Forecasting High Resolution Migration in Nigeria Under Different Climate Scenarios

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Abstract

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Existing research indicates that most climate-induced migration occurs and will continue to occur within rather than between nations. This can be harder to track than international migration but is crucial for understanding how climate change influences population trends, urbanization, and public health. Internally displaced people can have unique health, economic, and social challenges for which governments will need to prepare as climate change alters the distribution of undesirable or uninhabitable land.

In this research, a gravity model was fit with past population, precipitation, and temperature trends to forecast population distributions in Nigeria to 2100 under different climate scenarios. The base gravity model is trained on 1km^2 gridded population changes from WorldPop between 2000-2010. This model uses unique parameters for urban and rural cells to capture general urbanization trends based on each cell's distance from urban spaces and the population of urban spaces within the country. The error in each cell of the population forecast from this first stage of the model is used to fit a model that predicts error from percentage changes of average temperatures, maximum temperatures, and precipitation changes of the same period. This model creates a cell-specific scalar to the population distribution forecast from the first stage based on that cell's unique climate factors and how they affect the desirability to live there.

Using Coupled Model Intercomparison Projects 6th iteration (CMIP6) data for future temperature and precipitation, population distributions were forecasted to 2100 under Shared Socioeconomic

Pathway (SSP) 2-4.5 and SSP 5-4.5 scenarios. SSP 2-4.5 and SSP5-8.5 represent a “middle of the road” effort with respect to climate adaptation and mitigations and an improved technologies but continued high fossil fuel greenhouse gas (GHG) emissions scenario, respectively. The results show that under the higher emissions scenario Nigeria urbanizes faster as climate change reduces the desirability of rural areas, particularly those in the east. Western cities in Nigeria have 2-3 times the population weights in 2100 under a higher emissions future compared to lower emissions future. The implications of this research are that Nigeria may have different population distributions with unique needs in the future depending on how global policies do or do not reduce greenhouse gas emissions. Higher urbanization will not only mean a reduction in agricultural workforce but also denser cities and a higher population of urban migrants who may have unique health, education, and economic needs. Understanding what populations may look like in the future under different climate scenarios will be important for government planning to best support the Nigerian population.

I. Introduction

Background on climate change and climate-based migration

Since the industrial revolution, anthropogenic emissions of greenhouse gases have led to increased global temperatures and a range of environmental changes.[1] These changes can include increased risk of floods, extreme heat, damage to ecosystems needed for agriculture and fishing, and innumerable other harms that cause people to migrate away from where they live.[1,2] Those living in rural areas whose livelihoods are tied to the land and environment they live in are considered especially vulnerable to displacement.[2] Climate migration most commonly occurs as people leave rural areas for urban ones in middle-income countries.[3] Most climate migrants stay within their country, as opposed to international migration, and move to locations where there is less dependence on agriculture.[3–5]

Climate migration drivers can act in the short and long term. Short-term drivers like sudden floods, wildfires, or extreme weather events are easier to track and are more widely reported.[6] The Intergovernmental Panel on Climate Change (IPCC) reports it's likely that climate change will increase the speed at which people are forced to migrate from rural to urban areas due to unsustainable agriculture in the long term.[7] A synthesis of available data in 2021 found that high temperatures, droughts, and generally decreased precipitation are likely drivers for out-migration over long periods.[3]

Although many individuals choose to leave where they live due to climate change, there is a portion of the population that may fall into the "trap" of being so low in resources that despite wanting or needing to migrate, they are incapable of doing so.[8] This can disproportionately affect women who must stay home while the men in their community migrate to urban areas searching for better economic opportunities.[8] It is important to note that not all populations persisting in environments growing less habitable are doing so out of a lack of agency; many people have important social and cultural connections to where they live and would prefer staying with any adaptations possible rather than relocate or migrate despite increasingly unsatisfying living conditions.[8] The long-term effects of climate drivers on migration are uncertain. Some populations have significantly better health and economic outcomes after migration, while others find new obstacles at their destination.[9] Migrants have better outcomes when barriers to migration are reduced as much as possible and governments have adequately planned for health, education, and economic opportunities.[9,10]

Internal migration is harder to track than international migration, but is crucial for countries to understand to predict the urbanization, labor allocation, and health needs of their changing populations.[11] In 2010 at the biennial Conference of Parties (COP) meeting to discuss climate change, members included climate migration concerns in their meeting outcomes for the first time in the Cancun Adaptation Framework. This asked involved nations to include plans for internal migration and even plan relocation as climate change makes it necessary.[4] The lack of clear research and predictions on climate-induced migration will prove to be key obstacles in planning for the likely increase in climate change migration. Existing research often produces opposing results about drivers, magnitude, speeds, and outcomes of migration driven by climate factors.[6,12] This can complicate efforts to make legislation of specific plans for internal migration as there is little consensus on what is likely to happen.[12]

Country of Focus: Nigeria

Nigeria has and will continue to experience shifting temperatures, precipitation, and other environmental changes due to climate change.[13–16] Existing research shows climate change will adversely affect the economy in Nigeria, particularly for the over 70% of the population whose livelihood is associated with agriculture.[15,17] Nigeria has four distinct climate zones: the Niger Delta is a monsoon region, the northeast is a warm dessert area, the rest of the north is a warm semiarid zone, and across the center and southwest are a tropical savannah.[18] The North in particular is considered most vulnerable to the harms of climate change through increased desertification and lack of precipitation necessary for agriculture.[15,18] Research suggests that if current climate change trends continue, Nigeria may suffer significant desertification in the north that has the potential to encroach south through the whole savannah.[19] This poses the risk of drastically harming agriculture and those who are reliant on it for income and food.[19]

Internally displaced people (IDPs) from climate change have continued to grow in Nigeria with the highest annual recorded number, 2.4 million IDPs, reported in 2022.[20] A 2019 research project analyzed if migration was a used adaptation strategy in Nigeria for households affected by climate change in the long and short term. They found those who once lived in ideal conditions for farming became the most likely to leave once climate change impaired the farming conditions in their area compared to those who already lived in less-than-ideal climates.[21,22] Research across sub-Saharan Africa suggests that decreased rainfall drove increased urbanization, particularly as countries gained independence from colonial rule and people were able to move more freely.[23]

Climate change, directly and indirectly, influences migration. Besides reducing agricultural productivity, poor growing conditions can increase violent conflict as resources become strained.[14] Growing desertification has increased poverty, particularly in Northern Nigeria, which research has linked to increased involvement and violence in these areas from the terrorist organization Boko Haram.[5] Migration in Nigeria is also gendered. Men are more likely to leave, which can place an extra burden on women left behind to care for households and children, worsening gender disparities.[24] Nigerian women are already overburdened by the harms of climate change as men were more able to move and adapt.[25]

Migration Modeling

The countless drivers for migration make modeling climate-induced migration difficult. A key challenge is parsing out migration specifically caused by climate change. Data sources such as censuses may lack the temporal resolution to capture these specific movement patterns.[26] Identifying causal effects and mediating effects can also be difficult. For example, migration is often attributed to local economies which are in turn affected by climate change, but it can be difficult to parse apart how the local economy might have amplified or dampened climate impacts.[26]

Researchers must question their models' generalizations, temporally and geographically. Different populations may have different responses to the same event, and often the relationships between drivers and responses are non-linear.[26] In addition, turning individual-level decision-making into a population-level model threatens to obfuscate important trends and potential future directions migration patterns will take.[27]

Common Migration Models Considered

Spatial Vulnerability/Exposure Mapping Models

These are a type of model that calculate hazards to different climate threats with population and climate data sets and assume specific relationships between these threats and migration.[28,29] These models often use a linear relationship between exposure and migration, which is an important oversimplification.[28]

Hazard Analysis Models

This model type focuses on specific individuals or sections of the population and how they respond over time to specific events.[28] This model is useful in considering behavior and decision-making, however there often is insufficient data to apply to large population areas.[28]

Agent-based Models

These models are essentially multi-level versions of the hazard analysis models.[28] These utilize all available empirical and theoretical relationships between humans and their environments and follow the movements and behaviors of individuals or groups, called agents.[29,30] A benefit of these models is their ability to capture high-resolution demographic differences if they exist in the data. This makes it useful for small-scale research but limited to large regional analysis.[29]

System Dynamics Models

These are models that explore different outcomes from a specific climate event if different measures are taken to adapt to or mitigate the damage.[29] These are useful for answering specific questions or scenario ideas, but less ideal for longer-term or larger-scale modeling.[29]

Gravity Models

Gravity models are based on Newton's law of gravity, but rather than the pull between bodies of different masses, they calculate the migration between different locations with different desirable/undesirable characteristics such as GDP, climate risks, etc.[29] This is a longstanding migration model that has been used for decades in general migration models and notably is successful for large areas.[31] While there are many benefits to the gravity model approach, individual decision-making and behavioral factors are not included.[29]

Gravity models fit best with the scope of this research. There are two notable examples of gravity model-based research, Jones and O'Neil (2016) and the Groundswell Report (2018) alongside it's follow up Groundswell II: Acting on Internal Climate Migration (2021). Jones and O'Neil downscaled populations to ⅛° resolution for 232 countries and territories.[32] They used their model with forecasted Shared Socioeconomic Pathways (SSPs) which predict different temperatures, precipitation, and other climate factors under different adaptation and mitigation efforts for climate change.[32] Analysis of their models shows that their outcomes are most influenced by the national populations, then the rate of urbanization, and thirdly by assumptions they make about spatial development.[32] Their model was calibrated with historical data and they used region-specific parameters.[32] Their results were SSP-specific forecasted high-resolution population distributions globally.[32]

The Groundswell Reports build off the work done by Jones and O'Neil. They use the Representative Concentration Pathways (RCPs) as different global scenarios of greenhouse emissions and associated climate responses.[29] The authors chose a "middle of the road" and high emissions pathway, RCP 4.5 and RCP 8.5, which lead to changes in water and agriculture that drive their model.[29] These RCPs are matched with different SSPs to combine different scenarios of emissions, urbanization, population growth, GDP change, education improvements, and other factors that influence migration.[29] Their main climate factors are precipitation, agriculture, and sea level rise.[29] The authors have separate models for different global regions and provided ample instruction and clarity in their modeling methods.[29]

II. Methods

Data

Population inputs for the model were 1km^2 gridded population estimates from WorldPop for the years 2000, 2010, and 2020.[33] (Figure 1).

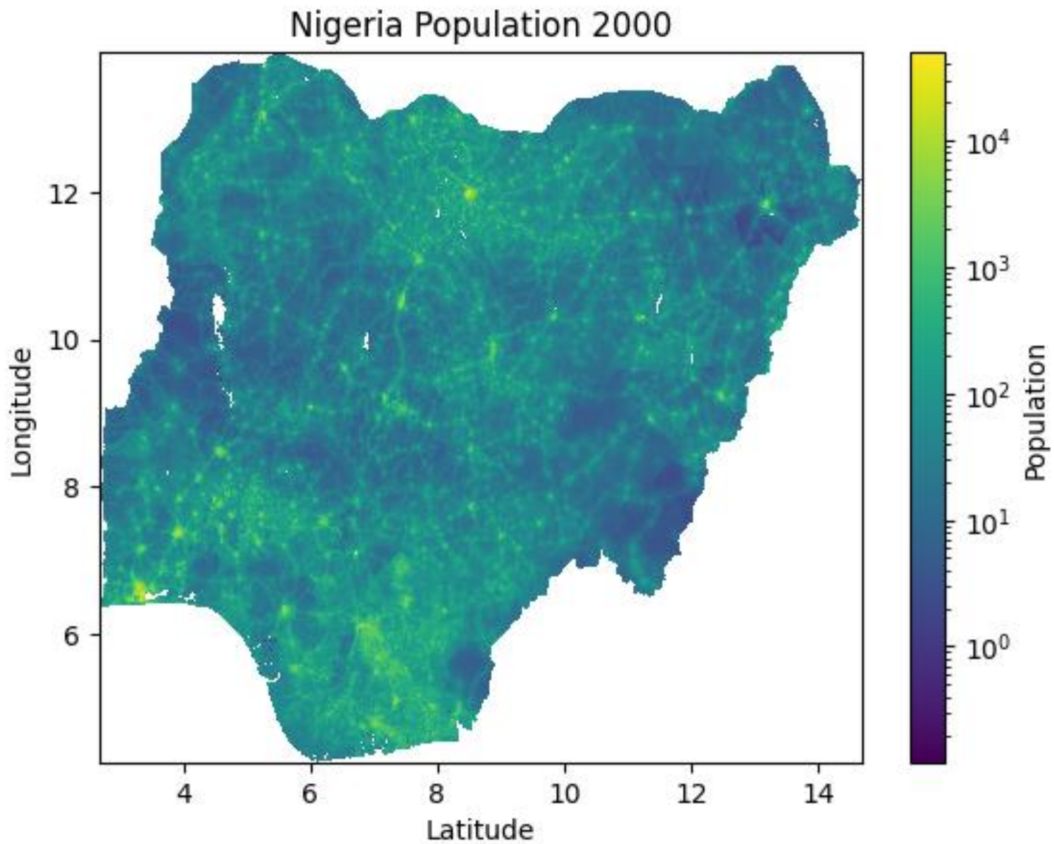

Figure 1: Nigeria's population on a logarithmic scale in 2000 [33]

Historical and forecasted average annual temperature, maximum daily temperature, and average annual precipitation were obtained from CMIP6. The data were spatially and temporarily rescaled to match the 1km^2 annual population data, then averaged across models. Models were selected based on evidence of the best performance in Nigeria for their historical data as assessed by Shiru and Chung, 2021. For precipitation, the models used were IPSL-CM6A-LR, NESM3, CMCC-CM2-SR5, and ACCESS-ESM1-5 and for temperature the models used were INM.CM4-8, BCC-CSM2-MR, MRI-ESM2-0, and ACCESS-ESM1-5.[34] These were downloaded for historical, SSP2-4.5, and SSP5-8.5 scenarios. SSP2-4.5 represents a "middle of the road" effort towards adaptation and mitigation where current historical trends continue, and SSP5-8.5 is a more pessimistic GHG emissions scenarios but assumes an increase in technological innovation and adaptation.[35] For each decade, the percentage change for the variable between the first three years and the last three years was calculated to use as the covariate in the model.

Gravity Model

The first step was to fit general urbanization trends in Nigeria to Equation 1, adapted from Rigaud et al, 2021. The equation finds v (population potential) for each cell i in the population grid of Nigeria as:

$$v_i = A_i \sum_{j=l}^{m} P_j^{\alpha}\, e^{-\beta d_{ij}}$$

Equation 1: Gravity Model, adapted from Rigaud et al, 2021

Where:

A_i = Local Characteristics

α = Population parameter

P = Population

β = Distance parameter

d = Distance

Population potential represents the number of people migrating to cell i for that distance unit (in this case kilometers squared). A_i is a geospatial scalar that represents how climate factors influence the desirability of that cell i. For each cell to m, representing cells within ~500km of cell i, we sum the population to the power of the population parameter and scale by the exponentiated distance between the cells multiplied by the negative distance parameter.

Fitting the Model

Cells were first divided into urban and rural divisions based on if their population was above or below 1500 people/km^2 as a commonly used cut-off [36]. The steps for fitting the two parameters are repeated for urban and rural cells as they have unique migration patterns. To find parameters α and β I fit the equation without the A scalar on the 1km^2 population data from between 2000 and 2010. "Brute force" optimization was used by repeatedly testing different values to minimize the total error between modeled migration and the actual migration in 2010. To do this, a range of values for each parameter were tested iteratively and evaluated to find which combination produced the least error.

After finding the best-performing parameters, an ordinary least squares regression was used to fit the percent error in each cell to the temperature and precipitation covariates (Equation 2). For this fitting, the top and bottom 2.5% of values were dropped to prevent outlier data from skewing the fit. These were transformed these into the scalar *A* using Equation 3:

$$Error_{predicted,i} = \gamma * MaxTemp_i + \sigma * AverageTemp_i + \tau * Precipitation_i + C$$

Equation 2: Error fitting with climate covariates

Where:

γ = Coefficient for maximum daily temperature decadal change

σ = Coefficient for average annual temperature decadal change

τ = Coefficient for average annual precipitation change

C = Intercept

$$A_i = \frac{1}{1 + Error_{predicted,i}}$$

Equation 3: A scalar from predicted error

Before deciding on this method for the *A* scalar, other methods tested included: converting the percent error into log space, testing a bivariate spline model, and including crop coverage as another CMIP6 variable. The OLS regression offered the best fit and most reasonable forecasts for future data.

Model Validation

To test the model, 2020 populations were forecasted from 2010 using the model fit and compared it to actual 2020 data. The percent error in population distributions before and after adding the climate scalar were used to evaluate performance with and without the predicted climate influences.

Forecasting Migration

The future decadal changes in temperature and precipitation along with the fit found on error were used to generate *A* scalars for each decade under the more optimistic and pessimistic climate scenarios. The *A* scalar only gets applied to rural cells because the model is fit for how poor climate scenarios might incentivize people to leave rural areas to go towards urban ones. For both scenarios, each decade's time step was modeled on the previous decade’s forecast with their unique *A* scalar applied. Because the gravity model does not consider key factors such as mortality and fertility changes, the actual values of the population forecasted are essentially meaningless and only useful when compared to each other. Because of this, the evaluated results are the differences in population distributions in 2100 between the two climate scenarios. To do this, population weights were calculated by dividing each cell by the total population forecasted for both scenarios. For the final results, how the population weights varied between the two forecasts was evaluated.

III. Results

Base Model Fit

After experimenting with a range of values for the base model, rural cells were found to have higher values for both α and β parameters (Table 1).

	α	**β**
Urban	0.57	100
Rural	0.7	1000

Table 1: Parameters selected for urban and rural cells in the base model

Applying these values to the model resulted in a forecasted 2010 population with a mean percent error of 2.1% and an absolute mean error of 24.9% compared to the actual 2010 (Figure 2). The urban values had a bimodal distribution and a mean of 14.4% with a median of 13.4% while the rural values for percent error were more normal with a longer left tail and the mean was 1.9% with a median of 3.3% (Figure 3). The rural values had more extreme negative values than the urban ones.

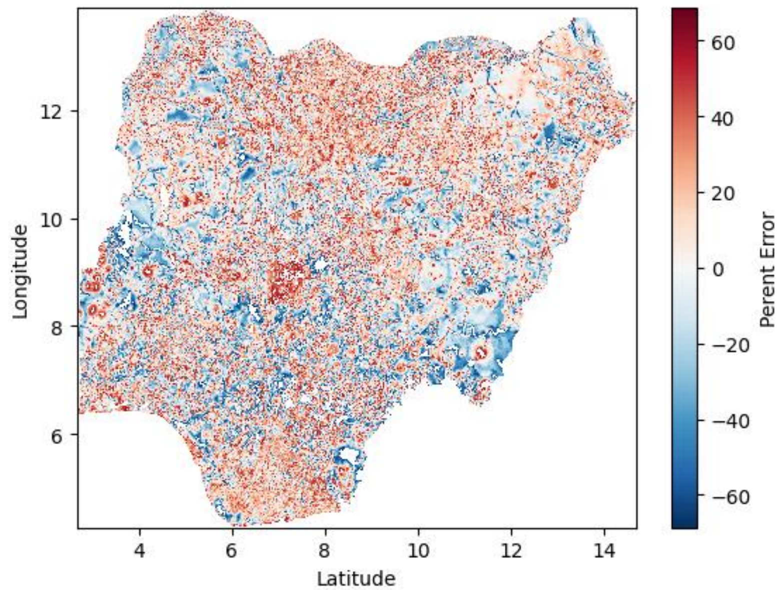

Figure 2: Percent error of modeled population to observed population

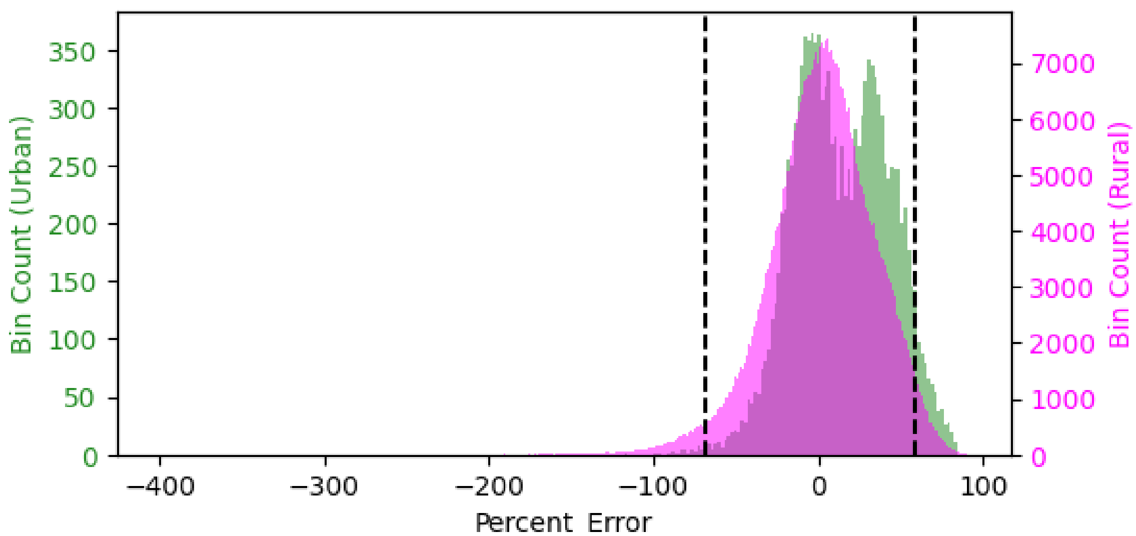

Figure 3: Distribution of modeled percent error from the model fit with horizontal lines on the 2.5 and 97.5 percent quantiles, colored by whether the cells are urban or rural

Climate Covariates

The CMIP6 decadal changes for maximum temperature, average temperature, and average precipitation, after regridding and averaging across the selected models, show how different regions of Nigeria experienced unique combinations of changing climate factors (Figures 4, 6 and 8). The percent error from Figure 2 is plotted against each of the temperature covariates and shows high variability in the error with weak correlation to the climate drivers (Figures 5, 7, and 9).

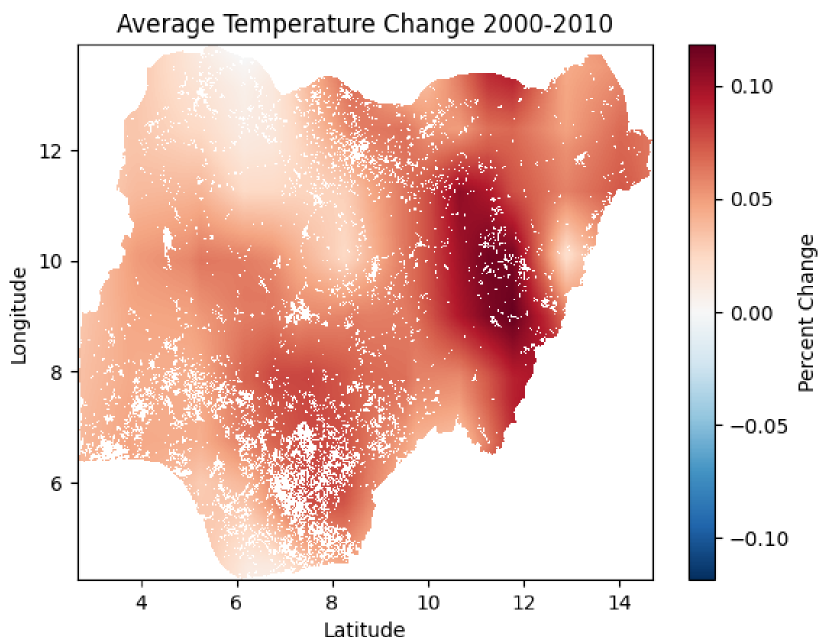

Figure 4: Percentage change in temperature between 2000-2010 in Nigeria from CMIP6 data

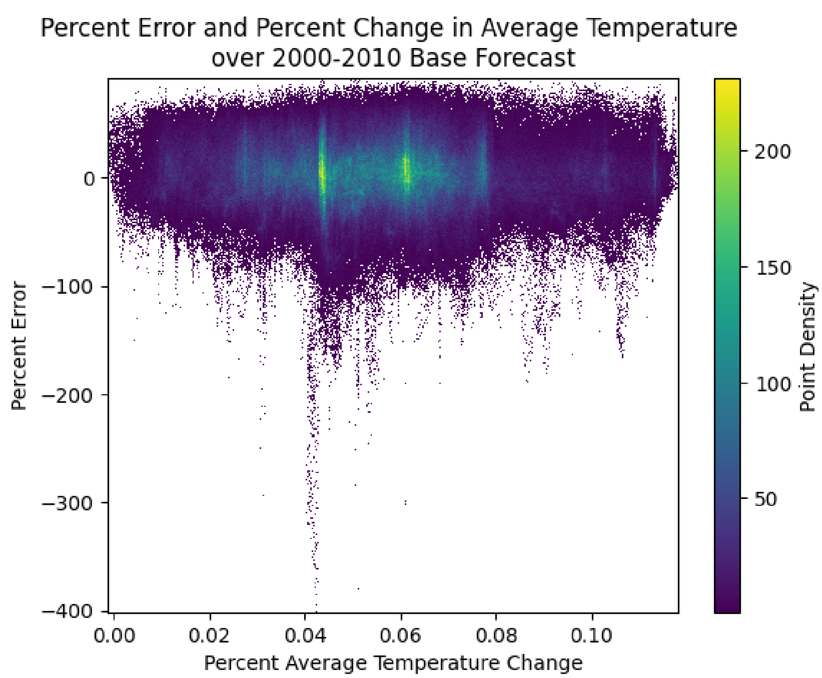

Figure 5: Percent error in population model and change in average temperature between 2000-2010

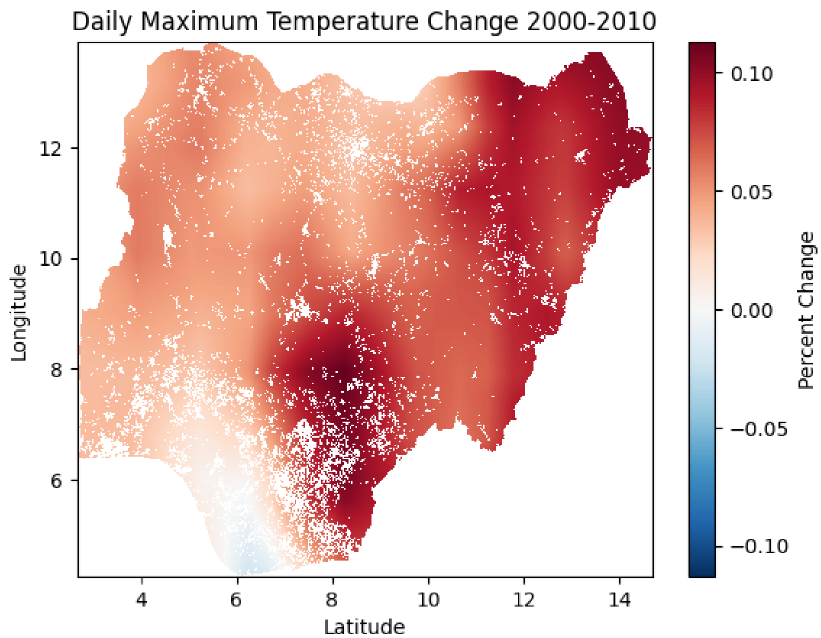

Figure 6: Percentage change in maximum temperatures between 2000-2010 in Nigeria from CMIP6 data

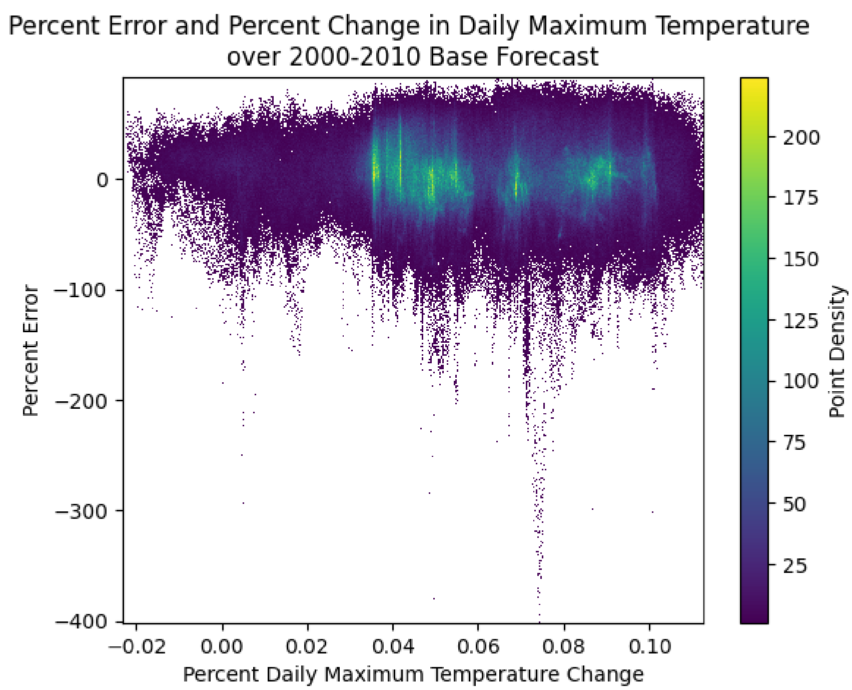

Figure 7: Percent error in population model and change in maximum temperature between 2000-2010

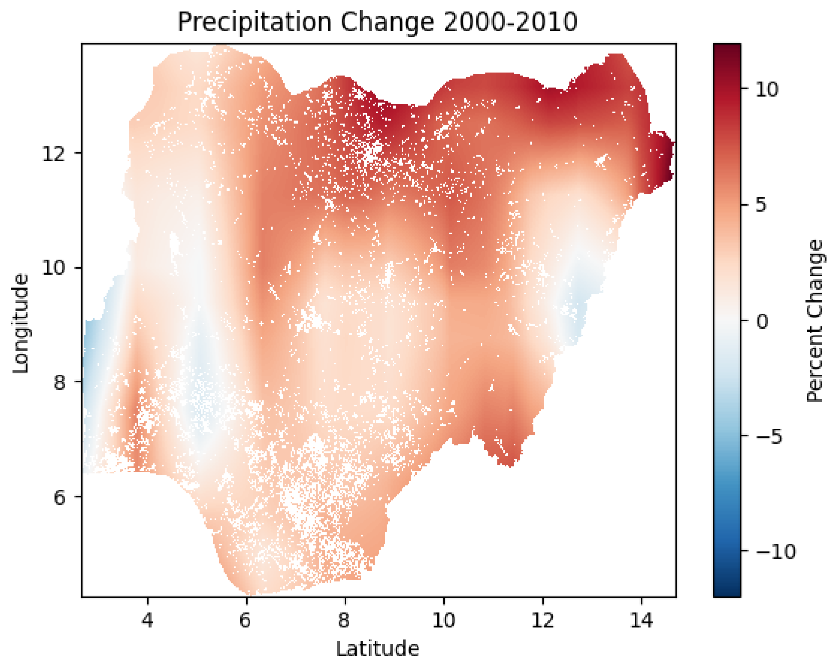

Figure 8: Percentage change in average precipitation between 2000-2010 in Nigeria from CMIP6 data

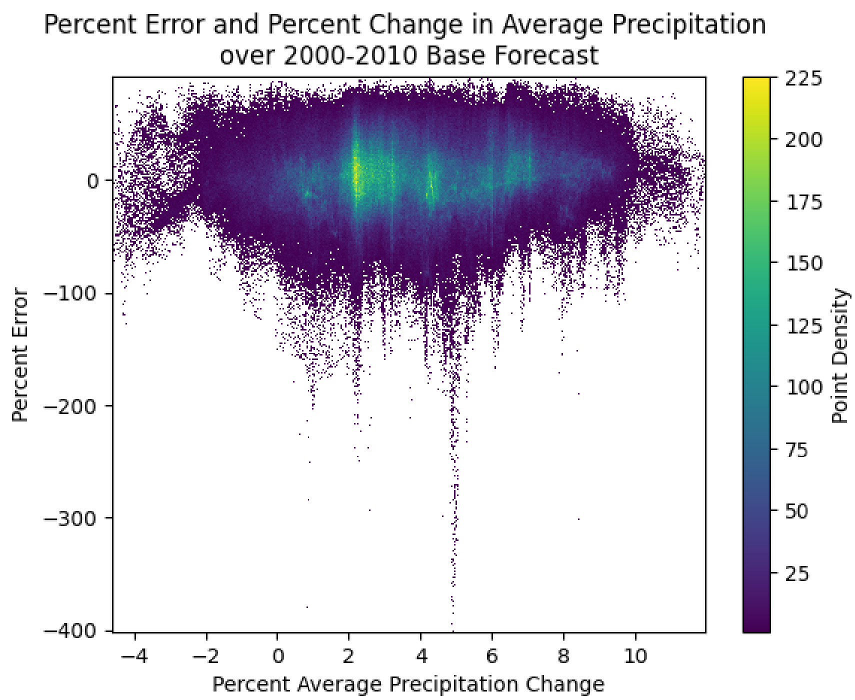

Figure 9: Percent error in population model and change in average precipitation between 2000-2010

The OLS model had a low R^2 of 0.01. The P values were 0 or extremely close to 0 (Table 2). The coefficients show that as annual average and maximum daily temperatures increased, the desirability of a cell decreased and as precipitation decreased, the desirability of a cell decreased (Table 2).

	Coefficient	Standard Error	P	95% Confidence Intervals
Intercept	0.0229	0.001	0.000	(0.021, 0.025)
Maximum Temperature	-55.0906	1.574	0.000	(-58.176, -52.005)
Average Precipitation	1.0611	0.012	0.000	(1.037, 1.085)
Average Temperature	-10.4704	1.733	0.000	(-13.867, -7.074)

Table 2: OLS regression results

Using the fit from Table 2 and inputting the climate factors in Figures 4-9 with Equations 2 and 3 yields the modeled *A* scalar for the 2000-2010 period which describes which areas are more or less desirable due to its unique climate factors (Figure 10).

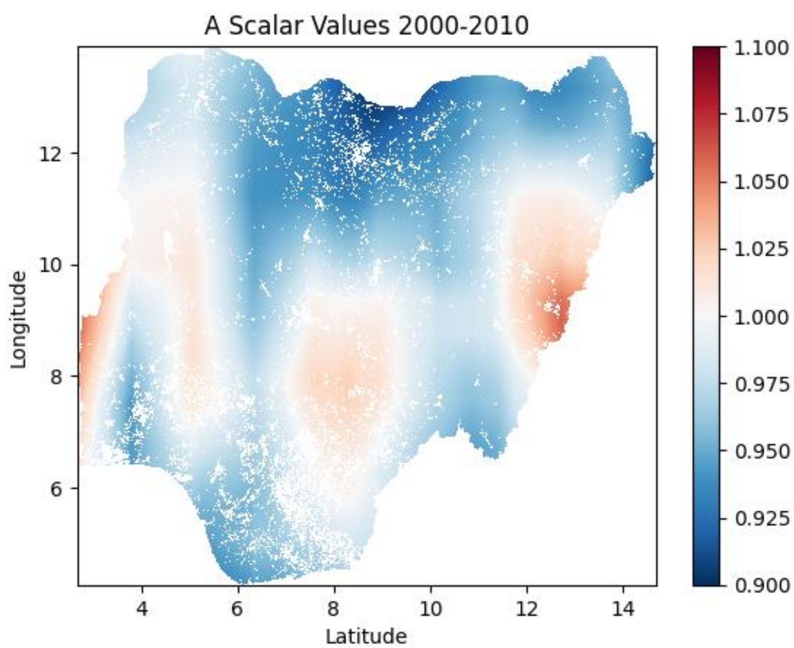

Figure 10: A Scalar values for the 2000-2010 time period as predicted by temperature and precipitation data

2020 Validation

The percent errors of the forecasted 2020 data based on the 2000-2010 model fit compared to true 2020 values can be seen in Figure 11. The mean percent error for actual population values forecasted was 10%. The percent error in population distributions between the modeled and actual 2020 values was -6.7%, reduced from -9% without including the climate drivers. (Figure 12). The mean absolute error was reduced from 23.5% to 22.7%.

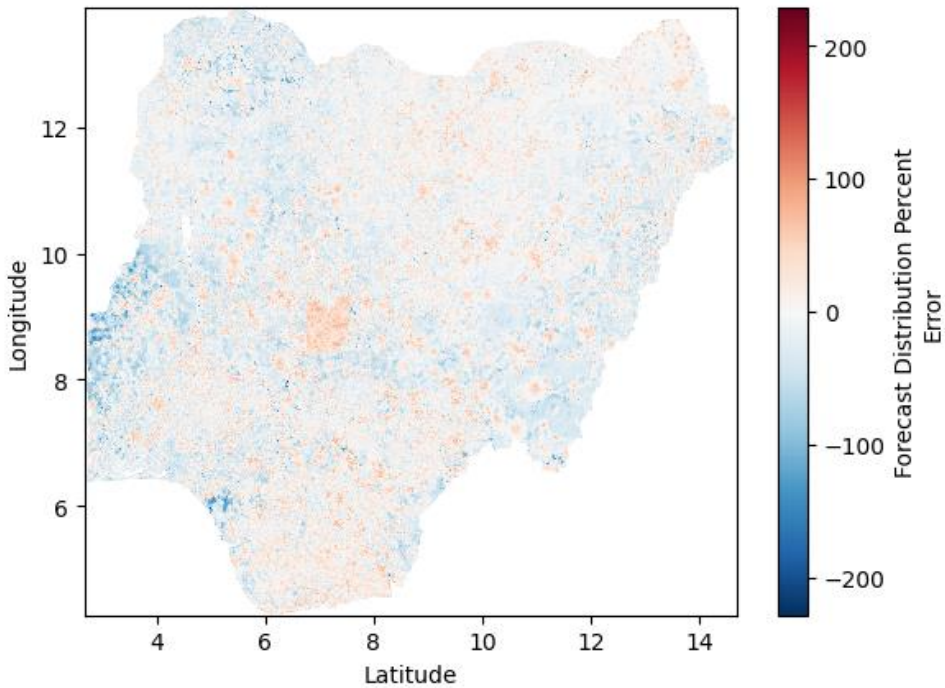

Figure 11: Percent error in population distributions between forecasted 2020 populations and actual 2020 populations

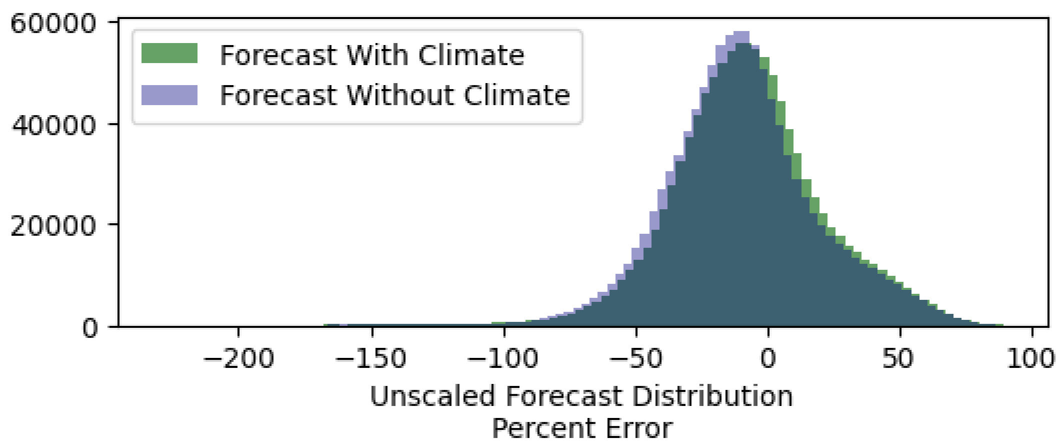

Figure 12: Distribution of percent error between forecasted 2020 population distributions and actual 2020 population distributions

Forecasts

The model from Table 2 was used with the future temperature drivers to create *A* scalars for each decade and each scenario to forecast populations to 2100. The final comparisons of 2100 population distributions between the forecasts using SSP2-4.5 and SSP5-8.5 show that western cities experienced faster urbanization in SSP5-8.5, the higher emissions model (Figure 13).

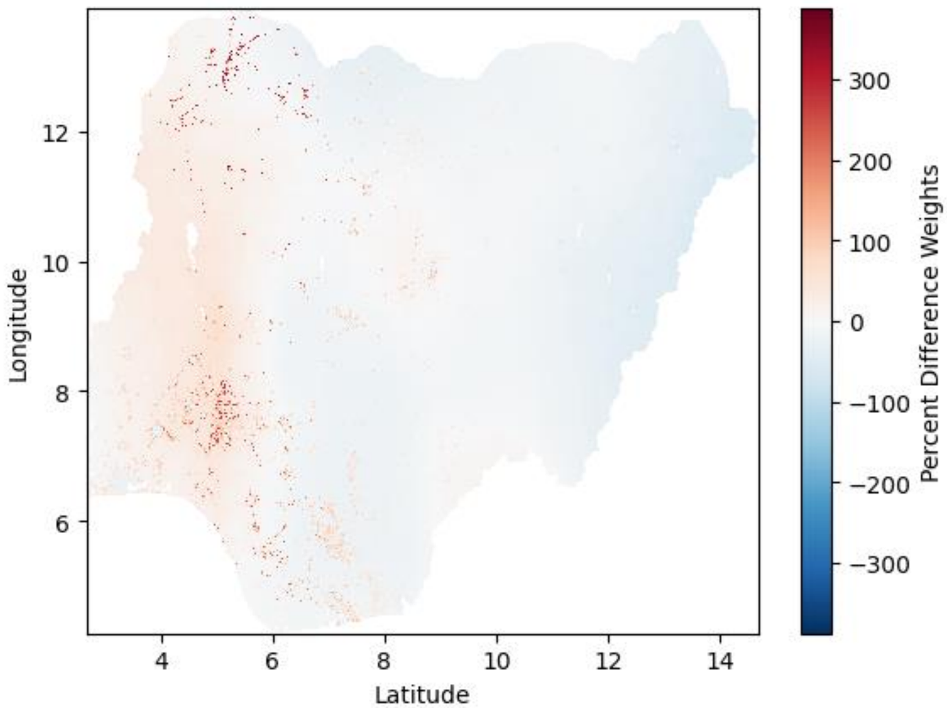

Figure 13: Percentage difference in population weights in 2100 for the optimistic and pessimistic climate scenarios

IV. Discussion

This research aims to assess how well average temperatures, maximum temperatures, and average precipitation combined with a gravity model can forecast high resolution modeling in Nigeria and use this model to predict and compare 2100 population distributions under difference climate scenarios. The high resolution and imperfect model parameterization result in high amounts of error between the modeled population and actual population when validating the model. Despite the error, the covariates have highly statistically significant correlations with migration in the directions expected and are used to forecast population distributions to 2100 under a high emissions scenario and a lower emissions scenario. The results show more rapid urbanization, particularly in Western cities, under the higher emissions scenario as more rural areas become less desirable.

Base Model Fit

Figures 2 and 3 show the high variability of error in the forecasted data for 2010. The distribution was randomly distributed across the country without a distinct pattern. Much of this noise may be introduced by using such high-resolution data where some rural areas have reported populations of less than 10 people per km^2. Some amount of the noise introduced by working with such high-resolution data will be unavoidable because of these small populations.

The error could likely be reduced by using a better optimization formula for selecting the parameters. Using the “brute force” technique helps narrow down values, but as these are exponents even small differences can be very influential. Computational time limited the number of iterations able to be tested in this research and is an area of limitation.

Figure 3 shows a bimodal distribution in the percent error for urban cells. This indicates that the model parameters could be improved upon more in future work and shows that the model is not ideally calibrated. The mean absolute error is also high and may be reducible with better model calibration.

Climate Covariates

The fit from the OLS model showed a very low R^2 value but strong statistical significance of the correlation between base model error and each of the climate covariates. This can be interpreted as evidence that climate drivers do explain some of the error, but there are many other factors driving migration and modeling factors contributing to the error. This means despite a highly statistically significant relationship, the climate drivers explain very little of the variation. This is not entirely unexpected, as in the 2000-2010 period most internal migration is unlikely to have been driven by climate change, and the plethora of other factors are likely to account for more of it. The randomness of the noise in the base model error also cannot be explained by the climate drivers.

The directions of the coefficients make sense with existing data. They can be interpreted as showing that a place becomes less desirable as its average and maximum temperature increase or its precipitation decreases.

2020 Validation

The high error between the modeled 2020 values and the actual values highlights some of the flaws of using the gravity model over a long period going through rapid development and population changes. The gravity model does not consider fertility and mortality change or national in/out migration. A better way to assess the accuracy of the model in its goal of describing urbanization was to compare population distributions. Once the data were converted from absolute population values to population weights, the average percent error in population weights was shown to be -6.7%. Without the climate scalar, the percent error was -9%. This shows that the climate scalar did help improve the accuracy of the model. Figure 12 shows how adding the climate scalar shifted the distribution of errors closer to zero than without it.

Forecasts

The goal of this project is to see how different climate scenarios could increase or decrease urbanization in 2100. Figure 13 is where these final differences in population distributions can be seen. The most notable difference seen here is that western urban areas including Sokoto, Ogbomoso, Oshogbo, and Ibadan have population weights 2-3 times greater under the pessimistic scenario than under the more optimistic scenario.

The Western side of the country in general has higher population densities in the pessimistic than optimistic scenario. There is not an obvious immediate reason why populations migrate more out of the center and eastern parts of the country in terms of climate factors. The area in red spans the semi-arid climate and tropical savannah which also expand eastward across the rest of the country. Most of the literature suggests the pattern will be strongest in people leaving rural areas in the north faster than in other areas, but this pattern is not present in the results. There are complicated relationships going on between temperature and precipitation that might be driving these results. While in the North decreasing precipitation is a clear problem, in other areas of the country, particularly the Delta, flooding and increased sudden precipitation may be a greater issue. Thus, the model may be struggling to accurately apply the ways climate change affects different climate zones across the whole country.

Limitations

Fitting the OLS regression on error from 2000-2010 data may produce weaker relationship between climate change with migration. This is not a high climate migration period like the following and future decades are likely to be as climate change becomes more severe. As CMIP6 forecasts start in 2015, the data are constrained to start earlier than the past population data would allow for.

A key limitation of this research is room for improved fit of the base model. Reducing the error there would allow for a better fit of the error with climate data and an overall improved model. Another limitation is in using decadal changes in climate drivers for the climate scalar. By using percentage changes, the model ignores the absolute values and the way the response to increasing temperature or decreasing precipitations is likely to be nonlinear. There may be specific absolute temperature or precipitation thresholds that make agriculture for key crops impossible or where extreme heat days make a place uninhabitable.

These variables also do not consider variation. Particularly for precipitation, dramatic variation between heavy rains and dry periods might make a place unfarmable or uninhabitable but are not being picked up on by looking at decadal changes.

Implications

Our findings suggest that Nigeria may need to prepare for already rapid urbanization rates to increase under worsening climate change. This means offering support and services for migrants, preparing to support rural women who may be left behind as more men migrate to urban areas, protecting vulnerable populations from increased violence exacerbated by climate change, and preparing for countrywide economic and agricultural changes as people leave rural areas. Increased rates of urbanization will require cities to plan for increased housing, employment, and social services for their increased population which may have unique needs as migrants are often more vulnerable to health and economic stressors.

Other Research

There are few studies doing comparable research besides the Groundswell Report II. There are a few key differences between the methods used in that report and used here. One is data resolution; Groundswell models data at 7.5 arc-minutes resolution (approximately 14 km^2) while this research used 1km^2 resolution.[37] The *A* scalar was also calculated differently using a special crop model they developed in addition to other climate factors. They also adjusted their forecasts to produce absolute population values rather than just weights by using national population forecasts and report their results in absolute numbers rather than weights. Despite these differences, many of the final results in Nigeria from the special focus report Groundswell Africa: Internal Climate Migration in West African Countries are in agreement: Both find more migration and faster urbanization under the more pessimistic climate scenario, and both highlight Sokoto as a region with rapid growth.[38] Groundswell Africa also highlights Katsina and Kano as areas of rapid growth across the north while this research points to more Western cities such as Ibadan and Osobo as key growth cities.[38] Groundswell Africa notes that more than 6 million Nigerians live on the coast with low elevation where sea-level rise may cause increased displacement; the authors note that Nigeria might have the highest amount of coastal out-migrants in all of West Africa.[38] This research does not consider sea level rise and uses a simpler set of climate drivers.

V. Conclusion

This research aims to explore how climate change may drive population distributions in Nigeria in 2100. The secondary goal was to explore the successes and challenges of using a gravity model with climate factors to forecast population distributions. The model can find a reasonable fit but is limited by high computational needs to find ideal parameters, noise generated in high-resolution data, and oversimplified parametrization of climate drivers in the model. Despite this, the associates of the climate drivers were highly statistically significant and in the directions expected. The final 2100 results also were in line with the hypothesis that more severe climate change temperature increases and precipitation decreases would increase the rate of urbanization. The methods development is not at a strong enough stage to confidently offer specific recommendations of the exact number and locations of future migrants. But the results suggest Nigeria will need to invest in and plan for meeting the health, education, and economic needs of these migrants to mitigate the harm caused by climate change.s

VI. References

1. Gulev, S. *et al.* IPCC AR6 WGI Chapter 2: Changing state of the climate system. in (2021).
2. Calvin, K. *et al. IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva,*

Switzerland. https://www.ipcc.ch/report/ar6/syr/ (2023) doi:10.59327/IPCC/AR6-9789291691647.
3. Šedová, B., Čizmaziová, L. & Cook, A. A meta-analysis of climate migration literature. (2021).
4. Warner, K. Human migration and displacement in the context of adaptation to climate change: the Cancun Adaptation Framework and potential for future action. *Environ. Plan. C Gov. Policy* **30**, 1061–1077 (2012).
5. Heslin, A., Deckard, N. D., Oakes, R. & Montero-Colbert, A. Displacement and Resettlement: Understanding the Role of Climate Change in Contemporary Migration. in *Loss and Damage from Climate Change: Concepts, Methods and Policy Options* (eds. Mechler, R., Bouwer, L. M., Schinko, T., Surminski, S. & Linnerooth-Bayer, J.) 237–258 (Springer International Publishing, 2019). doi:10.1007/978-3-319-72026-5_10.
6. *World Migration Report 2022*. (International Organization for Migration (IOM), 2021).
7. Birkmann, J. *et al.* Poverty, livelihoods and sustainable development. (2022).
8. Adams, H. Why populations persist: mobility, place attachment and climate change. *Popul. Environ.* **37**, 429–448 (2016).
9. McLeman, R. *et al.* Conceptual framing to link climate risk assessments and climate-migration scholarship. *Clim. Change* **165**, 24 (2021).
10. de Sherbinin, A. *et al.* Preparing for Resettlement Associated with Climate Change. *Science* **334**, 456–457 (2011).
11. Lucas, R. E. B. Internal Migration in Developing Economies: An Overview of Recent Evidence. *Geopolit. Hist. Int. Relat.* **8**, 159–191 (2016).
12. Ferris, E. Research on climate change and migration where are we and where are we going? *Migr. Stud.* **8**, 612–625 (2020).
13. Akpodiogaga-a, P. & Odjugo, O. General overview of climate change impacts in Nigeria. *J. Hum. Ecol.* **29**, 47–55 (2010).
14. Sayne, A. *Climate Change Adaptation and Conflict in Nigeria*. https://www.jstor.org/stable/resrep12197 (2011).
15. Haider, H. Climate Change in Nigeria: Impacts and Responses. (2019).
16. Ayoola, S. O., Idowu, A. A., Ikenweiwe, N. B. & Opele, A. I. Impact of climate change in Nigeria. (2011).
17. Ogbuabor, J. E. & Egwuchukwu, E. I. The impact of climate change on the Nigerian economy. *Int. J. Energy Econ. Policy* **7**, 217–223 (2017).
18. Akande, A., Costa, A. C., Mateu, J. & Henriques, R. Geospatial Analysis of Extreme Weather Events in Nigeria (1985–2015) Using Self-Organizing Maps. *Adv. Meteorol.* **2017**, e8576150 (2017).
19. Abdulkadir, A., Lawal, A. M. & Muhammad, T. I. Climate change and its implications on human existence in Nigeria: a review. *Bayero J. Pure Appl. Sci.* **10**, 152–158 (2017).
20. *2023 Global Report on Internal Displacement*. https://www.internal-displacement.org/global-report/grid2023/ (2023).
21. Cattaneo, C. & Massetti, E. Does Harmful Climate Increase or Decrease Migration? Evidence from Rural Households in Nigeria. *Clim. Change Econ.* **10**, N.PAG-N.PAG (2019).
22. Cattaneo, C. & Massetti, E. Migration and Climate Change in Rural Africa. SSRN Scholarly Paper at https://doi.org/10.2139/ssrn.2576196 (2015).
23. Barrios, S., Bertinelli, L. & Strobl, E. Climatic change and rural–urban migration: The case of sub-Saharan Africa. *J. Urban Econ.* **60**, 357–371 (2006).

24. Abebe, M. A. Climate change, gender inequality and migration in East Africa. *Wash J Envtl Pol* **4**, 104 (2014).
25. Onwutuebe, C. J. Patriarchy and Women Vulnerability to Adverse Climate Change in Nigeria. *SAGE Open* **9**, 2158244019825914 (2019).
26. Hoffmann, R., Šedová, B. & Vinke, K. Improving the evidence base: A methodological review of the quantitative climate migration literature. *Glob. Environ. Change* **71**, 102367 (2021).
27. Adams, H. & Kay, S. Migration as a human affair: Integrating individual stress thresholds into quantitative models of climate migration. *Environ. Sci. Policy* **93**, 129–138 (2019).
28. McLeman, R. Developments in modelling of climate change-related migration. *Clim. Change* **117**, 599–611 (2013).
29. Rigaud, K. K. *et al. Groundswell: Preparing for Internal Climate Migration*. https://openknowledge.worldbank.org/handle/10986/29461 (2018) doi:10.1596/29461.
30. Hassani-Mahmooei, B. & Parris, B. W. Climate change and internal migration patterns in Bangladesh: an agent-based model. *Environ. Dev. Econ.* **17**, 763–780 (2012).
31. Poot, J., Alimi, O., Cameron, M. P. & Maré, D. C. The Gravity Model of Migration: The Successful Comeback of an Ageing Superstar in Regional Science. SSRN Scholarly Paper at https://doi.org/10.2139/ssrn.2864830 (2016).
32. Jones, B. & O'Neill, B. C. Spatially explicit global population scenarios consistent with the Shared Socioeconomic Pathways. *Environ. Res. Lett.* **11**, 084003 (2016).
33. WorldPop. Global 1km Population Individual countries. (2020) doi:10.5258/SOTON/WP00670.
34. Shiru, M. & Chung, E.-S. Performance evaluation of CMIP6 global climate models for selecting models for climate projection over Nigeria. *Theor. Appl. Climatol.* **146**, (2021).
35. Grubb, M. *et al.* Introduction and framing. in *IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Shukla, P. et al.) 150–213 (Cambridge University Press, 2022).
36. Jiang, S. *et al.* Spatiotemporal Characteristics of Urban Land Expansion and Population Growth in Africa from 2001 to 2019: Evidence from Population Density Data. *ISPRS Int. J. Geo-Inf.* **10**, 584 (2021).
37. Clement, V. *et al. Groundswell Part 2: Acting on Internal Climate Migration*. https://openknowledge.worldbank.org/handle/10986/36248 (2021).
38. Rigaud, K. K. *et al.* Groundswell Africa: Internal Climate Migration in West African Countries. (2021).