




# AgePopDenom: Geostatistical Modeling for Fine-Scale Population Age-Structures

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## Software

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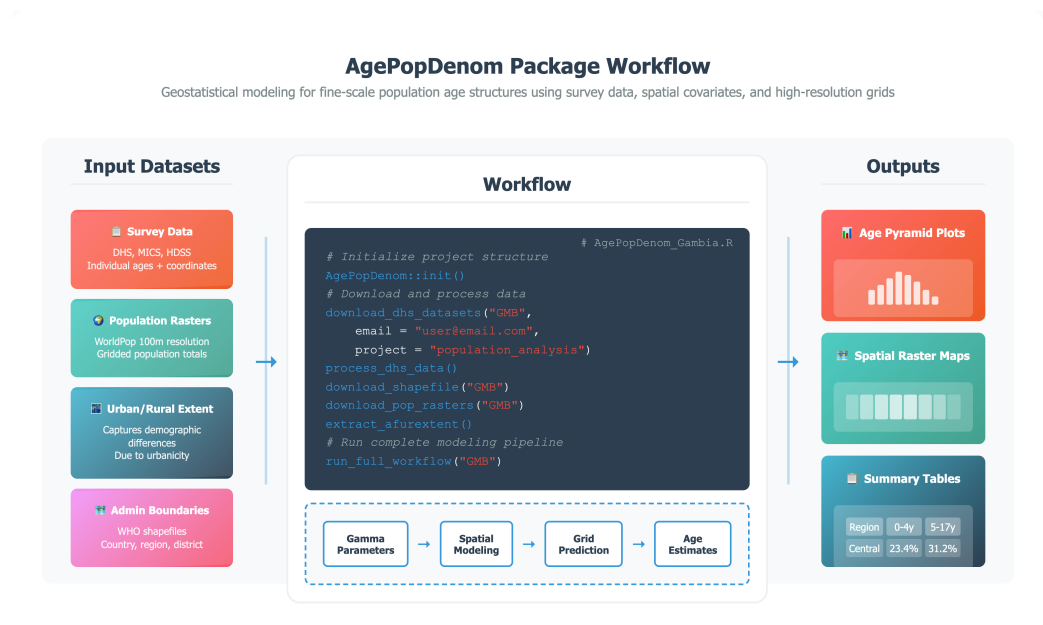
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## Summary

AgePopDenom is an R package that generates high-resolution (5 km × 5 km) estimates of population by single year of age using publicly available datasets including Demographic and Health Surveys (DHS) ([Fabic et al., 2012](#)), WorldPop gridded population data ([Andrew J. Tatem, 2017](#)), and administrative boundaries. It is designed for settings where recent, detailed age data are missing or outdated, common in many low- and middle-income countries.

The package models age distributions using a Gamma distribution framework, well-suited for representing typical age structures. It predicts distribution parameters across space using bivariate geostatistical models with Gaussian processes, capturing spatial autocorrelation in demographic characteristics. Users can include covariates such as urban/rural status to guide predictions. This approach models age structure as a high-resolution surface, capturing spatial heterogeneity rather than assuming uniformity within large regions, producing spatially continuous age-disaggregated estimates even in unsampled locations ([Figure 1](#)).

AgePopDenom is, to our knowledge, the first R package to operationalize a parameter-based geostatistical approach for modeling full age structures at fine spatial resolution. Unlike existing tools that focus on demographic simulation or limited health indicators, it integrates survey microdata, gridded population rasters, administrative boundaries, and user-defined covariates into a single streamlined workflow. The spatial modeling uses Template Model Builder (TMB) ([Kristensen et al., 2016](#)) for efficient C++-based optimization, reducing computation time from 2–3 hours to 7–10 minutes per country.



**Figure 1:** AgePopDenom workflow schematic showing the integration of input datasets, core processing pipeline, and resulting outputs.

## Statement of need

Accurate and spatially explicit age-structured population data are essential for public health planning, disease surveillance, and development efforts. Such data form the basis for estimates of disease burden, vaccination coverage, and intervention impact, aiding governments and organizations in allocating resources effectively (Diaz et al., 2021; Hay & Snow, 2006; A. J. Tatem et al., 2014). Yet granular age-disaggregated data remain scarce. Census data are infrequent and often lack subnational detail. National projections offer interim estimates, but their aggregate assumptions limit utility for local planning. Microdata from National Statistical Offices are often inaccessible due to restrictions (Linard et al., 2010; Stevens et al., 2015). Household surveys such as DHS and MICS provide rich demographic data but are not designed for subnational estimation (Boerma et al., 1993; Ye et al., 2012). This creates a persistent gap in small-area, age-structured population estimates.

Despite advances in fine-scale population modeling, particularly for total population and select age groups like under-fives (Alegana et al., 2015; Pezzulo et al., 2017; Stevens et al., 2015; Wardrop et al., 2018), methods for estimating full age distributions remain limited. Traditional techniques like spline interpolation (Fukuda, 2010; McNeil et al., 1977) lack spatial detail, top-down census disaggregation relies on outdated baselines, and bottom-up models typically exclude age (Wardrop et al., 2018). AgePopDenom addresses this gap by modeling continuous age distributions via Gamma parameterization with bivariate Gaussian processes, delivering high-resolution estimates with built-in uncertainty quantification.

## State of the field

Several existing R packages address adjacent topics but none support empirical, geostatistical modeling of full age structures at fine spatial resolution. Simulation-oriented tools such as IBMPopSim (Giorgi et al., 2023), demogR (J. H. Jones, 2007), demography (Hyndman, 2024), popdemo (Stott et al., 2012), and mpmsim (O. R. Jones, 2025) focus on cohort or matrix-based demographic modeling rather than empirical spatial estimation. SUMMER (Li et al., 2025)

55 supports small-area estimation of survey-based indicators but is limited to specific outcomes  
56 like under-five mortality. Similarly, `ungroup` (Pascariu, 2018), `sptotal` (Higham & Souza,  
57 2019), and `APCtools` (Bauer, 2018) address age unbinning, spatial aggregation, and cohort  
58 analysis respectively, without modeling full age structures spatially. The `wpp2024` (United  
59 Nations Department of Economic and Social Affairs, Population Division, 2024) package,  
60 based on official UN model life table projections, provides standardized national age patterns  
61 but lacks spatial granularity and the ability to incorporate covariates.

62 AgePopDenom fills this gap by operationalizing a parameter-based geostatistical approach for  
63 modeling full age structures. Rather than contributing to existing packages, we built a  
64 standalone tool because the core requirement—joint spatial prediction of Gamma distribution  
65 parameters via bivariate Gaussian processes—is architecturally distinct from the single-outcome  
66 focus of packages like `SUMMER` or the simulation paradigms of demographic modeling tools.  
67 AgePopDenom integrates well-maintained packages (`rdhs` for survey microdata, `terra` for gridded  
68 population rasters) into a reproducible pipeline with modular functions for each workflow stage.

## 69 Software design

70 AgePopDenom's architecture reflects three key design decisions: (1) a parameter-based approach  
71 to age modeling, (2) computational efficiency through compiled code, and (3) an end-to-end  
72 automated workflow.

73 Rather than storing and interpolating raw age counts, which would be memory-intensive and  
74 noisy, we model age distributions via Gamma parameters (shape and scale), reducing the  
75 problem to predicting two smooth spatial surfaces. This parameterization naturally captures  
76 typical age-structure shapes while enabling uncertainty quantification through the fitted  
77 distribution. For computational efficiency, spatial modeling is implemented using Template  
78 Model Builder (TMB) (Kristensen et al., 2016), which compiles model specifications to  
79 C++ and uses automatic differentiation for optimization, making the approach practical for  
80 operational use.

## 81 Research impact statement

82 AgePopDenom addresses a critical data gap in low- and middle-income countries where detailed  
83 age-structured population estimates are essential for public health planning but rarely available  
84 at subnational scales. The package represents a novel capability: to our knowledge, it is  
85 the first R tool to operationalize geostatistical modeling of full age structures at fine spatial  
86 resolution. The primary outputs are age-disaggregated population denominators for downstream  
87 epidemiological and demographic analyses.

88 The package is distributed under an MIT license, includes CI/CD testing across macOS,  
89 Windows, and Ubuntu, and provides documented, runnable workflows. The package integrates  
90 with established data ecosystems including the DHS Program and WorldPop, facilitating  
91 immediate application in settings where these data sources are already used.

92 Collaboration with WHO AFRO and WorldPop (University of Southampton) makes evaluation  
93 and potential near-term use of AgePopDenom in operational settings possible. Target applications  
94 include vaccination coverage estimation, disease burden assessment, and resource allocation,  
95 all domains where age-disaggregated denominators directly influence policy decisions. The  
96 package's efficiency makes it practical for routine use by national statistical offices and health  
97 ministries, supporting evidence-based health planning in data-sparse settings. Future extensions  
98 will incorporate temporal dynamics, Bayesian uncertainty frameworks, and support for additional  
99 survey types.

## Mathematics

Ages are modeled using a Gamma distribution for each survey cluster. Let  $A_{ij}$  represent the age of the  $j$ -th individual in cluster  $i$ . Each  $A_{ij}$  is assumed to follow a Gamma distribution with spatially varying shape  $\alpha(x_i)$  and scale  $\lambda(x_i)$ , modeled as latent fields:

$$A_{ij} \sim \text{Gamma}(\alpha(x_i), \lambda(x_i))$$

The parameters are estimated via maximum likelihood as functions of a bivariate Gaussian Process over spatial locations  $x_i$ . The fitted Gaussian process generates predictions of Gamma parameters at unobserved locations, capturing spatial correlation and allowing smooth interpolation across space. The Gamma cumulative distribution function is then applied to compute proportions in any defined age group, supporting fine-scale age-disaggregated estimation.

## Example

```
# Note: Run within an RStudio Project for correct relative paths
install.packages("AgePopDenom")
AgePopDenom::init()
AgePopDenom::download_dhs_datasets("GMB", email = "email@example.org", project = "demo")
AgePopDenom::process_dhs_data()
AgePopDenom::download_shapefile("GMB")
AgePopDenom::download_pop_rasters("GMB")
AgePopDenom::extract_afurextent()
AgePopDenom::run_full_workflow("GMB")
```

## AI usage disclosure

Generative AI tools were used during the development of this work. Specifically, AI assistance was used for debugging during software development and for editing and refining the manuscript text. All AI-generated suggestions were reviewed, validated, and modified by the authors. The corresponding author takes full responsibility for the final content.

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