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The Influence of Environmental Change (Crops and Water) on Population Redistribution in Mexico and Ethiopia

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Abstract: This paper discusses the effects of long-term environmental change (represented by the abundance or scarcity relative to the long-term average level of crop yield/river flow) and short-term environmental shock (represented by the maximum number of consecutive years below the median crop yield/river flow per decade) on population redistribution in Mexico and Ethiopia. Crop production and water resources, which are affected by climate change and influence human survival and activities, were selected as research variables. Two developing countries, namely, Mexico and Ethiopia, were selected as comparison cases. The results showed that short-term environmental shocks had no correlation with population redistribution. Short-term environmental shocks might fail to influence migration decisions or cause only temporary displacements that cannot be detected by demographic statistics. Among the long-term environmental change factors, only crop yield deviation was found to have a significant positive correlation with population redistribution. Based on two different datasets and two different decades, crop yield deviation is positively correlated with population redistribution; the correlation coefficients between crop yield deviation and population redistribution were 0.134 to 0.162 in Mexico and 0.102 to 0.235 in Ethiopia. When urbanization was considered as the control variable, the correlation coefficient between crop yield deviation and population redistribution in Mexico dropped by half, while it was almost the same in Ethiopia. However, Ethiopia's population redistribution was more clearly influenced by the population itself. Crop yield deviation relative to water flow deviation meant changes in livelihoods. Population redistribution is a possible means of adapting to changes in livelihood. Mexico exhibited high resilience to changes in livelihoods caused by long-term environmental change, especially in its densely populated areas. In contrast, Ethiopia was characterized mainly by high population growth and low population migration. People in some areas of Ethiopia were forced to endure hardship of livelihood deterioration or to stay where they were due to the difficulty of obtaining sufficient resources to afford the cost of migration.

Keywords: population redistribution; climate change; environmental change; crop yield; water flow

1. Introduction

During the 20th century, the world population increased from 1.65 billion to six billion [1]. The world population is currently growing by approximately 74 million people per year, with most growth occurring in developing countries [2]. Much of the focus of the population–environment literature is on how population growth impacts the environment [3–5]. Specific focus areas include the effects of population dynamics on environmental degradation [6], water resources [7], deforestation [8], and food security [9]. However, few studies have investigated how environmental change influences demographic processes [10–12]. This study aimed to contribute to the literature on this topic.

Recent research illuminated the ways in which a number of population variables, such as age and sex composition, household demographics, and the elements and processes of the population balancing equation, are related to environmental change [3]. Some research found a reciprocal relationship between population dynamics or development and environmental change [3]. Population redistribution is driven by social, economic, geographical, and environmental factors in complex ways, making it very difficult to predict outcomes [13]. Economic development ([14], industrialization and urbanization [15], education [16], and environmental change [3] all influence population redistribution. For some countries, especially countries with rapid economic growth, population redistribution caused by environmental change is often masked by a variety of socio-economic factors. Identifying the relationships between population redistribution and environmental variability and change is a challenging task. Under the background of global climate change, the relationship between environment and population redistribution attracted extensive attention [17]. Climate change has observable effects on the environment and has the potential to impose additional pressure in some regions [18]. Climate change is recognized as a “threat multiplier” that compounds the difficulties currently facing developing countries [19,20]. Some environmental factors driven by climate change were shown to affect population redistribution, but the effects are often non-linear [21,22]. Environmental change includes not only slow processes, such as changes in precipitation or temperature [23], but also rapid, extreme events, such as extreme wet and dry events [24]. Some studies found that it has a different response of population spatial movement for these two different categories of environmental changes. Slow environmental change may lead to population migration [25], whereas sudden natural disasters or extreme events are more likely to cause temporary displacement [12].

In this paper, we estimate the contributions of changes in water availability and agricultural crop yields to past changes in population distribution. We select Mexico and Ethiopia as study cases for a few reasons. Firstly, Mexico and Ethiopia are both developing countries, but the former is an upper–middle-income economy, whereas the latter is a low-income economy [26]. In addition, these countries represent contrasting cases in terms of dependence on agriculture; Mexico has 13% of its population working in the agricultural sector and obtains 4% of its gross domestic product (GDP) from agriculture, whereas, for Ethiopia, the corresponding percentages are 73% and 37% [26,27]. Secondly, these two countries have moderate population sizes and land areas relative to world averages, lending them a certain amount of comparability. Thirdly, they are both low-latitude countries. A growing body of evidence shows that low-latitude countries will experience the greatest impacts from global warming [28]. Finally, regardless of the differences in overall income between the countries, both have large proportions of their populations living in poverty, and poor populations are generally more vulnerable to the effects of climate change than wealthier populations [29]. The world’s demographic center of gravity will continue to shift from developed countries to developing countries and less developed countries, many of which will face unprecedented and daunting challenges related to the supply and distribution of food and water [4]. The relationship between environmental change and population redistribution can be analyzed more comprehensively by selecting and comparing two developing countries with different degrees of development.

Although water resources and agriculture are not the only environmental influences on populations, these two factors are considered essential to rural livelihoods [30,31]. Water and food security are major concerns, particularly in the least developed countries [32]. By correlating population redistribution directly with model-based estimates of historical crop yield and river flow, our analysis represents an important advance over previous studies that used weather-based proxies for these variables, usually temperature or precipitation.

2. Data and Methods

2.1. Data

Three databases were used, including The Gridded Population of the World version 4 (GPW-v4) population count grids database, the Global Human Settlement (GHS) Built-Up grids database, and the Inter-Sectoral Impact Model Intercomparison Project phase 2a (ISIMIP2a) database.

These different databases are inconsistent in resolution. The resolutions of the GPW and GHS datasets are 30 arc-seconds (~1 km), and that of the ISIMIP2a database is 0.5 degrees. For this study, we selected an intermediate resolution of 0.25 degrees. We used the Zonal Statics tool of ArcGIS/ArcToolbox to aggregate the first two databases and used the Resample tool to resample the third database (ISIMIP2a database). The purpose of unifying the resolution of the different databases was to obtain sufficient data accuracy and data samples (2537 cells for Mexico and 1090 cells for Ethiopia) to analyze the spatial distribution characteristics of the two countries. A detailed description of potential factors influencing population redistribution and their data sources is given below (Table 1).

Table 1. Potential factors influencing population redistribution and their data sources.

Category	Variable	Abbreviation	Database	Institution
Dependent variable	Population redistribution	PopReDist	GPW [1]	CIESIN [2]
Independent variable	Crop yield deviation	MeanYield	ISIMIP [3]	PIK [4]
	Water flow deviation	MeanFlow	ISIMIP	PIK
	Maximum number of consecutive years below median crop yield	ConsecLowYield	ISIMIP	PIK
	Maximum number of consecutive years below median water flow	ConsecLowFlow	ISIMIP	PIK
Control Variables	Built-up	Built-up	GHS [5]	EC [6]
	Population	Pop	GPW	CIESIN

[1] Gridded Population of the World. [2] Center for International Earth Science Information Network. [3] The Inter-Sectoral Impact Model Intercomparison Project. [4] Potsdam Institute for Climate Impact Research. [5] The Global Human Settlement. [6] the European Commission.

2.1.1. Population Redistribution

The Gridded Population of the world (GPW) version 4 [33] is a gridded data product that facilitates the integration of population data with earth science data. It models the distribution of human populations on a continuous global surface [34]. The data source is based on census data from all countries in the world, and the statistical unit of census data varies from country to country (https://sedac.ciesin.columbia.edu/data/collection/gpw-v4). The population data of Mexico and Ethiopia discussed in this paper were based on census data of cities and towns (administrative units below the state level). The identification degree of its census data was about 15 min (about 30 km), and some urban areas had a higher identification degree. Population redistribution (PopReDist) in this paper was the spatial population change over decades, which is the absolute change for each grid with the resolution of 0.25 degrees. This database provides variables of spatial distribution of population (Pop) for the years 1990, 2000, and 2010 and spatial population redistribution (PopReDist) for 1990–2000 and 2000–2010 by subtracting data of the previous year from the last year.

2.1.2. Built-Up

The Global Human Settlement (GHS) database distributed by the European Commission (EC) provides built-up grid data and contains a multi-temporal information layer on built-up presence as derived from Landsat image collections (GLS1975, GLS1990, GLS2000, and ad hoc Landsat 8 collection 2013/2014). Through data-interpolation processing, this database provides variables of Built-Up for the years 1990, 2000, and 2010.

2.1.3. Climate Change Impacts

The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) addresses climate impacts in a range of systems and sectors such as health, coastal infrastructure, and forests and other ecosystems.

The first ISIMIP simulation round, the ISIMIP Fast Track, had a focus on providing cross-sectorally consistent projections of the impacts of different levels of global warming in the 21st century. The common set of scenarios made use of climate projections from five global climate models (GCMs) driven by the recommended concentration pathways (RCPs), making ISIMIP a natural extension of the work done within the Coupled Climate Model Intercomparison Project (CMIP) [35]. ISIMIP2a includes modeling intercomparison efforts in fisheries, permafrost, biodiversity, regional water, forests, and energy, as well as those sectors already covered in the Fast Track. This serves as a basis for model evaluation and improvement, allowing for improved estimates of the biophysical and socio-economic impacts of climate change at different levels of global warming [36]. ISIMIP2b is designed to provide robust information about the impacts of 1.5 °C global warming and related low-emission pathways [37,38]. In this paper, we used the simulation data of crops yield and water resources provided by ISIMIP2a. In the present work, the focus was on impacts of surface freshwater availability and crop yields since these factors are likely to have the greatest direct impacts on the livelihoods life and development of population [39]. Both factors were modeled using the global gridded biosphere model LPJmL [40,41]. The model LPJmL ("Lund–Potsdam–Jena managed Land") was designed to simulate vegetation composition and distribution, as well as stocks and land–atmosphere exchange flows of carbon and water, for both natural and agricultural ecosystems. Using a combination of plant physiological relations, generalized empirically established functions, and plant trait parameters, it simulates processes such as photosynthesis, plant growth, maintenance and regeneration losses, fire disturbance, soil moisture, runoff, evapotranspiration, irrigation, and vegetation structure [42–44]. Annual crop yields are simulated for each of the four major crops (maize, wheat, rice, and soy beans) and for rain-fed and irrigated cultivation assuming crop growth on all land grid cells [45]. These yields are weighted by each cell's corresponding growing area around the year 2000. The resulting index has units of production (tons per hectare), but its variability represents yield variability because the growing areas are static. The weighted yield indices for all four crops are summed to obtain an overall yield index that is comparable across countries (assuming that these four crops represent, in both countries, the majority of crops produced). Water availability is represented by monthly river flow (discharge) averaged over each year. Importantly, the simulations do not take into account any water withdrawals for human use (such as irrigation) or any other human-induced changes to the water cycle. This means that any changes over time in simulated water availability can be attributed to changes in weather patterns.

The model is driven by two different climate reanalysis datasets to account for potential uncertainties in climate reconstructions: the Global Soil Wetness Project phase 3 forcing dataset (GSWP3) [46] (http://hydro.iis.u-tokyo.ac.jp/GSWP3/), based on the 20th century reanalysis (20CR), and the Princeton Global Forcing dataset version 2 (PGFv2) [47], based on NCEP/NCAR reanalysis (The NCEP/NCAR Reanalysis data set is a continually updated (1948–present) globally gridded data set that represents the state of the Earth's atmosphere, incorporating observations and numerical weather prediction (NWP) model output from 1948 to present. It is a joint product from the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR)). Both sets of simulations extend from 1970 to 2010.

We investigated the influences of changes in mean environmental conditions and in the occurrence of prolonged adverse conditions (bad harvests, droughts) on population redistribution. The resulting variables are called MeanYield and MeanFlow and represent the abundance or scarcity level relative to the long-term average. We then calculate the maximum number of consecutive years below the median crop yield/river flow for each decade. The resulting variables are called ConsecLowYield and ConsecLowFlow and measure the successive shocks to crop production and water availability systems in each decade.

Of course, extreme wet and dry events may significantly affect the water and agricultural systems [24]. For example, Lesk et al. analyzed the influence of extreme weather disasters on global crop production and found that production losses due to droughts were associated with a reduction in both harvested area and yields, whereas extreme heat mainly decreased cereal yields [48]. The societal infrastructure is becoming more sensitive to weather and climate extremes, which would be exacerbated by climate change [49]. However, on the one hand, a majority of climate change models underestimate the extremeness of impacts in important sectors such as agriculture, terrestrial ecosystems, and heat-related human mortality [38]; on the other hand, environmental change is expected to increase the likelihood and impacts of extreme weather events, and the scientific argument of climate-related disasters is increasingly confident, but the impacts on human population patterns are unclear and unpredictable. [50]. Therefore, the effects of extreme weather events on population redistribution are not considered in this paper.

2.2. Methods

In this paper, we used crop–water model variables as independent variables and investigated their correlations with population redistribution. Of course, there are discussions about migration and climate change, such as climate migration [23,51,52]. However, it is difficult to get reliable net migration data. In addition, either the mechanical growth of the population (through migration) or the natural growth is likely to be affected by climate change. Therefore, it was reasonable to use population redistribution as a dependent variable. The reason for using these variables was that crop and water models do not include any changes in human management, such as growing areas. There is no feedback from population to crops and water. As for validation data or observed data on crop yields, both climate change and socioeconomic change have impacts on the results; however, perhaps the latter is more important and significant. In addition, the population redistribution also affects crop yield output (such as changes in labor input), thus forming a circular argument. For our purposes, it was preferable to use simulation data over observed data. To reduce the influence of model simulation errors on regression results, two different sets of modeling data on crop production and water discharge distributed by ISIMIP were adopted: Lpjml_Gswp3 and Lpjml_Princeton. The two sets of data were obtained by using the agricultural and water resources model LPJmL, which was driven by two different observational climate datasets (GSWP3 and Princeton Global Forcing data PGFv2) to assess the effects of the choice of climate data on the results. Considering the availability of population data, correlation and regression analyses are performed for the two eras of the 1990s and the 2000s. Environmental variables, including crop yield deviation (MeanYield), water flow deviation (MeanFlow), maximum number of consecutive years below median crop yield (ConsecLowYield), and maximum number of consecutive years below median water flow (ConsecLowFlow) were included as independent variables. Built-up area (Built-up) and population (Pop) were included as control variables. These two control variables are factors that have significant impacts on population redistribution and can objectively reflect the demographic characteristics in the two countries.

Pearson's correlation coefficients between the dependent variable (PopReDist), independent variables (MeanYield, MeanFlow, ConsecLowYield, and ConsecLowFlow) and control variables (Built-up and Pop) were calculated with the water–crop modeling data for each of the periods the 1990s and the 2000s.

OLS (ordinary least squares) regression was then conducted to investigate the influences of the independent variables. Three different models were considered in the OLS regression. OLS Model 1 examined the impacts of four environmental variables on population redistribution. OLS Model 2 explored the impacts of environmental variables on population redistribution while controlling for the impact of urbanization level. OLS Model 3 included Pop as control variable; it explored the impacts of the environmental change variables on population redistribution while controlling for population density. VIF (Variance inflation factor) was used to assess the degree of multicollinearity among the independent variables.

Formal studies of population redistribution tended to focus on identifying patterns that are presumed to hold universally [4,53,54]. The global regression assumes that the relationships between the variables are homogeneous across space. However, spatial dependences often are not homogeneous across large geographical regions [55]. We were more concerned about areas where spatial redistribution is sensitive to climate change. In addition, GWR can be used to statistically avoid the influence of multicollinearity. To address this issue, a geographically weighted regression (GWR) model was used to explore the spatially varying relationships between the dependent variable and the potential influencing variables [13,56]. The spatial regression coefficients of each grid in GWR were not the regression results of itself, but the spatial coefficients in the local area based on optimal bandwidth. Of course, spatial regression methods are not limited to GWR; there are other spatial regression methods, such as kriging, spatial error regression, etc.

In the OLS multiple regression model, the dependent variable y (population redistribution) is statistically related to a set of N independent variables x as follows:

$$y_i = \beta_0 + \sum_{j=1}^{N} x_j \beta_j + \varepsilon_i, \tag{1}$$

where i = 1 to M, where i is an index of the number of cells for which data are available, M is the total number of cells of the country, β_0 is the intercept, β_j represents the beta coefficients for each dependent variable, and ε is a randomly distributed error term. An OLS regression model can be converted into a GWR (geographically weighted regression) model by substituting each beta coefficient (the intercept and the dependent variable coefficients) with its local counterpart such that the beta coefficients can vary across space.

$$y_i = \beta_{0(u_i,v_i)} + \sum_{j=1}^{N} x_j \beta_{j(u_i,v_i)} + \varepsilon_i, \tag{2}$$

where i = 1 to M, and (u_i, v_i) is the location in geographic space of the i-th observation. A set of beta coefficients (and, hence, a regression model) is estimated at each location based only on neighboring, geographically weighted data cells. A key feature of this approach is the ability to calibrate the spatial weighting function to identify the bandwidth, i.e., the number or proximity of neighboring cells included that results in a "best-fit" model. In this paper, AICc (corrected Akaike information criterion) is used as the bandwidth method.

If an environmental change variable (MeanYield, MeanFlow, ConsecLowYield, or ConsecLowFlow) was found to have a significant correlation with population redistribution consistently across both crop–water model datasets and both decades, it could be considered as having a robust effect on population redistribution. Urbanization level (Built-up) and population (Pop) were included as control variables. The effects of environmental change on population redistribution may differ between urban and rural areas and among areas with different population densities. The robustness of environmental changes on population redistribution was analyzed by comparing different control variables.

3. Case Study Countries

In this paper, we selected two countries at different stages in the demographic transition, Mexico and Ethiopia, as case studies. Mexico, located in the southern portion of North America, is the eleventh most populous country in the world and the second most populous country in Latin America (after Brazil), covering almost two million square kilometers. It has an estimated population of over 129 million, with 71.9% of the population living in urban areas. Ethiopia is in the horn of Africa. With over 104 million people, 20.4% of whom live in urban areas, Ethiopia is the second most populous nation on the African continent (after Nigeria); it occupies a total area of 1.1 million square kilometers [26].

Figure 1 presents the urban, rural, and total populations from 1990 to 2017. The data source is from the world bank open data (https://data.worldbank.org/). In 1990, the population of Mexico was 85.4 million, and that of Ethiopia was 48.1 million. The population of Ethiopia was only approximately half of that of Mexico in 1990. By 2017, the populations of Mexico and Ethiopia were 129.2 million and 105 million, respectively. The population numbers of the two countries are more similar currently. Over a period of nearly three decades, from 1990 to 2017, the annual population growth rates of Mexico and Ethiopia were 1.6% and 3.05%, respectively. Currently, Ethiopia has a rapidly growing population, whereas Mexico's population has a low growth rate. The proportion of Ethiopia's population living in urban areas increased from 12.6% in 1990 to 20.4% in 2017, whereas Mexico's urban population increased from 52.1% in 1990 to 71.9% in 2017. The rural population of Ethiopia in 1990 and 2017 was 42 million and 80 million, respectively; thus, the rural population nearly doubled in three decades. However, in Mexico, the rural population in 1990 and 2017 was 40 million and 36.9 million, respectively, revealing a slight decline in the rural population. Given that the total population is growing, the shift from a farming population to non-farming is evident in Mexico. Much of the migration (~65%) in Mexico from 2005 to 2010 was to urban destinations [57]. Mexico is a highly urbanized country with a rapidly rising urban population, whereas Ethiopia remains a predominantly agricultural country with a slowly increasing urban population.

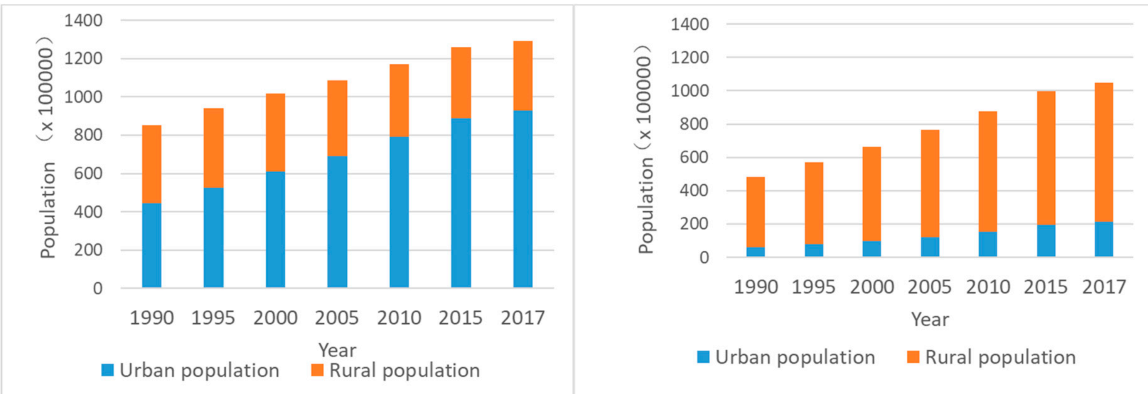

Figure 1. Urban, rural, and total population of Mexico (**left**) and Ethiopia (**right**).

Figure 2 shows the population distribution of Mexico and Ethiopia in 2000. Mexico's population distribution is highly concentrated, with high densities in the capital and surrounding areas and with the population in the northern, eastern, and coastal areas being highly concentrated in urban areas. While having high population density in the capital, Ethiopia has low population density overall and low densities in remote areas far from the capital.

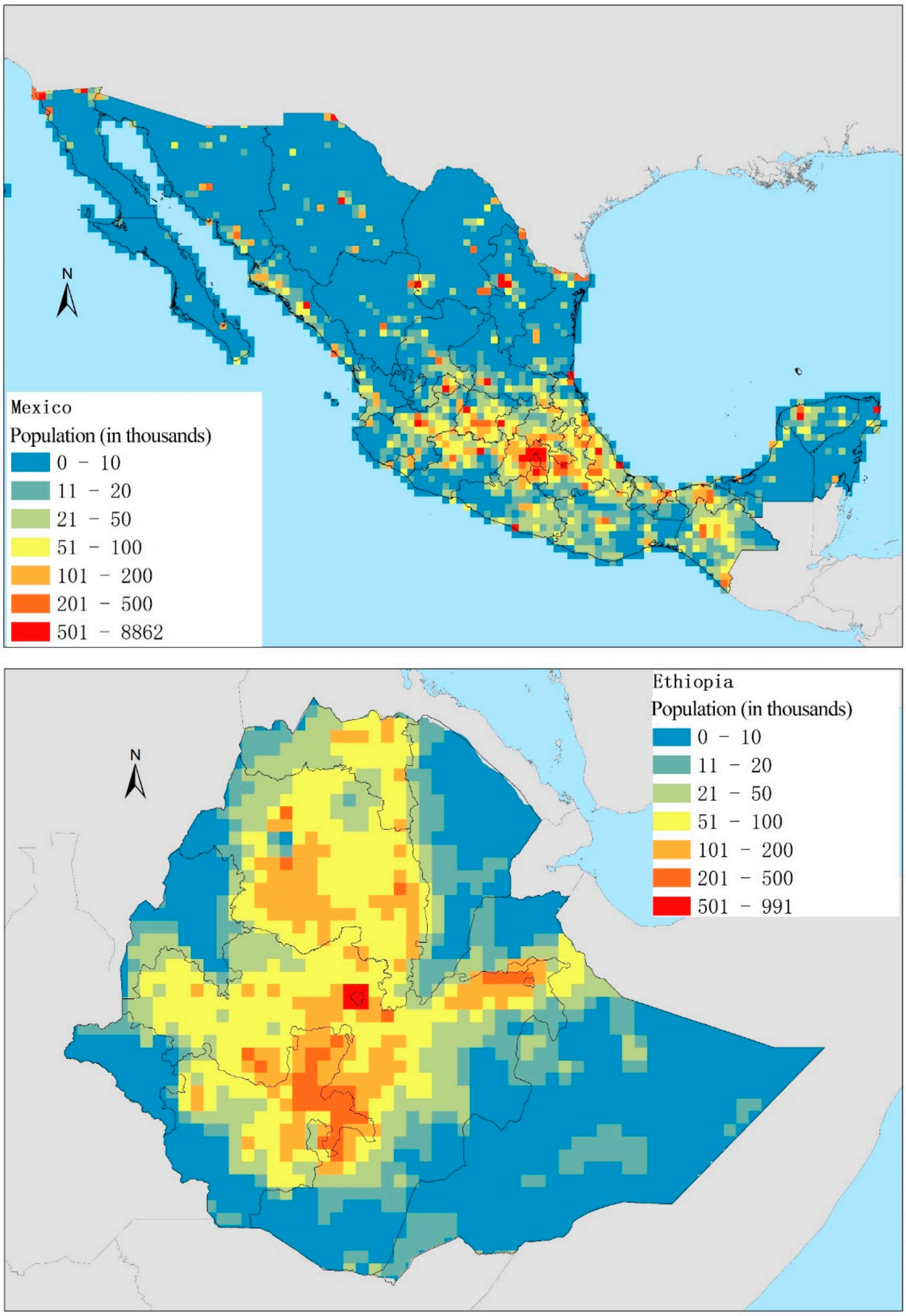

Figure 2. Population distribution in Mexico (**upper panel**) and Ethiopia (**lower panel**) in 2000.

4. Analysis

4.1. Correlation Analysis

An exploratory correlation analysis was performed to examine the relationships between the independent and dependent variables. Table 2 shows the correlation matrix of all variables. The correlations for Mexico and Ethiopia were calculated separately for each of the past two decades (the 1990s and the 2000s). Four environmental variables, i.e., MeanYield, MeanFlow, ConsecLowYield and ConsecLowFlow, were calculated based on the Lpjml_Gswp3 and Lpjml_Princeton datasets.

Table 2. Correlation matrix of the dependent and independent variables.

	Lpjml_Gswp3						Lpjml_Princeton					
Mexico 1990–2000	**PopReDist**	**MeanYield**	**MeanFlow**	**ConsecLowYield**	**ConsecLowFlow**	**Built-Up**	**PopReDist**	**MeanYield**	**MeanFlow**	**ConsecLowYield**	**ConsecLowFlow**	**Built-Up**
MeanYield	0.167 **						0.143 **					
MeanFlow	0.051 **	0.168 **					0.006	0.053 **				
ConsecLowYield	0.025	0.073 **	0.039 *				0.089 **	0.120 **	−0.102 **			
ConsecLowFlow	−0.024	−0.006	−0.054 **	0.110 **			0.006	−0.021	0.009	0.002		
Built-up	0.605 **	0.147 **	0.042 *	0.001	−0.012		0.605 **	0.137 **	−0.002	0.050 *	0.027	
Pop	0.512 **	0.162 **	0.033	0.026	−0.008	0.859 **	0.512 **	0.151 **	−0.008	0.060 **	0.004	0.859 **
Mexico 2000–2010	**PopReDist**	**MeanYield**	**MeanFlow**	**ConsecLowYield**	**ConsecLowFlow**	**Built-Up**	**PopReDist**	**MeanYield**	**MeanFlow**	**ConsecLowYield**	**ConsecLowFlow**	**Built-Up**
MeanYield	0.142 **						0.146 **					
MeanFlow	0.011	0.171 **					0.038	0.223 **				
ConsecLowYield	−0.036	−0.180 **	−0.053 **				−0.003	−0.154 **	−0.072 **			
ConsecLowFlow	0.028	−0.046 *	−0.233 **	0.075 **			0.028	−0.021	−0.109 **	−0.005		
Built-up	0.609 **	0.124 **	0.009	−0.028	0.033		0.609 **	0.115 **	0.032	−0.001	0.034	
Pop	0.454 **	0.113 **	0.012	−0.014	0.015	0.928 **	0.454 **	0.102 **	0.032 *	−0.003	0.017	0.928 **
Ethiopia 1990–2000	**PopReDist**	**MeanYield**	**MeanFlow**	**ConsecLowYield**	**ConsecLowFlow**	**Built-Up**	**PopReDist**	**MeanYield**	**MeanFlow**	**ConsecLowYield**	**ConsecLowFlow**	**Built-Up**
MeanYield	0.109 **						0.252 **					
MeanFlow	0.163 **	0.393 **					0.171 **	0.566 **				
ConsecLowYield	−0.002	0.043	0.089 **				−0.176 **	0.024	−0.009			
ConsecLowFlow	−0.066 *	0.029	0.249 **	0.147 **			-0.55	−0.064 *	−0.059	0.070 *		
Built-up	0.361 **	0.003	0.072	0.009	−0.012		0.361 **	0.027	0.019	0.028	0.019	
Pop	1.000 **	0.109 **	0.163 **	−0.001	−0.066 **	0.363 **	1.000 **	0.252 **	0.172 **	−0.177 **	−0.055	0.363 **
Ethiopia 2000–2010	**PopReDist**	**MeanYield**	**MeanFlow**	**ConsecLowYield**	**ConsecLowFlow**	**Built-Up**	**PopReDist**	**MeanYield**	**MeanFlow**	**ConsecLowYield**	**ConsecLowFlow**	**Built-Up**
MeanYield	0.182 **						0.100 **					
MeanFlow	0.171 **	0.269 **					0.080 **	−0.161 **				
ConsecLowYield	−0.114 **	−0.198 **	−0.152 **				−0.144 **	−0.213 **	−0.114 **			
ConsecLowFlow	−0.077 *	−0.020	−0.176 **	0.187 **			−0.109 **	0.150 **	−0.155 **	−0.084 **		
Built-up	0.339 **	−0.028	0.029	−0.030	−0.012		0.339 **	−0.050	0.043	−0.043	0.014	
Pop	0.977 **	0.181 **	0.186 **	−0.134 **	−0.094 **	0.391 **	0.977 **	0.120 **	0.048	−0.133 **	−0.059	0.391 **

** Correlation is significant at the 0.01 level (two-tailed). * Correlation is significant at the 0.05 level (two-tailed).

In both Mexico and Ethiopia, the two control variables (Built-up and Pop) had strong positive correlations with the dependent variable (PopReDist). In Mexico, the correlation coefficient of the Built-up was 0.605 for the 1990s and 0.609 for the 2000s; these values were higher than the correlation coefficient of Pop, which was 0.512 for the 1990s and 0.454 for the 2000s. Possible reasons for the greater influence of Built-up on population redistribution in Mexico are higher migration from rural areas to urban areas or higher natural population growth rate in urban areas. In Ethiopia, the correlation coefficient of population distribution was 1.0 for 1990 and 0.977 for 2000, which indicates that population redistribution in Ethiopia is largely determined by natural population growth, and migration plays a relatively limited role.

Regarding the environmental variables, in Mexico, with both sets of modeling data and in both decades, MeanYield was significantly and positively correlated with population redistribution; it was the only environmental variable to exhibit a significant correlation. In contrast, in Ethiopia, MeanYield and MeanFlow were positively correlated with population redistribution, whereas ConsecLowYield and ConsecLowFlow were negatively correlated with population redistribution. The correlation results were consistent across datasets and across decades, although not all correlations were significant in all cases. For Ethiopia, we must carefully demonstrate the correlation between environmental change factors and population redistribution.

4.2. OLS Results

In the OLS analysis, we examined the regression coefficients describing the relationships between independent variables and dependent variables. MeanYield and MeanFlow can be expected to be positively correlated with population redistribution. In theory, an increase in crop production or water resources indicates improved living conditions, which promotes population increase; decreases in these factors can be expected to result in population decrease. Furthermore, ConsecLowYield and ConsecLowFlow can be expected to be negatively correlated with population redistribution, as continuous shortages of agriculture or water resources worsen living conditions, resulting in population decrease.

For Mexico, when no control variable was considered (Model 1), there was a significant positive correlation between MeanYield and population redistribution with both datasets and in both decades; correlations between the other three environmental variables and population redistribution were not detected (Table 3). When Built-up (Model 2) or Pop (Model 3) were introduced as control variables, MeanYield continued to show a significant positive correlation with the dependent variable. However, after including the control variables, the standardized correlation coefficient between crop yield deviation and population redistribution was significantly reduced. We can conclude that crop yield deviation (MeanYield) in Mexico has a robust effect on population redistribution. Tables 3 and 4 show the OLS regression results between the four environmental change variables in Mexico and Ethiopia and the dependent variable (population redistribution). The correlation coefficients between the independent variable and the dependent variable in Tables 3 and 4 are standardized correlation coefficients.

Table 3. Ordinary least squares (OLS) regression results for Mexico.

	1990–2000						2000–2010					
Lpjml_Gswp3	**Model 1**	**VIF**	**Model 2**	**VIF**	**Model 3**	**VIF**	**Model 1**	**VIF**	**Model 2**	**VIF**	**Model 3**	**VIF**
MeanYield	0.162 *** (0.000)	1.033	0.076 *** (0.000)	1.055	0.082 *** (0.000)	1.059	0.143 *** (0.000)	1.062	0.068 *** (0.000)	1.078	0.091 *** (0.000)	1.076
MeanFlow	0.022 (0.273)	1.033	0.011 (0474)	1.033	0.019 (0.259)	1.033	−0.006 (0.759)	1.087	−0.004 (0.794)	1.087	−0.005 (0.782)	1.087
ConsecLowYield	0.015 (0.451)	1.019	0.020 (0.199)	1.019	0.007 (0.670)	1.020	−0.013 (0.509)	1.038	−0.008 (0.623)	1.038	−0.016 (0.382)	1.038
ConsecLowFlow	−0.024 (0.225)	1.016	−0.018 (0.248)	1.016	−0.019 (0.255)	1.016	0.035 (0.087)	1.062	0.011 (0.482)	1.063	0.026 (0.152)	1.062
Built-up			0.593 *** (0.000)	1.022					0.600 *** (0.000)	1.017		
Pop					0.076 *** (0.000)	1.027					0.443 *** (0.000)	1.013
Adjusted R^2	0.027		0.371		0.268		0.020		0.374		0.214	
Lpjml_Princeton	**Model 1**	**VIF**	**Model 2**	**VIF**	**Model 3**	**VIF**	**Model 1**	**VIF**	**Model 2**	**VIF**	**Model 3**	**VIF**
MeanYield	0.134 *** (0.000)	1.020	0.054 *** (0.001)	1.038	0.061 *** (0.000)	1.042	0.149 *** (0.000)	1.078	0.080 *** (0.000)	1.091	0.104 *** (0.000)	1.088
MeanFlow	0.005 (0.782)	1.014	0.010 (0.523)	1.014	0.012 (0.479)	1.014	0.006 (0.755)	1.070	−0.002 (0.918)	1.070	0.001 *** (0.955)	1.070
ConsecLowYield	0.074 *** (0.000)	1.026	0.055 *** (0.001)	1.027	0.053 *** (0.002)	1.028	0.021 (0.293)	1.026	0.010 (0.510)	1.026	0.015 (0.410)	1.026
ConsecLowFlow	0.008 (0.664)	1.001	−0.009 (0.559)	1.001	0.005 (0.773)	1.001	0.032 (0.106)	1.012	0.009 (0.570)	1.014	0.023 (0.193)	1.013
Built-up			0.595 *** (0.000)	1.021					0.600 *** (0.000)	1.015		
Pop					0.499 *** (0.000)	1.025					0.443 *** (0.000)	1.011
Adjusted R^2	0.024		0.371		0.268		0.021		0.376		0.215	

Dependent variable: population redistribution. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 4. OLS regression results for Ethiopia.

	1990–2000						2000–2010					
Lpjml_Gswp3	**Model 1**	**VIF**	**Model 2**	**VIF**	**Model 3**	**VIF**	**Model 1**	**VIF**	**Model 2**	**VIF**	**Model 3**	**VIF**
MeanYield	0.173 *** (0.000)	1.190	0.140 *** (0.000)	1.191	0.001 (0.577)	1.192	0.137 *** (0.000)	1.112	0.152 *** (0.000)	1.114	0.010 (0.146)	1.130
MeanFlow	0.044 (0.173)	1.270	0.056 * (0.066)	1.279	−0.001 (0.732)	1.301	0.117 *** (0.000)	1.119	0.105 *** (0.000)	1.121	−0.010 (0.148)	1.137
ConsecLowYield	−0.003 (0.908)	1.026	−0.006(0.828)	1.026	−0.001 ** (0.048)	1.026	−0.061 ** (0.046)	1.084	−0.050 * (0.082)	1.085	0.015 ** (0.024)	1.091
ConsecLowFlow	−0.110 *** (0.000)	1.091	−0.097 *** (0.001)	1.093	0.001 (0.558)	1.104	−0.042 (0.170)	1.064	−0.042 (0.143)	1.064	0.086 * (0.086)	1.067
Built-up			0.350 *** (0.000)	1.007					0.338 *** (0.000)	1.003		
Pop					0.990 *** (0.000)	1.042					0.958 *** (0.000)	1.068
Adjusted R^2	0.037		0.158		1.000		0.052		0.165		0.955	
Lpjml_Princeton	**Model 1**		**Model 2**		**Model 3**		**Model 1**		**Model 2**		**Model 3**	
MeanYield	0.235 *** (0.000)	1.474	0.226 *** (0.000)	1.475	0.001 (0.166)	1.535	0.102 ** (0.001)	1.100	0.122 *** (0.000)	1.103	−0.010 (0.116)	1.113
MeanFlow	0.035 (0.311)	1.472	0.033 (0.307)	1.472	−0.001 * (0.075)	1.474	0.063 ** (0.042)	1.074	0.052 * (0.072)	1.075	0.022 ** (0.001)	1.076
ConsecLowYield	−0.180 *** (0.000)	1.006	−0.189 *** (0.000)	1.007	0.001 (0.216)	1.043	−0.126 *** (0.000)	1.079	−0.109 *** (0.000)	1.082	−0.019 ** (0.004)	1.092
ConsecLowFlow	−0.026 (0.377)	1.010	−0.032 (0.227)	1.010	−0.001 (0.395)	1.011	−0.125 *** (0.000)	1.048	−0.133 *** (0.000)	1.048	0.048 *** (0.000)	1.054
Built-up			0.360 *** (0.000)	1.002					0.340 *** (0.000)	1.007		
Pop					0.990 *** (0.000)	1.109					0.972 ** (0.000)	1.036
Adjusted R^2	0.095		0.224		1.000		0.043		0.158		0.958	

Dependent variable: population redistribution. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

In Ethiopia, we firstly examined the correlation between population redistribution and environmental change factors (Model 1). MeanYield and MeanFlow had positive correlations with population redistribution, and ConsecLowYield and ConsecLowFlow had negative correlations with population redistribution (Table 4). Although the correlation results were consistent with our expectations, the correlations were not consistently significant across two crop–water datasets in two decades. When Built-up, which reflects urbanization level, was included in the model as a control variable (Model 2), the adjusted R^2 for Mexico was significantly increased to approximately 0.37, whereas Ethiopia's adjusted R^2 was approximately 0.16. Compared with that in Ethiopia, the degree of urbanization in Mexico has a greater impact on population redistribution. In Ethiopia, urbanization is still in the primary development stage, and population redistribution is only weakly influenced by Built-up. However, when Built-up was introduced as a control variable, population redistribution and crop yield deviation (MeanYield) in Ethiopia were significantly and positively correlated in both decades and with both datasets.

When Pop was included as the control variable (Model 3), the adjusted R^2 value of Ethiopia was much higher than that of Mexico. When the influence of Pop on population redistribution was controlled, in Ethiopia, there was no correlation between crop yield deviation (MeanYield) and population redistribution under Model 3.

In general, for Mexico, with or without the control variables, MeanYield consistently showed a significant positive correlation with population redistribution. However, there were no obvious correlations between the other three environmental change factors and population redistribution. In Ethiopia, there was the suggestion of a possible effect of crop yield deviation on population redistribution, but the coefficients were small and of opposing signs between decades under OLS Model 3. The lack of consistent results between decades might be due to poor population data and poor crop–water model performance.

In summary, no significant impact of short-term environmental shock on population redistribution was found. Crop yield deviation (MeanYield) was the key environmental change factor influencing population redistribution in both Mexico and Ethiopia, as evidenced by models based on two different datasets and two different decades.

4.3. GWR Results

Here, we explore the spatially varying relationships between the dependent variable and potential influencing variables with GWR with the two sets of crop–water modeling data for the 1990s and the 2000s. In the OLS analysis, we found that crop yield deviation had a relatively strong correlation with population redistribution, whereas there was no obvious correlation between any of the other three environmental change factors and population redistribution. In the GWR analysis, we investigated the spatial correlation between crop yield deviation and population redistribution. The white part of Figures 3 and 4 shows the area without data, and the gray part represents areas that did not exhibit significant correlations (t-values with significance less than 90%). The green areas represent areas with positive spatial correlations, and the red areas represent those with negative spatial correlations. The results show that MeanYield was positively correlated with population redistribution in most areas.

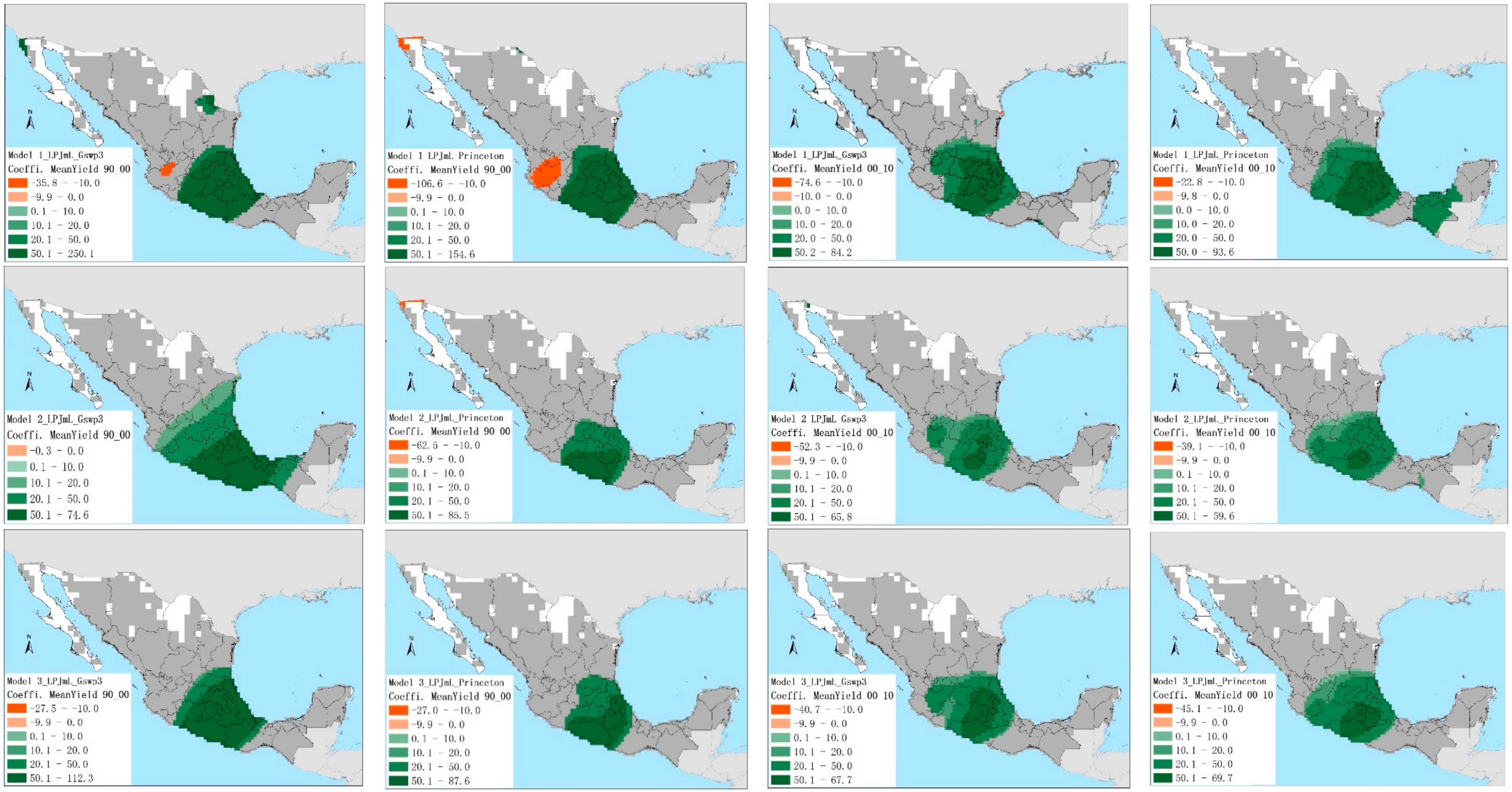

Figure 3. Spatial distribution of correlation coefficients of MeanYield and population redistribution in Mexico. The first, second, and third rows show the distributions of the correlation coefficients under no control variable (Model 1), with Built-up as a control variable (Model 2), and Pop as a control variable (Model 3), respectively. The first and second columns present the coefficient distributions of MeanYield calculated using the LPJmL_Gswp3 and LPJmL_Princeton model data, respectively, for 1990–2000, and the third and fourth columns present the corresponding distributions for 2000–2010.

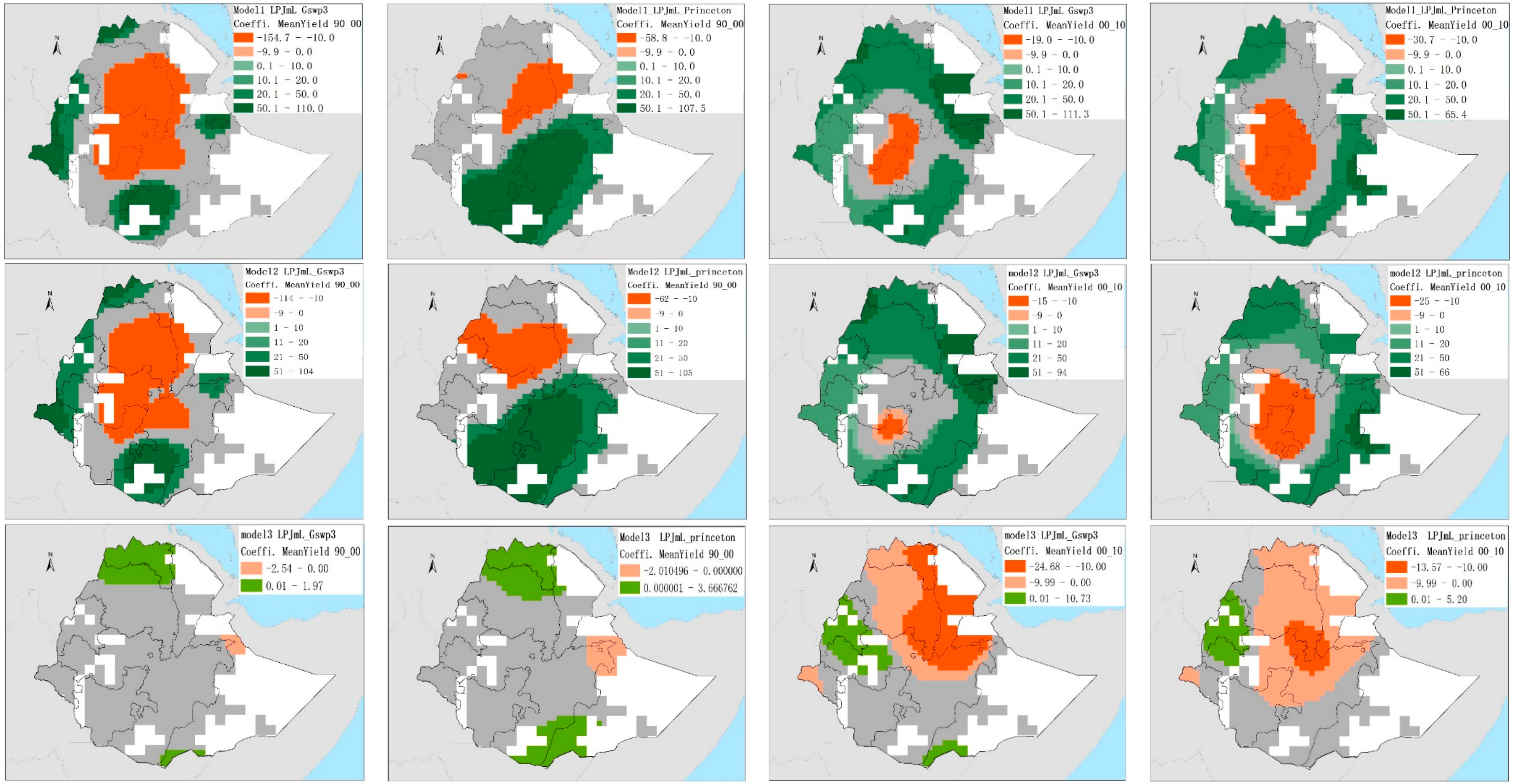

Figure 4. Spatial distribution of correlation coefficients of MeanYield and population redistribution in Ethiopia. The first, second, and third rows show the distributions of the correlation coefficients under no control variable (Model 1), with Built-up as a control variable (Model 2), and Pop as a control variable (Model 3), respectively. The first and second columns present the coefficient distributions of MeanYield calculated using the LPJmL_Gswp3 and LPJmL_Princeton model data, respectively, for 1990–2000, and the third and fourth columns present the corresponding distributions for 2000–2010.

Figure 3 shows the spatial distribution of the correlation coefficients between crop yield deviation and population redistribution in Mexico. The first, second, and third rows show the distributions of the correlation coefficients of MeanYield with no control variable (Model 1), Built-up as a control variable (Model 2), and Pop as a control variable (Model 3), respectively. The first and second columns present the coefficient distributions of MeanYield calculated using the LPJmL_Gswp3 and LPJmL_Princeton model data, respectively, for 1990–2000, and the third and fourth columns present the corresponding distributions for 2000–2010. Figure 4 shows the spatial distribution of the coefficients of the correlation between crop yield deviation and population redistribution in Ethiopia, which is consistent with Figure 3.

In Mexico, with no control variable (Model 1), the correlation between MeanYield and population redistribution was positive; positive coefficients were mainly distributed in the capital and nearby areas and gradually decreased from the capital to the surrounding areas. For 1990–2000, only parts of the west coast showed negative correlations (Figure 3, top row of panels). When including Built-up as a control variable (Model 2), the distribution of correlation coefficients was similar to that for Model 1; however, under Model 2, the positive coefficient areas were more concentrated in the densely populated capital city and nearby areas, and there were almost no areas with negative correlation coefficients. Therefore, the influence of crop yield deviation on population redistribution was more apparent when Built-up was controlled for. When population was included as the control variable (Model 3), we obtained results similar to those obtained with Model 1, with positive coefficients.

In Ethiopia, population development was mainly reflected in the rapid growth of population, and crop yield deviation and population redistribution were positively correlated at the country scale. Crop yield deviation in Ethiopia was positively correlated with population redistribution in peripheral areas but negatively correlated in the central areas with high population density (Figure 4, row 1). When Built-up was included as the control variable (Model 2), the results (second row of Figure 4) were similar to those obtained with Model 1 except that the area of positive correlation was expanded and that of negative correlation was reduced. However, when population was included as the control variable (Model 3), no significant correlation between population redistribution and crop yield deviation was observed at the country level, and the distribution of coefficients revealed no specific patterns.

In conclusion, in Mexico, crop yield deviation has a robust positive correlation with population redistribution in the densely populated capital and nearby areas; however, in other areas, population redistribution is not significantly affected by crop yield deviation. Thus, in the capital and nearby areas, population redistribution effectively adapts to environmental changes (manifested as crop yield deviation). In Ethiopia, crop yield deviation impacts population redistribution at the country level. Unlike the pattern in Mexico, in the peripheral areas in Ethiopia, which are mainly non-urbanized areas, there are positive spatial correlations between crop yield deviation and population redistribution. However, in the densely populated capital and nearby areas, the correlations are negative. In local areas, population development and environmental changes cannot be coordinated, and people's lives may deteriorate further. The potential decline of living standards may further hinder the free flow of the population.

5. Discussion

This paper aimed to explore the potential impacts of long-term and short-term environmental changes on population redistribution. Crop production and water resources, which are closely related to human living conditions, were selected as environmental change factors. Some related studies showed that short-term environmental shocks have different effects than long-term processes, typically resulting in temporary and short-distance population movements [58]. In some poor countries, because people lack sufficient resources for supporting migration, displaced people often have to return to their hometowns, and some people remain stationary [59]. Migration due to short-term environmental shocks is difficult to predict and observe [58]. In this paper, short-term environmental shocks, as measured by consecutive years below median crop yield (ConsecLowYield) and consecutive years below median water flow (ConsecLowFlow), were not found to be correlated with population redistribution. It is possible that population redistribution is not affected by short-term environmental shocks or that demographic data do not capture temporary population movements.

Some studies yielded conflicting results about the impacts of long-term environmental change on population redistribution. Large-scale population displacement caused by drought was observed in some countries in Africa, Latin America, and the Middle East [60]. However, in some poor counties, such as Mali in the mid-1980s, due to the lack of adequate resources to support migration, migration declined relative to past levels [61]. Furthermore, Cattaneo found that temperature rise gradually reduced international migration in some poor countries [62]. By using Mexico and Ethiopia as case studies, employing two different model datasets, considering two decades, and considering Pop and Built-up as control variables, it was found that crop yield deviation was significantly correlated with population redistribution at the country level. However, there was no consistent significant correlation between water flow deviation and population redistribution. Long-term environmental changes tended to result either in migration, which is generally perceived as being voluntary and predominantly economically motivated, or in immobility [58]. Reduced crop production means the deterioration of livelihoods for people, especially farmers. Economic losses from environmental change might have a more direct impact on people's migration decisions than short-term environmental shocks.

Analysis at the local level of the relationship between crop yield deviation and population redistribution in Mexico and Ethiopia revealed spatial heterogeneity. The main factor causing population redistribution in Mexico was population migration, whereas the natural population growth rate in the country was low. In the face of the challenges imposed by environmental change, migration was a common response. As one of the least developed countries in the world, Ethiopia is characterized by a high population growth rate. Because it is difficult to obtain enough resources to support migration, environmental change may also result in immobility [61,63]. The notion of "trapped" populations was used to describe those who are not able to migrate even if they wish to do so. Immobility may be a forced choice [58].

6. Conclusions

Environmental changes caused by climate change are increasingly affecting human survival and development. Crop production and water resources are the most important factors affecting human survival. The present study found no correlation between short-term environment shocks and population redistribution. Regarding long-term environmental change, crop yield deviation was found to have robust impacts on population redistribution at the country level in Mexico and Ethiopia. Based on two different datasets and two different decades, the correlation coefficients between crop yield deviation and population redistribution were 0.134 to 0.162 in Mexico and 0.102 to 0.235 in Ethiopia. When urbanization was considered as the control variable, the correlation coefficient between crop yield deviation and population redistribution in Mexico dropped by half, while it was almost the same in Ethiopia. However, when population was introduced as a control variable, there was little significant correlation between crop production deviation and population redistribution in Ethiopia. There was a suggestion of a possible effect of crop yield deviation on population redistribution, but the correlations were not significant and not consistent across areas in Ethiopia. Crop production deviation is associated with changes in livelihood in developing countries and indirectly affects population growth and migration. Another long-term environmental change factor, water flow deviation, did not exhibit a significant correlation with population redistribution in either country. A possible reason for this result is that this factor does not directly affect the survival and development of human beings and does not necessarily entail a shortage of absolute water resources.

There was marked spatial heterogeneity in the relationship between crop yield deviation and population redistribution. In Mexico, crop yield deviation mainly affected population redistribution in the densely populated capital area and nearby areas. However, in Ethiopia, crop yield deviation showed a positive correlation with population redistribution in the peripheral areas but a negative correlation in the capital and nearby areas.

Regarding population adaptability to environmental changes, people in Mexico were able to adapt to crop yield deviation by migrating, whereas, in Ethiopia, although crop yield deviation was positively correlated with population redistribution, the relationship appears to be indirect. In some places, declines in crop production were accompanied by population increases, which aggravated the vulnerability of populations to environmental change.

There is no doubt that climate change had some effects on population redistribution in developing countries, as shown by the cases of Mexico and Ethiopia. The effect of environmental changes factors related to climate change was indirectly related to population redistribution, especially in densely populated areas with more prominent human–land conflict. As a developing country with slow population growth but high migration rates, Mexico's internal migration was conducive to adapting to the effects of climate change. However, in Ethiopia, an underdeveloped country with a fast-growing population, people had to passively endure the adverse effects of climate change. For developing countries like Mexico, the key question is to properly arrange and guide climate migration, including how to find new livelihoods for migrants from rural to urban areas. For underdeveloped countries such as Ethiopia, the unaffordable cost of migration becomes an obstacle to migration. The rapid population growth rate further aggravates the contradiction between human and land. At the present stage, the focus should be on how to strengthen the local climate adaptation capacity.

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