2023 COASTAL MASTER PLAN

POPULATION PROJECTIONS FOR THE 2023 COASTAL MASTER PLAN

ATTACHMENT H7

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COASTAL PROTECTION AND RESTORATION AUTHORITY

This document was developed in support of the 2023 Coastal Master Plan being prepared by the Coastal Protection and Restoration Authority (CPRA). CPRA was established by the Louisiana Legislature in response to Hurricanes Katrina and Rita through Act 8 of the First Extraordinary Session of 2005. Act 8 of the First Extraordinary Session of 2005 expanded the membership, duties, and responsibilities of CPRA and charged the new authority to develop and implement a comprehensive coastal protection plan, consisting of a master plan (revised every six years) and annual plans. CPRA's mandate is to develop, implement, and enforce a comprehensive coastal protection and restoration master plan.

CITATION

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1.0 INTRODUCTION

As a technical document of great importance to citizens of Louisiana and the nation, it is important that CPRA works with experts to develop clear, concise, and accurate information regarding the future of coastal Louisiana as part of the 2023 Coastal Master Plan. To this end, CPRA intends to improve the treatment of population dynamics in the 2023 Coastal Master Plan. These improvements may have important implications for understanding the challenges of a future without action condition and the benefit of implementation of the 2023 Coastal Master Plan. Population projections provide an input for Risk Assessment modeling that informs the 2023 Coastal Master Plan. Additional information about the Coastal Louisiana Risk Assessment (CLARA) model and how population projections are employed within the model can be found in the relevant master plan appendix.

This report describes the methodology, assumptions, and data sources used to prepare population, household income, and poverty rate projections for coastal Louisiana for the period of 2020-2070. A cohort-change ratio projection technique was used to project resident population for Louisiana census block groups, with additional census-derived data used to develop income and poverty rate projections. These projections, like all projections, involve the use of certain 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 and with extensive attempts made to account for existing demographic patterns, they may not accurately project future populations in Louisiana. 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.

This report contains three sections: Section 1.0 details the methodology used to project total populations in census block groups in Louisiana for the period 2020-2070, Section 2.0 details the methodology used to project household income and poverty rates in census block groups, and Section 3.0 details a proposed approach to model projected migration patterns in Louisiana.

2.0 TOTAL POPULATION

2.1 PROJECTIONS OF TOTAL POPULATION FOR LOUISIANA BLOCK GROUPS, 2020-2070

The cohort-component method is the most accepted methodology to produce population projections and is employed to provide total population projections for Louisiana in support of the 2023 Coastal Master Plan. This 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. The basic structure of a cohort-component model is outlined below:

$$P_{t+1} = P_t + B_t - D_t + IN_t - OUT_t$$

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 IN/OUT_t refers to in- or out-migration at time *t*.

Cohort-component analysis requires data on each component process to be disaggregated by the dimensions (i.e., by age, sex, race) of the population to be projected. To produce detailed projections by age, sex, and race, detailed dimensional data for each component of change must be available. Certain elements of the components of change data can be difficult to obtain for sub-county geographies like census block groups making a pure cohort-component difficult, if not impractical, to implement.

An alternative to cohort-component is the Hamilton-Perry (H-P) method (Hamilton & Perry, 1962; Swanson, Schlottmann, & Schmidt, 2010), which uses cohort-change ratios (CCRs) in place of components to project populations and an extension of H-P, cohort-change differences (CCDs) (Hauer, 2019). The following equations show the general form for CCRs and CCDs.

$$CCR_{x,t} = \frac{{}_nP_{x,t}}{{}_nP_{x-y,t-y}}$$

$${}_n\hat{P}_{x,t+y} = CCR_{x,t} * {}_nP_{x-y,t}$$

$$CCD_{x,t} = {}_nP_{x,t} - {}_nP_{x-y,t-y}$$

$${}_n\hat{P}_{x,t+y} = CCD_{x,t} + {}_nP_{x-y,t}$$

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* − *y* to *x* + *n* − *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*, and in each census block group *c*. Thus, to find the population of ten to fourteen year olds (${}_5P_{10}$) in five years (*t* + 5), the ratio of the population aged 10–14 in time *t* (${}_5P_{10,t}$) is multiplied by the population aged 5–9 five-years prior in time t-5 (${}_5P_{5,t\text{-}5}$) by the population aged 5–9 in time t (${}_5P_{5,t}$). Therefore, if there are 100 5–9 year olds five years ago and now there are 125 10–14 year olds and 90 5–9 year olds, the number of 10–14 year olds in 5 years is projected to be (125/100·90 = 112.5). CCDs are similar to CCRs but take the difference, rather than the ratio, and this difference is then added to the underlying population (125 – 100 + 90 = 115).

2.2 SPECIAL CONSIDERATIONS

AGE GROUPS

There must be special consideration for two specific age groups: the populations aged 0–4 (${}_5P_0$) and the population comprising the open-ended interval (${}_\infty P_{85}$). 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, the child-woman ratio (CWR) is used as follows,

$$CWR_t = \frac{{}_5P_{0,t}}{{}_{35}W_{15,t}}$$

$${}_5\hat{P}_{0,t+y} = CWR_{t+y} * {}_{35}\widehat{W}_{15,t+y}$$

Where ${}_{35}W_{15,t+y}$ is the projected population of women in childbearing ages 15–49 at time $t + y$. State/race-specific CWRs for member census block groups are used.

The population aged 0–4 in time t + 5 are projected by assuming a 1.05 sex ratio at birth for the projected children born of women of childbearing age (5, 50), in time t + 10.

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

$$CCR_{85,t} = \frac{{}_\infty P_{85,t}}{{}_\infty P_{80,t-y}}$$

$${}_\infty\hat{P}_{85,t+y} = CCR_{85,t+y} * {}_\infty P_{80,t}$$

$$CCD_{85,t} = {}_\infty P_{85,t} - {}_\infty P_{80,t-y}$$

$${}_\infty\hat{P}_{85,t+y} = CCD_{85,t+y} + {}_\infty P_{80,t}$$

To project the CCRs/CCDs, an autoregressive integrated moving average (ARIMA) model for forecasting equally spaced univariate time series data is employed. The ARIMA(0, 1, 1) model produces forecasts equivalent to simple exponential smoothing. Where an ARIMA(0, 1, 1) model is

$$Y_t = Y_{t-1} + e_t - \theta e_{t-1}$$

$$\hat{Y}_{t+1} = Y_t - \theta e_{t-1}$$

where e_t is independent and identically distributed as $N(0,\sigma_e^2)$.

For each census block group *c*, all individual CCRs/CCDs and CWRs (CCR_{asrc}) are modeled over all series in individual ARIMA models. The projected CCRs and CCDs are then input into Leslie matrices to create projected populations.

GROUP QUARTERS

The Group Quarters (GQ) population is a relatively small percentage of the US total population, but still requires extra consideration. Prisons, college dormitories, nursing homes, and military barracks are some examples of GQ. This analysis also includes those without permanent living facilities (i.e., the homeless population) in an estimate of GQ. Unlike the resident population, the typical demographic structure of a GQ oftentimes remains constant and the underlying populations lack exposure to typical demographic processes in the same manner as the resident population. College dormitory populations do not age; – they are almost always between the ages of 18 and 22. Additionally, fertility rates among college students are very low. Rather than demographic processes that change GQ populations, change is often the result of local, state, and federal policymaking resulting in a new prison, military base realignment, a new college dormitory, etc. These structural changes are difficult to predict without detailed knowledge of local decision-making. For this reason, GQ is held constant throughout the projection horizon.

GQ is calculated as the difference between the household population and the total population in each age/sex/race group from Summary File 1 of the 2000 and 2010 Decennial Censuses. However, household population disaggregated by age/sex/race is only available at the Census Tract level as the smallest geography and not available at census block group (i.e., the disaggregated data is of a different geographic scale than the GQ data). To overcome this issue, an iterative proportional fitting algorithm is used to allocate household population to block groups.

Using the methodology above, household populations are projected such that the populations at launch year are equal to the total population minus the GQ population. GQ populations at time *t* are then added back into the projected household population to obtain the projected resident populations at time *t* + 5. This effectively projects the GQ population of each census block group as constant at its base value.

2.3 CONTROLLED TOTALS TO THE SHARED SOCIOECONOMIC PATHWAYS

Any set of population projections using the methods outlined above is likely to produce higher than expected populations due to runaway population growth in small populations (i.e., 1 person -> 2 persons implies a doubling every five years). To prevent runaway growth, two strategies were employed. First, if a given census block group is projected to increase, a cohort-change difference was used, producing linear rather than exponential growth. And if a given census block group is projected to decline, cohort-change ratios were used to prevent potential negative populations due to linear decline over long time horizons.

Second, the projected output was controlled to the Shared Socioeconomic Pathways (SSPs) produced by Hauer (2019) and the International Institute for Applied Systems Analysis (Samir & Lutz, 2017) such that the summation of the Louisiana population projections equal Hauer (2019) at the county-level. The SSPs use cohort-component and are a global population projection for all countries.

2.4 DATA AND OUTPUTS

One primary data source is used to produce these projections. This data source, available from the International Public Use Microdata System (IPUMS) and the National Historic Geographic Information System (NHGIS) at the University of Minnesota provides the census block group harmonized boundaries necessary for this methodology.

Population projections were produced by census block group by:

- 18, 5-year age groups (0-4, 5-9, … ,85+)
- 2 sex groups (Male, Female)
- 2 Race/ethnic groups (White Non-Hispanic, Non-White)

3.0 HOUSEHOLD INCOME AND POVERTY RATES

3.1 PROJECTIONS OF HOUSEHOLD INCOME FOR LOUISIANA BLOCK GROUPS, 2020-2070

Norman Ryder's (1985) cohort approach to demographic change (nicknamed the "*demographic metabolism*") is an ideal methodological framework for projecting sociodemographic characteristics. Demographic metabolism is a theoretical framework that argues that "the process of social change can be analytically captured through the process of younger cohorts replacing older ones" along multi-dimensional sociodemographic characteristics (e.g., age, gender, race, educational attainment, income, poverty, etc.). The cohort aged 15-19 in 2020 becomes the 20-24 cohort in 2025 after adjusting for the components of population change.

This approach creates remarkably reliable sociodemographic forecasts over decadal time scales for two key reasons: 1) many sociodemographic characteristics are either established at a young age (e.g., the proportion of people with a high school education aged 25-29 in 2015 is a good predictor of those aged 60-64 with a high school education in 2050), and 2) sociodemographic change is embedded within the age-structure (e.g., life course analysis shows that earnings steadily increase after age 18, peaking around age 65, before declining through retirement).

The framework is relatively straightforward in its implementation. Given an underlying age-schedule of a sociodemographic of interest, future age groups are "exposed" to their age-specific sociodemographic variable. Thus, the underlying age-schedule remains unchanged but the change in demographic groups creates projected changes when aggregated.

These projections take the following general form:

$$\hat{P}_{t+5}^{a,s,r,e} = \left(\frac{P_t^{a,s,r,e}}{P_t^{a,s,r}}\right) * P_{t+5}^{a,s,r}$$

Where $P_t^{a,s,r,i}$ refers to a given population age group *a*, sex group *s*, race group *r*, and social indicator *e* at time *t*. Thus, the future population in a given social indicator (household income, poverty, etc.) is the product of the ratio of individuals in that indicator grouping ($P_t^{a,s,r,e}/P_t^{a,s,r}$) to the total population and the projected population ($P_{t+5}^{a,s,r}$).

Here, the age, sex, race, block group specific household income schedule was used and then future age, sex, race, block group populations were exposed to that schedule to produce changes in household income based on demographic changes where the proportion of each age, sex, race group in any given income group comprise the sociodemographic schedule. For example, if 10% of the population of white, females, aged 20-24 earn a household income of $30,000-$35,000, then 10% of all future cohorts of white females aged 20-24 will be projected to earn between $30,000-$35,000. Change occurs when most of the population shifts into different age groups (i.e., from poorer to wealthier age groups), rather than changes in the underlying income distribution (i.e., white females aged 20-24 getting wealthier).

3.2 DATA AND OUTPUTS

To estimate the household income, data was used from the Census Bureau's Public Use Microdata System (PUMS). These data are available in Public Use Microdata Areas (PUMAs), which contain at least 100,000 people, to protect the privacy of respondents. The PUMA household income schedules were then applied to all block groups within the PUMA and calculated the median household income. In other words, the equation in Section 2.1 was modified such that the ratio of individuals in a given household income category was based on the PUMA ($P_t^{a,s,r,e,PUMA}/P_t^{a,s,r,PUMA}$) and applied to each census block group ($P_t^{a,s,r,CBG}$). Household income categories were (0-10,000, 10-14,000, … ,45-50,000, 50-60,000, 60-75,000, 75-100,000, 125-150,000, 150-200,000, 200,000+). These were then summarized to median household income. Median household income projections were produced by census block group in ten-year increments.

3.3 PROJECTIONS OF POVERTY RATES FOR LOUISIANA, 2020-2070

Poverty rate estimates are generally unavailable for block groups. The tract-level estimates were used to produce age/sex poverty rate schedules and were applied to the age/sex distribution in each block group in each year, modifying the equation in Section 2.1, ($P_t^{a,s,r,e,CT}/P_t^{a,s,r,CT}$) $*$ ($P_t^{a,s,r,CBG}$), where CT refers to Census Tract. Projections of household income and poverty do not account for any expected economic development over the projection time horizon and represent strictly demographic changes.

3.4 DATA AND OUTPUTS

To estimate poverty rates, data from the Census Bureau's American Community Survey on Poverty Rates by Age and Sex (Table B17001) at the Census Tract level were used.

Poverty Rate projections were produced by census block group in ten-year increments.

4.0 MIGRATION PATTERNS

4.1 A PROPOSED APPROACH TO MODEL PROJECTED MIGRATION PATTERNS IN LOUISIANA

Modeling prospective migration destinations for Louisiana involves multiple inputs and will result in multiple outputs. This involves combining a migration systems approach with matrix population models and a flood hazard model. Figure 1 shows the general inputs and outputs for this proposed effort.

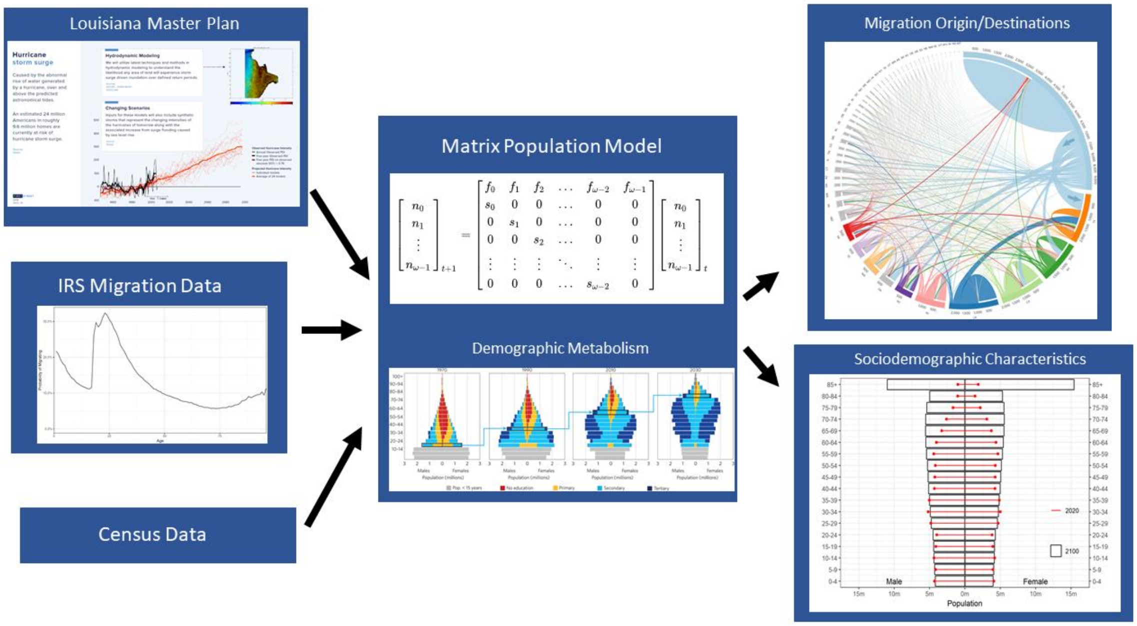

Figure 1. Overall modeling schema using. Using data from the 2023 Coastal Master Plan flood data, IRS migration data, and Census Data as inputs to a Matrix Population Model based on the Demographic Metabolism. The output of the model includes origins/destinations of projected migrants and their associated sociodemographic characteristics.

A matrix population model would be built based on three primary sources of data: 1) the 2023 Coastal Master Plan's flood hazard data (e.g., % of relevant land area that becomes permanently inundated) or a metric that provides the necessary modeling for displacement, 2) Internal Revenue Service (IRS) migration data which provides the probabilities of individuals migrating from county to county, and 3) Census and American Community Survey data that provide the necessary sociodemographic data (e.g., age, sex, race). While all three primary data sources of this project are described separately below, all three sources will ultimately be incorporated into a single multi-regional matrix model.

4.2 MATRIX POPULATION MODEL

The proposed migration matrix population model can be described through an example with just three age groups. In a typical Leslie matrix,

$$\boldsymbol{P}_{t+1} = \boldsymbol{S}_t * \boldsymbol{P}_t$$

Where P_t refers to the population matrix containing *k* age groups and S_t contains the age-specific fertility and mortality rates.

Thus, to produce a population projection, the Leslie matrix operation looks akin to

$$\begin{bmatrix} 0 & F & F \\ S & 0 & 0 \\ 0 & S & S \end{bmatrix} * \begin{bmatrix} P \\ P \\ P \end{bmatrix} = \begin{bmatrix} 0 & 0.2 & 0.2 \\ 0.62 & 0 & 0 \\ 0 & 0.35 & 0.35 \end{bmatrix} * \begin{bmatrix} 100 \\ 100 \\ 100 \end{bmatrix} = \begin{bmatrix} 40 \\ 68 \\ 71 \end{bmatrix}$$

Where S and F refer to the age-specific survival and fertility rates and P refers to the population in a given age group.

A “super-matrix” can be used in a multi-regional projection. A two-region model would take the following general form:

$$\mathbf{P_{t+1}} = \left[\begin{array}{c|c} \mathbf{S_i} & \mathbf{M_{j \to i}} \\ \hline \mathbf{M_{i \to j}} & \mathbf{S_j} \end{array} \right]$$

Where $\boldsymbol{M}_{j \to i}$ refer to age-specific migration probabilities for moving from *j* to *i*.

Therefore, three matrices are required: $\boldsymbol{P_t}$ representing the population vector, $\boldsymbol{S_t}$ containing the mortality/fertility information, and $\boldsymbol{M_t}$ containing migration information. $\boldsymbol{M_t}$ would contain the age-sex-region specific migration probabilities where the diagonal represents the proportion of movers from *i->i* or the non-migrants and the matrices in the off-diagonals would contain the proportion of people migrating from *i->j,* etc.

To project a population, the population vector is first multiplied by the survival matrix and then by the migration matrix.

$$\boldsymbol{P}_{t+1} = (\boldsymbol{S}_t * \boldsymbol{P}_t) * \boldsymbol{M}_t$$

4.3 DATA AND OUTPUTS

Data to produce these matrices would come from several sources. In this case, $\boldsymbol{P_t}$ and $\boldsymbol{S_t}$ come from the same data sources as those outlined in Section 1.4 above. $\boldsymbol{M_t}$’s directionality and general proportions (i.e., those moving from *i->j*) comes from the IRS county-to-county migration data. The IRS began publishing annual county-to-county migration data in 1990, using every Form 1040, 1040A, and 1040EZ in the IRS Individual Master File. These data cover 95% to 98% of the tax-filing universe and their dependents (approximately 87% of US households) (Hauer & Byars, 2019). The IRS data conveys the destinations of migrants but does not detail the number of migrants.

The number of migrants (not just their destinations) must come from the 2023 Coastal Master Plan data based on the proportion of anticipated displacements in each census block group.

This involves the development of a displacement migration model to estimate age-specific migration probabilities. To do so, a statistical outlier detection algorithm is combined to first identify major environmental displacement events in US counties since 1980. Displacement events are identified where the actual county-level population is >5σ different from the predicted county-level population in a given year. This identified 60 displacement events since 1980, ranging from a low of -76% in St. Bernard Parish, LA related to Hurricanes Katrina and Rita in 2006, displacing 50,000 people, to a high of -0.3% in Duval County, FL related to a snowstorm in 1989, displacing 15,000 people.

These displacement events allow for a one-dimensional, age-specific, log-quadratic displacement model based on these findings. The model relies on the relationship between displacement of the total population and the change in migration, ΔM, for age group x such that

$$\log(\Delta \mathrm{M}_x) = a + b_x h + c_x h^2$$

h equals the log$(P_t/\hat{P}_t)$ and $\hat{P}_t$ is the counter-factual population in time *t* had the displacement event not occurred. The fraction inside of *h* can be interpreted as the percentage of the population displaced by the event. Specifics regarding what events would trigger displacement would need to be defined by CPRA.

Table 1. R^2 for the fit of the displacement model. n refers to the number of displacement events (> 5σ) since 1980.

Age Group	R^2	n
0	0.931	60
5	0.918	60
10	0.935	60
15	0.841	60
20	0.772	60
25	0.800	60
30	0.838	60
35	0.912	60
40	0.926	60

Age Group	R²	n
45	0.951	60
50	0.959	60
55	0.956	60
60	0.871	60
65	0.850	60
70	0.861	60
75	0.811	60
80+	0.543	60

Thus, the inputs for the matrix population model include the IRS migration data to model destinations from i->j, census data for the overall model, and 2023 Coastal Master Plan data to generate the percentage of the population likely to be displaced.

Population projections will be produced by census block group – inclusive of climate migration – by:

- 18, 5-year age groups (0-4, 5-9, … ,85+)
- 2 sex groups (Male, Female)
- 2 Race/ethnic groups (White Non-Hispanic, Non-White)

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