Release Statement

Modelled gridded population estimates for Lualaba Province in the Democratic Republic of Congo version 4.3.

29 August 2025

Abstract

This data release provides gridded population estimates (spatial resolution of 3 arc-seconds, approximately 100-metre grid cells) for Lualaba Province in the Democratic Republic of Congo (DRC), along with estimates of the number of people belonging to various age-sex groups. The project team used the Pre-Distribution Registration Survey (PDRS) data from the National Malaria Control Programme (PNLP) collected as part of anti-malarial campaigns in the DRC for 2023, settlement extents and geospatial covariates to model and estimate population numbers at grid cell level using a Bayesian statistical hierarchical modelling framework. The approach facilitated simultaneous accounting for the multiple levels of variability within the data. It also allowed the quantification of uncertainties in parameter estimates. These model-based population estimates can be considered as most accurately representing the year 2023. This time period corresponds to the PDRS survey date for Lualaba. Although the methods were robust enough to explicitly account for key random biases within the datasets, it is noted that systematic biases, which may arise from sources other than random errors within the observed data collection process, are most likely to remain.

These data were produced by the WorldPop Research Group at the University of Southampton. This work was part of the GRID3 – Phase 2 Scaling project, with funding from the Gates Foundation (INV-044979). Project partners included GRID3 Inc, the Center for Integrated Earth System Information (CIESIN) within the Columbia Climate School at Columbia University, and WorldPop at the University of Southampton. The final statistical modelling was designed, developed, and implemented by Chris Nnanatu. Data processing was done by Ortis Yankey with additional support from Heather Chamberlain. Project oversight was done by Attila Lazar, Chris Nnanatu and Andy Tatem. The PDRS data from the malaria insecticide treated net (ITN) distribution campaigns were collected, processed, anonymised and shared by the PNLP and its implementing partners. The settlement extent data was prepared and shared by CIESIN (2024). The data has been clipped to GRID3-CIESIN health area extent (version 6.0) (CIESIN, 2025).

The authors followed rigorous procedures designed to ensure that the used data, the applied method and thus the results are appropriate and of reasonable quality. If users encounter apparent errors or misstatements, they should contact WorldPop at release@worldpop.org.

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RELEASE CONTENT

1. COD_Lualaba_province_population_v4.3_gridded.zip
2. COD_ Lualaba_province_population_v4.3_agesex.zip

LICENSE

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SUGGESTED CITATION

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FILE DESCRIPTIONS

The projection for all GIS files is the geographic coordinate system WGS84 (World Geodetic System 1984). Kindly note that while this data represents population counts, values contain decimals, i.e. fractions of people. This is because both the input population data and age-sex proportions contain decimals. For this reason, it is advised to aggregate the rasters at a coarser scale. For example, if four grid cells next to each other have values of 0.25 this indicates that there is 1 person somewhere in those four grid cells.

COD_Lualaba_province_population_v4_3_gridded.tif

This geotiff raster contains estimates of total population size for each approximately 100-metre grid cell (0.0008333 decimal degrees grid) across Lualaba Province. The values are the mean of the posterior probability distribution for the predicted population size in each grid cell. Grid cells within the national boundary with values of NA represent areas

that were mapped as unsettled according to building footprints data, while any other NA values represent areas mapped as being outside national boundary.

COD_ Lualaba_province_population_v4_3_lower.tif
This geotiff raster contains estimates of the lower bound credible interval (2.5% CI) for each grid cell across Lualaba. The values are the 2.5% posterior probability distribution for the predicted population size in each grid cell. The lower bound estimates cannot be summed across grid cells to produce a lower credible interval measure for a multi-cell area. Grid cells within the national boundary with values of NA represent areas that were mapped as unsettled according to building footprints data, while any other NA values represent areas mapped as being outside national boundary.

COD_ Lualaba_province_population_v4_3_upper.tif
This geotiff raster contains estimates of the upper bound credible interval (97.5% CI) for each grid cell across Lualaba. The values are the 97.5% posterior probability distribution for the predicted population size in each grid cell. The upper bound estimates cannot be summed across grid cells to produce an upper bound credible interval measure for a multi-cell area. Grid cells within the national boundary with values of NA represent areas that were mapped as unsettled according to building footprints data, while any other NA values represent areas mapped as being outside national boundary.

COD_ Lualaba_province_population_v4_3_agesex.zip
This zip file contains 40 geotiff rasters at a spatial resolution of 3 arc-seconds (approximately 100-metre grid cells). Each raster provides gridded population estimates for an age-sex group per grid cell across Lualaba. We provide 36 rasters for the commonly reported age-sex groupings of sequential age classes for males and females separately. These are labelled with either an “m”(male) or an “f” (female) followed by the number of the first year of the age class represented by the data. “f0” and “m0” are population counts of under 1-year olds for females and males, respectively. “f1” and “m1” are population counts of 1 to 4 year olds for females and males, respectively. Over 4 years old, the age groups are in five year bins labelled with a “5”, “10”, etc. Eighty-year-olds and older are represented by the groups “f80” and “m80”. We provide four additional rasters that represent demographic groups often targeted by programmes and interventions. These are “under1” (all females and males under the age of 1), “under5” (all females and males under the age of 5), “under15” (all females and males under the age of 15) and “f15_49” (all females between the ages of 15 and 49, inclusive). These data were produced using age-sex proportions from the 2024 WorldPop Global subnational population pyramids for the DRC. The age-sex proportions are available per a given province. Hence we applied the age-sex proportions for Lualaba to the gridded population estimates (COD_

Lualaba_Province _population_v4_3_gridded.tif) to allocate the population to the different age-sex classes.

RELEASE HISTORY

Version 4.3 (29 August 2025)

- This is the original release of the data for Lualaba Province [doi: 10.5258/SOTON/ WP00820] (as described in this release statement).
- This data release utilizes operational National Malaria Control Programme data, composite openly accessible building footprint datasets and a new mastergrid.
- This data is released as part of a collection of population estimates for 17 DRC provinces: https://wopr.worldpop.org/?COD/Population/v4.3

ASSUMPTIONS AND LIMITATIONS

These population estimates most likely represent the year 2023, but because of the different ages of the input data used to build the model, a more precise time point cannot be assigned. The PDRS data that was used as the response variable was collected in 2023, while geospatial covariates data were collected from different time periods between 2020 and 2023. Similarly, the CIESIN settlement layers were produced in 2024. The inherent heterogeneity in the temporal alignment of these datasets used in the modelling may introduce uncertainties and potential inaccuracies in the modelling process.

Data on population per household (household size), collected during ITN distribution campaigns, was aggregated to calculate total population count for a given spatial unit. Given that the number of ITNs received by a household is proportional to the household size, there is an incentive for respondents to potentially inflate counts of population per household. The presence of inflated household sizes in the input population data would likely introduce systematic biases in the modelled estimates.

The model does not account for external factors such as migration, displacement, or sudden demographic changes, which could significantly influence population dynamics.

Grid cell alignment is based on a mastergrid. Note that this version's (v4.3) mastergrid aligns with versions 4.1 and 4.2 but does not align with previous DRC gridded population

layers, namely versions v1.0, v2.0, v3.0. We updated the mastergrid in 2024 to ensure grid cell alignment across all new WorldPop data products.

SOURCE DATA

The key datasets used to produce the modelled population estimates are:

PDRS Data

The input population dataset used for the population modelling for Lualaba Province was the PDRS malaria bednet campaign data. The PDRS dataset, which was collected in 2023, provided detailed information on a given household for which a bednet was issued, such as the household size, the number of bednets issued, the number of children in the household, the number of males, and the number of females, among others.

Although the malaria bednet campaign was designed to distribute bednet to every household within the province, a preliminary exploratory data analysis carried out on the PDRS data indicated that some households were not visited during the campaign, while others were not completely covered.

The GPS points of all households within the province were provided in the PDRS data. We implemented population modelling for small spatial units, utilising unofficial boundaries similar to census Enumeration Areas ("pre-EAs"; Qader et al., 2024). The household-level data on population counts was spatially aggregated to these spatial units, by summing the household size data for all GPS points within each pre-EA boundary.

Settlement Data

Settlement data was provided by CIESIN in the form of raster files (CIESIN, 2024). We obtained two different settlement products, namely (i) settlement area, which indicates the area of all buildings whose centroid falls within a given cell, and (ii) building count, which is the number of building centroids within a given cell. Each of these settlement layers was used in separate analyses together with the observed population count and ancillary geospatial data in robust statistical modeling. After using each settlement layer in the analysis, we compared model metrics and the gridded population layer from both layers. Settlement building count provided more realistic population numbers at the gridcell level and hence was retained for the final population predictions.

Geospatial Covariates

A wide variety of geospatial covariates, which are related to population distribution, were considered in the modelling. These geospatial covariates include land use and land cover data, climate variables such as temperature and rainfall, physical features and infrastructure such as roads and schools, and conflict data. Population model covariates were selected using a generalized linear model (GLM) based stepwise selection method.

The selected covariates were further assessed for multi-collinearity and statistical significance. Eventually, of the 80 geospatial covariates initially tested, 9 were retained as the best fit covariates with variance inflation factor (VIF) of less than 5. The descriptions of these final geospatial covariates are presented in Table 1 below.

Table 1. Selected geospatial covariates for the modelling.

Description	**Source**	**Link/Reference**
Euclidean distance to herbaceous and grassland landcover type, 2020	WorldPop	Woods et al (2024)
Euclidean distance to trees landcover type, 2020	WorldPop	Woods et al (2024)
Euclidean distance to urban areas 2020	WorldPop	Woods et al (2024)
Euclidean distance to bare areas 2020	WorldPop	Woods et al (2024)
Mean – temperature, 2022	Copernicus	https://land.copernicus.eu/global/products/ba
Mean – Dry matter productivity, 2022	Copernicus	https://land.copernicus.eu/global/products/ba
Standard deviation – Dry matter productivity, 2022	Copernicus	https://land.copernicus.eu/global/products/ba
Euclidean distance to ACLED conflict locations 2022	ACLED	https://acleddata.com/
Euclidean distance to OSM educational facilities 2023	OSM	https://www.openstreetmap.org

Age-Sex Proportions

We used the 2024 WorldPop Global subnational population pyramids (Bondarenko et al 2025) to calculate the age-sex proportions for Lualaba. We multiplied our gridded population estimates (COD_ Lualaba_province_population_v4_3_gridded.tif) by the age-sex proportions(grouping) to produce COD_ Lualaba _province_population_v4.3_agesex.zip.

METHODS OVERVIEW

The key steps of our approach were as follows:

- Cleaning household dataset from the PDRS by removing extreme outliers from the data.

- Summarizing the household sizes from the PDRS dataset to get the total population at the pre- enumeration area (pre-EA) level (Qader at al. 2024).
- Geospatial covariates were subjected to robust covariate selection for model training and parameter estimation.
- We developed a hierarchical Bayesian statistical model using the INLA-SPDE approach (Lindgren et al. 2011) to fit and predict the population count.
- Population estimates were predicted at grid cell level using the grid cell values of the covariates selected at the model training level.

Data cleaning

The data cleaning consisted of two steps:

The CIESIN building count and the total observed PDRS population were summed-up for all model training units (i.e. EAs), and then the observed population density was calculated (i.e. people per building). Those EAs are dropped, where this observed population density was less than 1 or greater than 20. After the first step, 88 percent of EAs were retained.

In the second step, the observed total PDRS population was compared to the WorldPop global (WPGL) 2024 total population per EA. This ensured that the observations are not too large or small compared to a census projection-based population estimates. In this step, only those remaining EAs were kept, where the WPGL:PDRS ratio was greater or equal to 0.2 AND less or equal than 10. In another word, the WPGL sum can be maximum 10 times larger than PDRS (i.e. PDRS should not be too small, missing significant population) AND the PDRS cannot be more than 5 times larger than the WPGL estimates (i.e. the PDRS cannot be unrealistically too large).

After the two cleaning steps, approximately 84 percent of the EAs remained for model training.

Statistical Modelling

All data processing, statistical modelling, and analyses were carried out using R version 4.4.2 (R Core Team, 2023), tidyverse (v. 2.0.0) (Wickham et al., 2019), SF (v. 1.0-17) (Pebesma and Bivand, 2023), and Terra (v. 1.7–78) (Hijmans et al., 2024). Bayesian hierarchical modelling was implemented using the R-INLA package version 24.12.11 (Rue et al. 2009). Modelled estimates of the population were produced using a bottom-up population modelling framework (Wardop et al., 2018), which utilises a Bayesian statistical inference framework that can be implemented using either a Markov chain Monte Carlo (MCMC)-based strategy (Leasure et al., 2020; Boo et al. 2022; Darin et al., 2022) or the integrated nested Laplace approximation in conjunction with the stochastic partial differential equation (INLA-SPDE; Rue et al., 2009; Lindgren et al., 2011)

techniques recently developed by Nnanatu et al. (2022) in the context of Cameroon (Nnanatu et al., 2022; Nnanatu et al., 2025a), and applied in Papua New Guinea (Nnanatu et al., 2024) and the Democratic Republic of Congo (e.g., Nnanatu et al., 2025b).

Model Specification

In general, the population count N_i at a given (ideally geolocated) area unit is assumed to be Poisson-distributed, such that $N_i \sim Poisson(\lambda_i)$. However, in the context of small area population modelling (Leasure et al., 2020; Boo et al. 2022 ; Darin et al.,2022; Nnanatu et al., 2022; Nnanatu et al., 2024a; Nnanatu et al., 2024b; Nnanatu et al., 2025), a key assumption of the Poisson model which requires both mean and variance to be equal is often violated due to overdispersion in which case $mean(N_i) \neq var(N_i)$. For this reason, the mean parameter λ_i is usually expressed in terms of population density to account for spatial aggregation error (e.g., Leasure et al 2020, Nnanatu et al 2022). Typically, the mean parameter is given as $\lambda_i = \mu_i B_i$, where B_i is the total number of buildings within a pre- enumeration area (pre-EA) i and

$$D_i = \frac{pop_i}{B_i} \qquad (1)$$

is the population density defined as the number of people per building which follows a Gamma distribution given by

$$D_i \sim Gamma(\alpha_1, \alpha_2) \qquad (2)$$

where α_1 and α_2 are the shape and rate parameters with mean $\mu_i = \alpha_1/\alpha_2$ and variance $\phi = \alpha_1/\alpha_2^2$, respectively. The predicted population density $\widehat{D}_i$ for pre-EA i is given by

$$\widehat{D}_i = \exp\left(X_i^{\boldsymbol{T}}\boldsymbol{\beta} + Z_i^T\boldsymbol{\gamma} + \xi(s_i) + \zeta_i\right) \qquad (3)$$

where X and Z are the design matrices of fixed effect covariates (e.g., average annual precipitation, average annual temperature, distance to crop land) and random effects (e.g., settlement type), respectively. Also, the terms $\boldsymbol{\beta} \in \mathbb{R}^{(K\times 1)}$ and $\boldsymbol{\gamma}$ are the vectors of fixed effects regression parameters and random effects variances, respectively. While the terms $\xi(s_i)$ and ζ_i are the spatially varying and spatially independent random effects accounting for spatial autocorrelations and dissimilarities between observations, respectively. We have that the term $\xi(s_i)$ is a Gaussian Random Field (GRF) such that

$$\xi(s_i) \sim GRF(\mathbf{0}, \Sigma) \qquad (4)$$

where Σ is a dense covariance matrix. The INLA-SPDE approach allows us to approximate the GRF using a computationally efficient Gaussian Markov Random Field (GMRF) by discretising the continuous spatial domain using mesh (Lindgren et al., 2011). The random term ζ_i is assumed to follow a zero-mean Gaussian distribution specified by

$$\zeta_i \sim Normal\left(0, \sigma_\zeta^2\right) \qquad (5)$$

where $\sigma_\zeta^2 > 0$ is a variance parameter. Then, finally, the predicted population counts at grid cell g is obtained as

$$\widehat{N}_g = \widehat{D}_g \times B_g \qquad (6)$$

where $\widehat{D}_g$ is the predicted population density in grid cell g using the corresponding grid cell covariate values and the model parameter values based on equation (3); B_g is the corresponding building count for grid cell g $(g = 1, \dots, G)$. The prediction covariates included G grid cells at 100m-by-100m resolution, and population counts were predicted in each grid cell that contains values of building counts.

All models were implemented within the integrated nested Laplace approximation (INLA; Rue et al, 2009) in conjunction with the stochastic partial differential equation (SPDE Lindgren et al, 2011) frameworks. It allowed us to gain more computational advantage by discretizing the entire study location continuous space into a Gaussian Markov random fields (GMRF) process. To ensure flexibility and better capture local variabilities within the data, we used the Penalized Complexity (PC) (Simpson et al., 2017) on the standard deviation parameters throughout, such that a small probability of 0.01 is assigned to the standard deviation σ being greater than 1, that is, $P(\sigma > 1) = 0.01$.

Model fit checks and model validation

Model selection relied on the deviance information criterion (DIC) values while the selected model predictive ability was examined using the mean absolute error (MAE), the root mean square error (RMSE) and the correlation coefficient (CC). Smaller values of DIC, MAE and RMSE indicate better fit and predictive ability while larger values of CC indicate better predictive ability.

These model performance metrics were also used within k-fold cross-validation where the data was first divided into two with the model parameters trained with 80% of the data while the remaining 20% was used as a test to predict population density. This was repeated 10 times (10-fold) whilst ensuring that none of the test samples was repeated (that is, the test sets are mutually exclusive and exhaustive). The primary aim of the cross-validation is to test how well the best fit model parameters were able to predict population outside the observed locations. To more accurately capture the performance of the model, we carried out in-sample and out-of-sample cross validations. In the in-sample cross-validation, all the data points were used in the training set but 20% of the data points were used as test set to predict their population density. Whereas in the out-of-sample cross validation, the 20% test set was excluded completely from the 80% training set.

Further posterior inference and grid cell predictions were also carried out. The prediction at the grid cell uses the model parameters of the best fit training set model to

predict population counts at 100m-by-100m grid cells across the study location using the corresponding grid cell values of the geospatial covariates and the building counts.

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