Working title: Population Age-Structure and Forest Growth in Low-and-Middle-Income Countries

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Introduction

In 2011, the Bonn Challenge set to restore 350 million hectares (Mha) of forest by 2030 (http://www.bonnchallenge.org/). This goal has since had renewed commitment through initiatives such as the United Nations Decade on Ecosystem Restoration 2021–2030 to accelerate progress toward the Bonn Challenge (http://www.decadeonrestoration.org/). The research between population processes and forest growth is underdeveloped. Research on the human population-environment nexus has examined population as both a precondition and an outcome but has largely cast population as a variable of few dimensions. Human population is often included in environmental studies using population size or density - variables that assume all units (in this case, people) contribute equally to the mechanisms that affect or are affected by the environment.

An informative population variable that reveals the multidimensional nature of populations is their age structure. There are reasons to expect heterogeneous environmental impacts across age structures. The frequent omission of age as a central variable at any level of demographic measurement (individual, household, community or nation) when considering population impact is somewhat surprising. When studying individuals, age or life course status are frequent markers for understanding fertility, mortality, migration, and economic behavior. Family or household age structure is employed to explain patterns of household well-being across settings. For populations, age structure is the outcome and the engine of fertility, mortality, and migration patterns and is fundamentally important for demographers, policymakers, and other stakeholders. It is often used to forecast or explain economic development outcomes in both more and less-developed settings.

Recent literature mostly focuses on the deleterious effects of human populations on the environment, such as increased population growth, migration, or population density and their effects on land degradation, carbon emissions, and air quality. In either case, whether examining environmental impacts on population outcomes or population impacts on environmental outcomes, rarely do analyses examine how the age structure of populations may influence differential impacts of climate or environment or vice versa.

We aim to further these conversations by drawing attention to a rich and well-known population indicator that has been oft overlooked in environmental research: age structure. Age structure of a population is the final outcome and the engine of the fertility, mortality, and migration patterns of current, recent, and past regimes. Everyone has an age, and this simple fact locates individuals in societal and economic roles. Age structure leaves clues about family formation, health, migration patterns, and economic activity and opportunity. Without considering age structure, population size and density become featureless landscapes where every unit looks the same structures. Do these aging population structures lend themselves to a different kind of dividend, where age structure shifts result in land use change or other environmental transformations?

Data and Methods

Data

We utilize global, gridded data to describe demographic and forest-related variables in 139 low-and-middle-income countries during 5-year intervals during the time period 2005-2020.

WorldPop data provide population counts, broken down into 5-year age groups, and population density with a 1 km x 1 km resolution (www.worldpop.org). The European Space Agency (ESA) Copernicus Program provides information on tree cover at a 300 m x 300 m resolution (https://www.copernicus.eu/en). We include a globally gridded data layer of gross domestic product (GDP) made available through the Dryad repository (Kummu et al. 2018). Finally, we include information on migration from the Knowledge Centre on Migration and Demography (KCMD) Data Portal. These data estimate the number of migrants in gridded data with a resolution of 25 km x 25 km.

Sample

Our analysis focused on tree-cover gain during three five-year periods: 2005–2010, 2010–2015, and 2015–2020. We used five-year periods because that is the frequency of available gridded data on net migration (Alessandrini et al. 2023). Geographically, we focused on Level 2 administrative subdivisions in low- and middle-income countries (LMICs) in Africa, Asia and the Pacific, and Latin America and the Caribbean. These subdivisions would be labeled “counties” in the US but are known by various names (e.g., “districts”) in the LMICs in our sample. To our knowledge we have generated the first, level 2 integrated estimates of forest cover, land cover, potential tree cover, population characteristics (age structure and migration), and economic conditions (GDP per capita). We further restricted the sample by including only subdivisions where forests would occur under natural conditions (Dinerstein et al. 2017) and potential tree canopy cover at least 15% of land area, which is the minimal canopy density condition for land covers classified as “tree cover” by the source of our land-cover data (Buchhorn et al. 2020, 2021). Furthermore, divisions needed to exhibit tree cover that was below its maximum potential level (Bastin et al. 2019) and the subdivision was predominantly rural, defined as having a population density less than 300 people per km^2 (European Commission and Statistical Office of the European Union, 2021).

We modeled tree-cover gain (*Gain*; 0 or 1) as a function of tree-cover gap (*Gap*), GDP per capita (*GDPpc*; constant USD/person), and a set of demographic variables (*Demography*):

$$Gain_{it} = \beta_1 Gap_{i,t\text{-}5} + \beta_2 GDPpc_{it} + \beta_3 Demography_{it} + c_i + \Theta_t + \beta_4 Trend_{jt} + u_{it},$$

where subscripts *i*, *j*, and *t* denote Level 2 subdivision, country and year, respectively.

Gap_{it} is the positive difference between potential tree cover and current tree cover in subdivision *i* in year *t*, expressed as a percentage of land area and lagged one period (5 years) to avoid simultaneity with the dependent variable. c_i and Θ_t are fixed effects for subdivisions and years, respectively, and $Trend_{jt}$ is a set of country-level time trends. $Demography_{it}$ refers to a set of demographic variables—population density, in-migration and out-migration rates, and age-component shares—which we added sequentially to the model to investigate their effects. We expected population density to have a negative effect: more people create more land-use pressure instead of converting it to tree cover over the ensuing five years. Conditional on population density, we postulate younger populations (those with a higher share of those aged 0-14) would represent growing populations, and therefore have a negative effect on tree-cover gain via increased land and resource use. Similarly, older populations would have a positive effect on tree-cover gain through dwindling pressure on resource consumption and land use.

We estimated the model using a fixed-effects logit estimator. We weighted the observations by subdivisions' potential tree area (in km^2) to account for differences in subdivision size. The estimation sample included 8,033 subdivisions and was perfectly balanced (i.e., data were available for all subdivisions in all three years).

Preliminary Results

Table 1 presents the regression results. All models included *Gap* (lagged), *GDPpc*, and population density along with the subdivision and year fixed effects and country trends. Model I included only these variables. *Gap*, *GDPpc*, and population density had the expected signs and were highly significant. Crucially, the elderly share of the population is significantly associated with an increase in tree forest gain in the subsequent five-year period. The stratified model that examines the demographic clusters separately show that the elderly share has the strongest association with forest gain in countries still experiencing a demographic transition.

Table 1. Estimation results from fixed-effects logit model of tree-cover gain. Units of observation: Level 2 administrative subdivisions for three years (2005, 2010, 2015). Dependent variable: binary tree-cover gain during subsequent five-year periods (2005–

2010, 2010–2015, 2015–2020). In addition to the variables listed, all models included fixed effects for Level 2 subdivisions, dummy variables for time periods, and country-level time trends. *p*-values are shown in parentheses below coefficient estimates, with asterisks displaying significance: *** *p*<0.01, ** *p*<0.05, * *p*<0.1.

		Main Model	**Demographic Transition Status**			**Environmental Conditions**	
VARIABLES	**Without age shares**	**Add youth & elderly shares**	**Pre-transition**	**Transitioning**	**Post-transition**	**In moist tropics**	**Not in moist tropics**
Tree-cover gap	9.03***	**9.16*** **	9.59***	10.18***	8.97***	11.51***	6.60***
GDP per capita	7.96E-07	**-3.59E-06**	1.00E-05	-9.72E-05*	6.70E-06	-6.73E-06	-2.53E-06
Population density	-2.73E-04	**-2.01E-04**	3.15E-03*	-1.15E-03	-1.70E-03	-5.87E-04	2.52E-05
Net pos. migration rate	-0.59	**-0.98**	0.02	-1.08	-1.46	-1.79**	0.01
Net neg. migration rate	-0.91	**-0.80**	0.30	-3.07***	-0.26	-1.69	-0.67
Population share: youth		**7.97*** **	-2.19	20.49***	11.14***	12.24**	1.96
Population share: elderly		**16.79*** **	-2.02	52.52***	15.53***	36.13***	1.57
R2	0.25	**0.26**	0.40	0.34	0.20	0.26	0.37
Observations	23,598	**23,598**	2,739	7,320	13,539	13,947	9,651
Number of subdivisions	7,866	**7,866**	913	2,440	4,513	4,649	3,217
*** p<0.01, ** p<0.05, * p<0.1							

Next steps

This analysis shows our preliminary results, and we have crucial next steps planned before we can provide a full reflection of the implications of our findings. We plan to generate maps to show our descriptive and analytical findings and further elaborate on possible mechanisms between age structure and environment.

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