. In all three county types the age structures are preserved in the projections. All three county types exhibit differing age structures with important considerations. For college counties, the college-age population (those aged 15-24) do not age in place within those communities. The large population peaks in those counties show great in-migration at the college ages and then great out-migration afterwards. In suburban counties, a “double hump” age structure is typically present with large numbers of both adolescents and middle-aged adults. Most twenty-somethings either cannot afford to live in affluent suburban areas, move away for school or work, or do not have the family reasons for living there. Retirement communities are often identified by the large numbers of populations over the age of 55. The CCD/CCR model is able to reproduce the population dynamics present in these three archetype communities.

[Figure 4](#) shows the Algebraic Percent Errors by age group averaged for all three evaluation periods. For every age below 85+, the CCD and CCR/CCD models produce ALPEs closer to zero, but for the 85+ age group, the CCR model produces ALPEs much closer to zero. This could be reflective of mortality being the dominant population process for older age populations. Here, the 50th percentile ALPE for CCD and CCR/CCD is approximately 25% while the CCR model is just

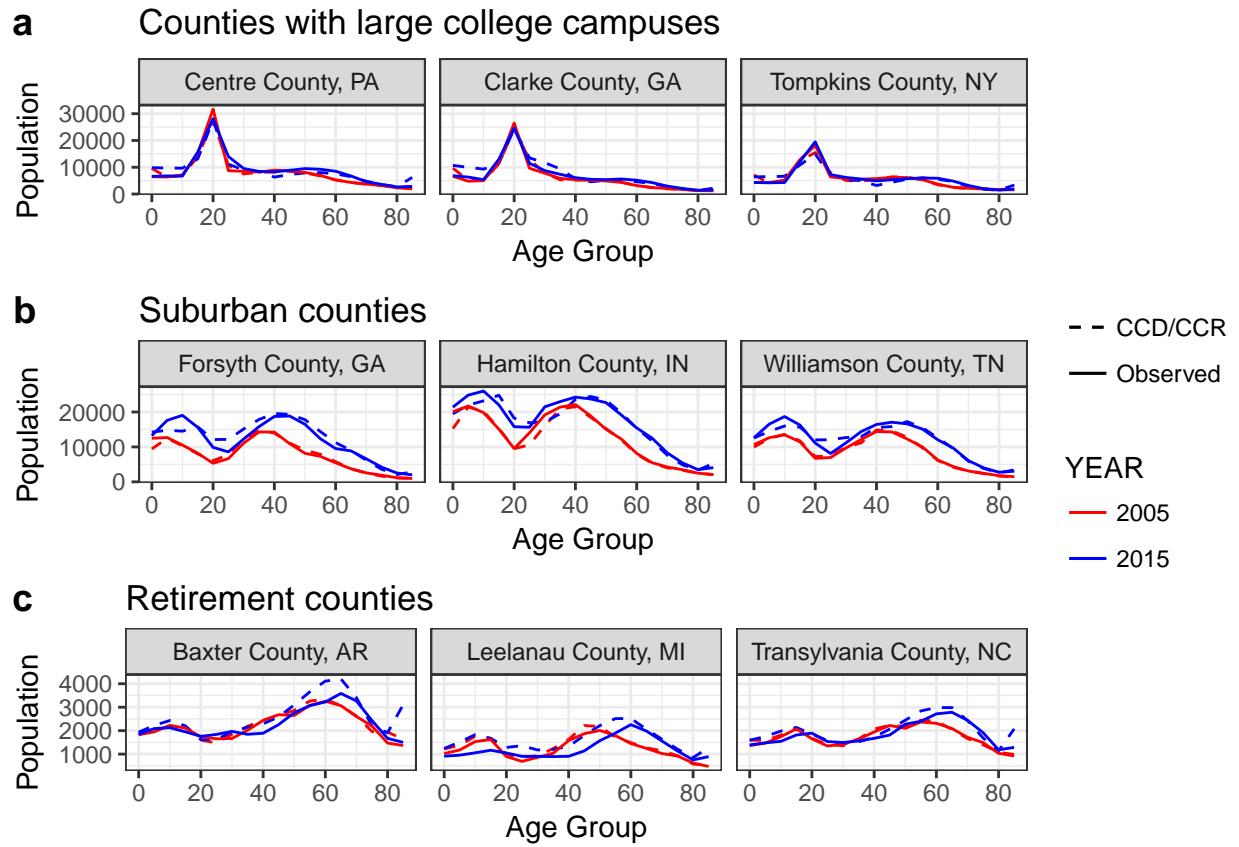


Figure 3: **Age structures of various county types.** I compare the projected age structures to the observed age structures in nine counties across three county types using the CCR/CCD model. (a) demonstrates counties with major universities, (b) demonstrates sample suburban counties, and (c) demonstrates sample retirement counties. All three county types have age structures largely preserved despite widely different age structures.

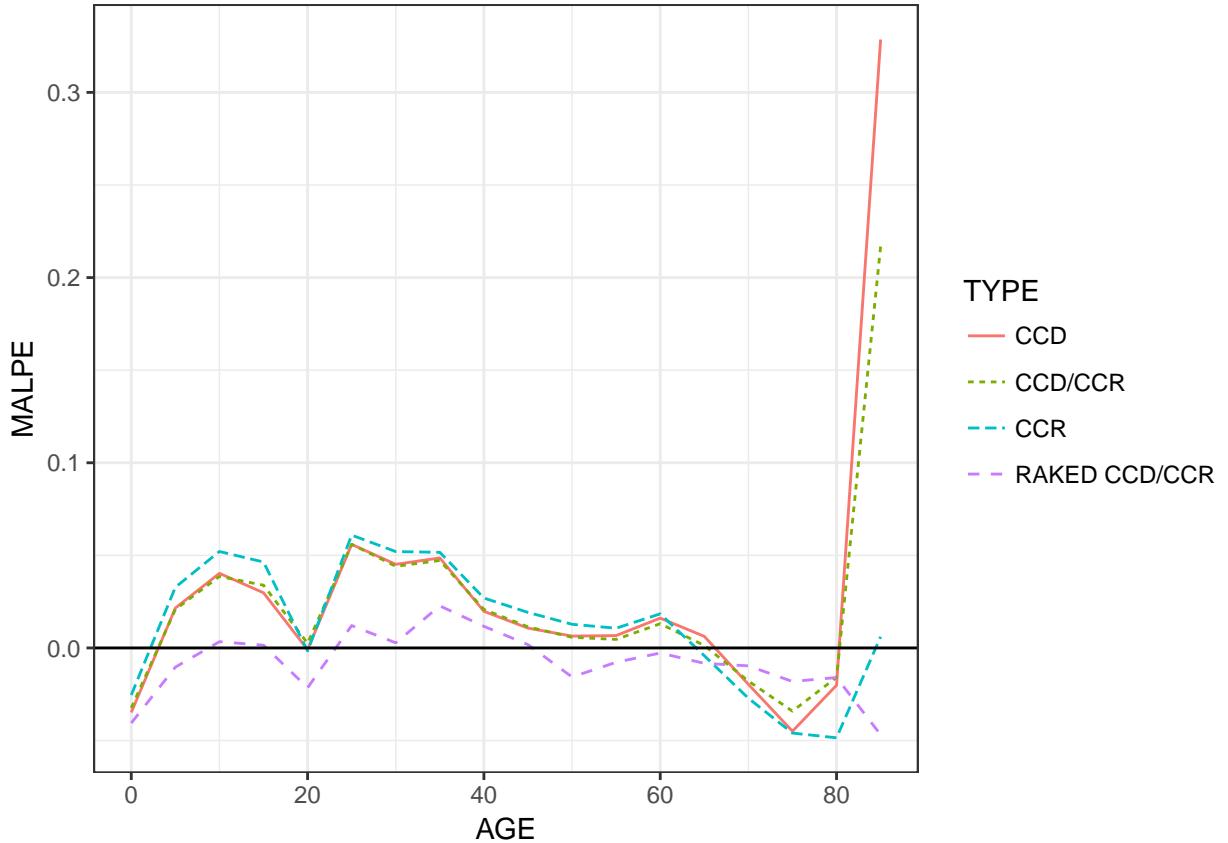


Figure 4: **Algebraic Percent Errors by age group.** I plot the 50th percentile Algebraic Percent Error (ALPE) by age group.

under 1%. This bias is virtually eliminated when controlling the populations to the Age/Sex total of the United States (“RAKED CCD/CCR”). The elimination of this bias is important because the actual projections are controlled to the SSPs, meaning the projected age distributions are persevered even if magnitudes differ lending credibility to the actual projections.

Race Errors

Figure 5 reports the ALPE and the APE distribution by race group for all counties. The White race group tends to have the lowest errors associated with the projections, followed by Black, and then Other. This is likely due to the relative population sizes within each race group. Black and Other populations tend to be located in more isolated pockets due to the effects of both institutional and self-assortive segregation from the White population leading to many counties with very small Black and Other populations.

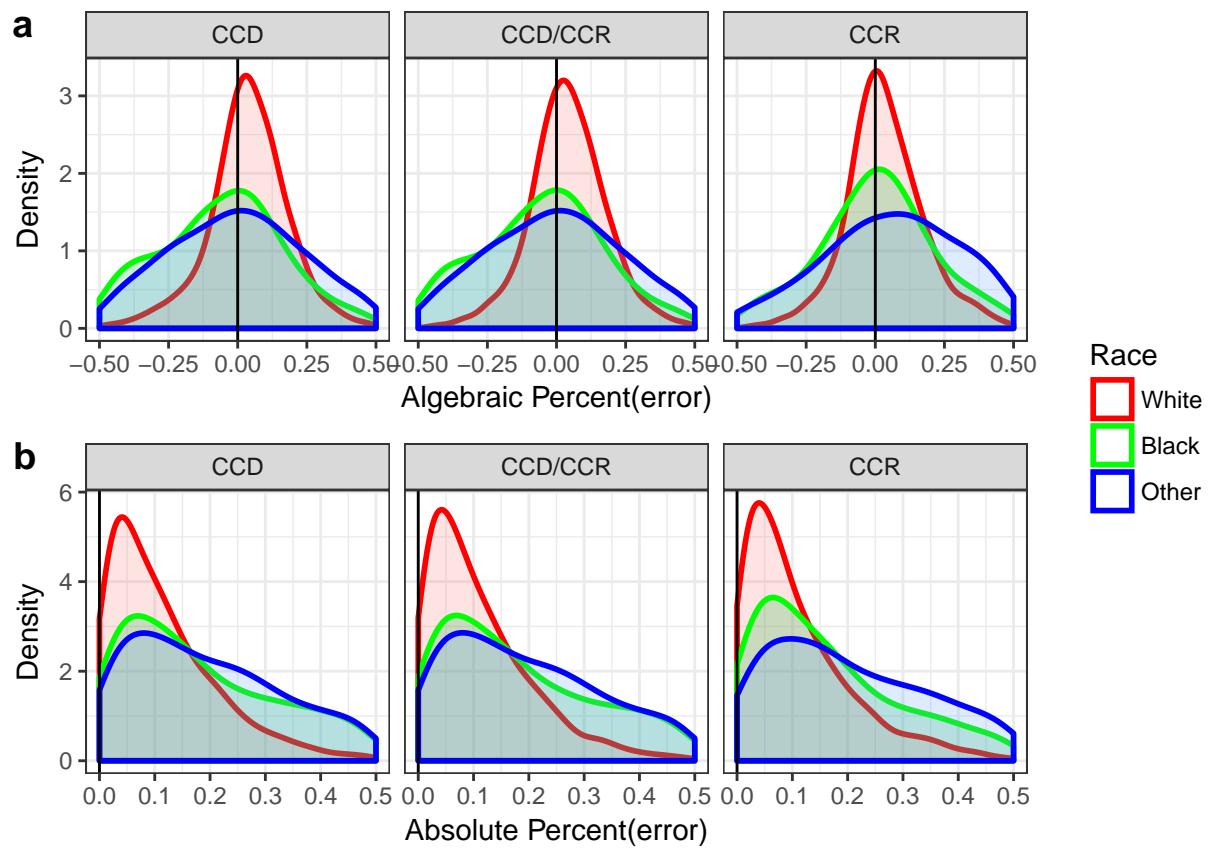


Figure 5: **Race group errors.** (a) shows the Algebraic Percent Errors for all three methods and (b) shows the APE distribution of errors.

Age, Sex, Race joint errors

Finally, I show the joint errors associated with all possible Age/Sex/Race/County combinations. Here the average error for any given ASRC combination (such as Black Females aged 20-24 in Lincoln County NV) are approximately 11-12% for all three methods after 15 years. These errors are on par with or better than many cohort-component models.

Table 4: **Evaluation of Age/Sex/Race/County joint Errors.**

TYPE	num	EVAL	2005	2010	2015
CCD	336744	Median SAPE	6.122%	8.609%	11.42%
CCD/CCR	336744	Median SAPE	6.000%	8.320%	10.99%
CCR	336744	Median SAPE	6.013%	8.666%	12.66%

Figure 6 shows county-level numeric population change for the period 2020-2100 under all five SSPs. The five SSPs lead to substantial differences in geographic growth patterns. For instance, most of California is projected to see increases in population in four of the five SSPs; only SSP3: Regional Rivalry shows projected population declines in southern California. Conversely, the heavily-populated North East is projected to see significant population declines in all SSPs except SSP5: Fossil-fueled development. The five SSPs represent different pathways by which the United States could be expected to grow this century.

DATA RECORDS

The projected populations by age.sex/race/county/year/SSP for all US counties for the period 2020-2100 are available at the Open Science Foundation. The data can be downloaded in a single zipped .CSV file format.

Data resulting from these projections can be found in SSP_asrc.csv.zip (Data Citation 1).

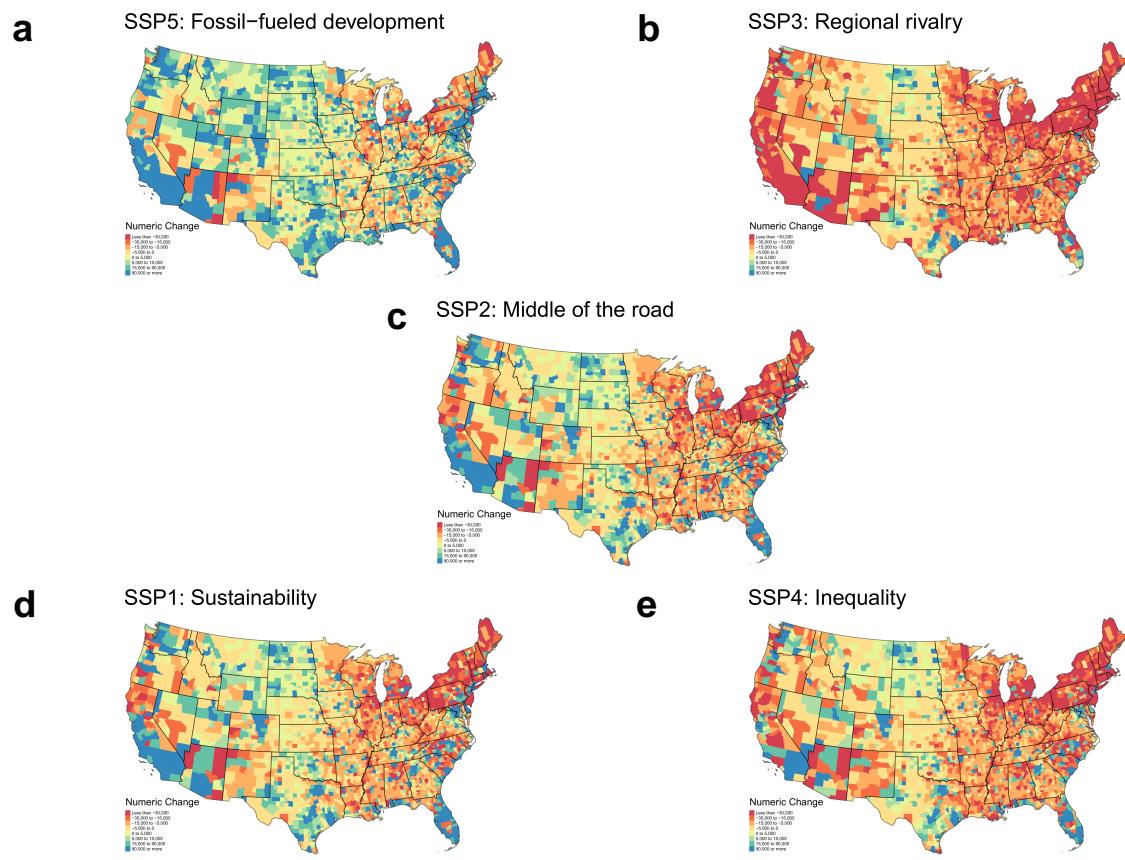


Figure 6: Projected numeric population changes for the five SSPs between 2020 and 2100 for counties in the continental United States.

Projected populations include each US county, 18 age groups ($1=0\text{-}4$, $2=5\text{-}9$, \dots , $18=85+$), two sex groups (1=Male and 2=Female), and four race groups (1=White NH, 2=Black NH, 3=Hispanic, and 4=Other NH).

USAGE NOTES

The dataset generated here provides detailed county-level population projections by age, sex, and race for US counties for the period 2020-2100 that are consistent with the SSPs. Producing high-quality, highly-detailed population projections is a challenging endeavor. With such a large need for sub-national projections and to better understand the changing demographics of the U.S. population, I produced such a set of high-quality, highly-detailed projections and make both the **R** code and subsequent projections available for dissemination to a wide audience. Here, I presented age-sex-race specific population projections for all U.S. counties, an ex-post facto evaluation of the projection methodology, and details on the calculations of these projections.

To ensure quality projections, I employed the use of ex-post-facto evaluations of the projection accuracy for three variant models: purely additive with CCDs, purely multiplicative with CCRs, and a blended model with CCDs in areas projected to grow and CCRs in areas projected to decline. I report the accuracy, bias, and uncertainties associated with these variants using absolute percent error and algebraic percent error. Overall, the errors reported here are on par with or better than many cohort-component population projection models^{[22,19,23,24,25,26,27,28,29,30,31](#)}. While overall the ex-post-facto evaluation showed relatively low errors, some areas in the United States, some demographic sub-groups, and some age-groups could exhibit greater error rates. These groups include but are not limited to non-white populations, young child under the age of 5, older adults over the age of 85, and parts of Colorado, New Mexico, and North Dakota.

These projections, like all projections, involve the use of assumptions about future events that may or may not occur. Users of these projections should be aware that although the projections have been prepared with the use of standard methodologies, documentation of their creation, open-source computer code, and extensive evaluations of their accuracy and uncertainty, they may not accurately project the future population of a state, county, age, sex, or race group. The projections are based on historical trends and current estimates. These projections should be used only with

full awareness of the inherent limitations of population projections in general and with knowledge of the procedures and assumptions described in this document.

References

1. Smith, S. K., Tayman, J., and Swanson, D. A. *State and local population projections: Methodology and analysis*. Springer Science & Business Media, (2006).
2. Passel, J. S. and Cohn, D. (2008).
3. Hebert, L. E., Scherr, P. A., Bienias, J. L., Bennett, D. A., and Evans, D. A. *Archives of neurology* **60**(8), 1119–1122 (2003).
4. Hales, S., De Wet, N., Maindonald, J., and Woodward, A. *The Lancet* **360**(9336), 830–834 (2002).
5. Hauer, M. E., Evans, J. M., and Mishra, D. R. *Nature Climate Change* **6**(7), 691–695 (2016).
6. Gerland, P., Raftery, A. E., Ševčíková, H., Li, N., Gu, D., Spoorenberg, T., Alkema, L., Fosdick, B. K., Chunn, J., and Lalic, N. *Science* **346**(6206), 234–237 (2014).
7. Colby, S. L. and Ortman, J. M. (2017).
8. O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., Mathur, R., and van Vuuren, D. P. *Climatic Change* **122**(3), 387–400 (2014).
9. Alexander, M., Zagheni, E., and Barbieri, M. *Demography* **54**(6), 2025–2041 (2017).
10. Chi, G. *Demography* **46**(2), 405–427 (2009).
11. Smith, S. K., Tayman, J., and Swanson, D. A. *A Practitioner's Guide to State and Local Population Projections*. Springer, (2013).
12. Raymer, J., Abel, G. J., and Rogers, A. *Environment and Planning A* **44**(11), 2664–2686 (2012).
13. Tatem, A. J., Adamo, S., Bharti, N., Burgert, C. R., Castro, M., Dorelien, A., Fink, G., Linard, C., John, M., Montana, L., et al. *Population health metrics* **10**(1), 8 (2012).
14. Jones, B. and O'Neill, B. *Environmental Research Letters* **11**(8), 084003 (2016).
15. Baker, J., Swanson, D. A., Tayman, J., and Tedrow, L. M. *Cohort change ratios and their applications*. Springer, (2017).
16. Hamilton, C. H. and Perry, J. *Social Forces* **41**(2), 163–170 (1962).
17. Swanson, D. A., Schlottmann, A., and Schmidt, B. *Population Research and Policy Review* **29**(1), 47–63 (2010).
18. Sprague, W. W. *arXiv preprint arXiv:1203.2313* (2012).
19. Wilson, T. *Population Research and Policy Review* **35**(2), 241–261 (2016).
20. Harvey, A. C. *Forecasting, structural time series models and the Kalman filter*. Cambridge university press, (1990).
21. West, M. *Bayesian forecasting*. Wiley Online Library, (1996).

22. Smith, S. K. and Tayman, J. *Demography* **40**(4), 741–757 (2003).
23. Smith, S. K. *International journal of forecasting* **13**(4), 557–565 (1997).
24. Rayer, S. *Journal of Planning Education and Research* **27**(4), 417–430 (2008).
25. Wilson, T. and Rees, P. *Population, Space and Place* **11**(5), 337–360 (2005).
26. Booth, H. *International Journal of Forecasting* **22**(3), 547–581 (2006).
27. Wilson, T. *International Journal of Population Research* **2012** (2012).
28. Raftery, A. E., Li, N., Ševčíková, H., Gerland, P., and Heilig, G. K. *Proceedings of the National Academy of Sciences* **109**(35), 13915–13921 (2012).
29. Boyle, J. P., Thompson, T. J., Gregg, E. W., Barker, L. E., and Williamson, D. F. *Population health metrics* **8**(1), 29 (2010).
30. Daponte, B. O., Kadane, J. B., and Wolfson, L. J. *Journal of the American Statistical Association* **92**(440), 1256–1267 (1997).
31. Lutz, W., Sanderson, W. C., and Scherbov, S. (1996).
32. Preston, S., Heuveline, P., and Guillot, M. (2000).
33. Martin, J. A., Hamilton, B. E., Osterman, M. J., Driscoll, A. K., and Drake, P. (2018).
34. Tiwari, C., Beyer, K., and Rushton, G. *American journal of public health* **104**(8), 1386–1388 (2014).
35. Caswell, H. *Matrix population models*. Wiley Online Library, (2001).
36. O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., van Ruijven, B. J., van Vuuren, D. P., Birkmann, J., Kok, K., et al. *Global Environmental Change* **42**, 169–180 (2017).
37. Samir, K. and Lutz, W. *Global Environmental Change* **42**, 181–192 (2017).
38. Shcherbakov, M. V., Brebels, A., Shcherbakova, N. L., Tyukov, A. P., Janovsky, T. A., and Kamaev, V. A. *World Applied Sciences Journal* **24**, 171–176 (2013).