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A Case study of the connection between hydroclimate/water availability and human migration – evidence from Mexico

A thesis submitted in partial satisfaction of the
requirements for the degree
Master of Science

in

Earth Sciences

by

Keita Kadokura

Committee in charge:

Professor Katharine Ricke, Chair
Professor Christopher Charles
Professor Jane Teranes

2021

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The thesis of Keita Kadokura is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

University of California San Diego

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ABSTRACT OF THE THESIS

A Case study of the connection between hydroclimate/water availability and human migration – evidence from Mexico

by

Keita Kadokura

Master of Science in Earth Sciences

University of California San Diego, 2021

Professor Katharine Ricke, Chair

Previous empirical studies have suggested that climate change induces human migration in Mexico by damaging agricultural livelihood and worsening habitability. However, these studies present different opinions on how water availability affects migration. Also, a high-spatial-resolution climate migration analysis that covers a long-time period is lacking. This study employs two water availability data sets and two migration data sets with high spatial resolution and extended temporal coverage. Firstly, I look at two hydroclimate data sets, ground-station-based and satellite-based, to examine the surface water dynamics in Mexico. Secondly, two migration data sets, modeled gridded data and census data, are analyzed to identify the internal and international migration patterns at the municipality-level in Mexico. Lastly, migration rate is regressed on various climate metrics, including temperature trend and variability, precipitation trend and variability, and surface water trend. In addition, climate metrics' impacts on rural-urban migration flow are examined separately. The investigation of two hydroclimate data reveals the limitation to capture surface water dynamics at fine-scale, the municipality-level, in Mexico. Also, the comparison of two migration data sets displays a huge international migration flow in Mexico. Lastly, the regression results suggest a closer climate's relationship with international migration than internal migration. They also show a consistent delay response of migration after environmental stressors.

1 Introduction

Migration occurs due to various reasons, such as economic, social, and environmental factors (Afifi, 2011). Examples of the economic factors are to improve salary or to seek employment opportunities. Moving to a different place to live with a family, to receive better education, and to improve social status are notable examples of the social drivers. The environmental stress such as degradation of soil, droughts, flood, and sea-level rise also causes migration (Neumann and Hermans, 2017). Most of the times, these three drivers are complexly interrelated. Migrants can have both economic and social motivations, economic and environmental, or all three of them (Afifi, 2011).

Several studies have shown that the economic and the social drivers play more important roles than the environmental driver (Warner et al. (2010), Black et al. (2011)). However, the environmental stressors are expected to strengthen due to environmental change induced by human activities, such as burning fossil fuels, deforestation, and pollution. Human actions are estimated to have caused about 1.0 °C of global warming so far, and this warming is expected to continue or even accelerate, reaching 1.5 °C by 2040 depending on the intensity of humans' mitigation actions (Climate change 2014: synthesis report. Contribution of Working Groups I and to the fifth assessment report of the Intergovernmental Panel on Climate Change, 2014). The global mean sea level is rising at the rate of 3 ± 0.4 mm/y since 1993, and this trend is accelerating, possibly resulting in a rise by 65 ± 12 cm by 2100 compared with 2005 (Nerem et al., 2018). Moreover, global warming is positively correlated with the frequency of river floods (Alfieri et al., 2017). Extreme heatwave events are expected to increase non-linearly as a result of global warming (Matthews et al., 2017). Two-thirds of the global population will experience the worsening of drought conditions. Dry places will especially suffer from droughts. (Naumann et al., 2018) suggested an increase in the duration by 2.0 month/°C even if the warming is held below 1.5°C.

These physical changes in climate damage humans' livelihood. Changes in precipitation and temperature patterns reduce crop production, which results in a threat to food security (Wiebe et al., 2015). Developing countries that highly depend on agriculture as a source of income receive damage from climate change more significantly (Fischer et al., 2005). In addition to the agricultural sector, climate change disrupts aquaculture. Changes in aquatic ecosystems, extreme weather events, water stress, and sea-level rise could reduce the availability of fish (Cochrane et al., 2009). Moreover, sea-level rise could impact people on low-lying land through frequent flooding (Hauer et al., 2020). These events will leave the livelihood of the workers in the aquacultural sector insecure. Concurrent with future global warming, these negative impacts are likely to expand. Consequently, people whose livelihood is contingent on natural resources will suffer from insecurity.

In addition to these slow-onset events, rapid-onset events, such as hurricanes, heatwaves, and cold waves, are expected to increase due to global warming (Mal et al., 2018). These extreme weather events sometimes make a town uninhabitable, leading to forced human displacement. Hurricanes associated with floods and landslides sometimes destroy buildings, infrastructure, and farmlands. Especially for vulnerable ecosystems such as coastal regions, low-lying land, high altitude locations, and high latitude locations, the magnitude of the extreme weather is increasing (Field and Barros, 2014). Even if inhabitants are forced to displace temporarily after these disasters, they often return to their hometown for reconstruction and do not permanently migrate. However, vulnerable people in developing countries who do not receive enough financial support from government or non-government organizations have a higher chance to migrate permanently (Tacoli, 2009). In brief, the poor in vulnerable ecosystems or developing countries receive the most damage from extreme weather events and have a high chance of migration. Therefore, the escalation of the extreme weather induced by climate change is presumed to impact vulnerable or developing countries unequally.

After receiving damages to their livelihoods,, people take various strategies other than migration, such as improving tools for better productivity, cultivating different crops, accepting a decrease in income, and changing jobs within the same place (Tacoli (2009), Hunter et al. (2013)). These strategies that consume less time and money are preferred over migration. However, when these strategies are ineffective, people pick migration. For example, when rapid-onset climate events, such as floods, physically destroy houses and sources of livelihood, an entire household is forced to emigrate from their hometown permanently or temporarily. When a slow-onset climate change, such as a gradual increase or decrease in temperature and precipitation, damages agricultural productivity, a household sends one or two family members to an urban area to diversify the income sources (Black et al., 2011).

When a person decides to migrate, there are two options: international and internal migration. International migration refers to displacement across different countries, while internal migration refers to displacement within a country. In 2000, about 2.8 % of the total population in the world were international migrants, and it increased to 3.4 % in 2017. Since 1990, the international migration rate had ranged between 1.13 and 1.29 % of the global population per 5-year period (Azose and Raftery, 2019). Out of these international migrants, more than 60 %, about 165 million, reside in high-income countries in 2017. Nevertheless, 84 %, about 22 million, of refugee or asylum seekers migrated to low- or middle-income countries (DESA, 2017). Despite a large number of international migrants, internal migration is generally much bigger than international because the barriers to migrate within a country are much smaller. The internal climate migration is expected to reach around 65 to 105 million in three regions; Sub-Saharan Africa, South Asia, and Latin America (Rigaud et al., 2018). How these migrants are affected by climate change differs among regions, so the climate internal migration should be studied and projected based on empirical data for each country to avoid an unexpected migration flow, which is problematic for both origin and host regions. (Thiede et al., 2016).

Case studies of internal climate migration has been carried out for vulnerable countries, such as Bangladesh, Brazil, and Ethiopia. The majority of Bangladesh consists of the delta, making it susceptible to flood and saline contamination of soil caused by sea-level rise. A study found that the combination of inundation and saline contamination induces a diversification into aquaculture and internal migration (Chen and Mueller, 2018). Similarly, in Brazil, where the agricultural sector employs a large share of the laborers, deterioration of crop yield caused by temperature rises would increase the internal migration by 9.65 % (Oliveira and Pereda, 2020). The rural Ethiopian highlands are also vulnerable due to endemic poverty, high population density, and exposure to recurrent droughts. Gray and Mueller (2012) found that the migration increased with drought the most for men in poor-land households.

Mexico is one of the countries that keeps migration data for a long time and is experiences large climate internal migration (Rigaud et al., 2018). The internal migration already rose in the 1940s in Mexico induced by urbanization before climate change began to impact Mexican's livelihood (Burnight et al., 1956). Since the 1970s, many researchers have indicated an increase in out-migration from Mexico to the U.S. to improve the quality of life. For certain communities, migrating to the U.S. became a normative method, especially for young males. Witnessing and interacting with households who improved the socioeconomic situation by U.S. labor, more Mexicans sought to migrate to the U.S instead of investing more time in Mexico (Kandel and Massey, 2002). As a result, the amount of Mexico-U.S. international migration became anomalously large. In 2017, 11.6 million Mexicans lived in the U.S. India-U.A.E was the second largest, followed by Russia-Ukraine, and both of them accounted for about 3.3 million poeple (Bank, 2017). Due to this anomaly, cross-boarder migration has been focused by Mexican immigration study. However, as climate change becomes noticeable, several researchers warned that environmental factors are becoming increasing drivers of both international and internal displacement in Mexico. Monterroso and Conde (2015) states, "out of ten Mexicans, three live in flood-prone zones, three may suffer the passage of tropical cyclones, five reside in drought zones and two live in extreme drought regions." Cuervo-Robayo et al. (2020) concluded that the mean annual temperature in Mexico increased by 0.2 °C from 1970 to 2000 based on the stations' observation. They also mentioned a spatially nonuniform pattern of climate change; a temperature increase was more prominent in the northern region than tropical regions, and precipitation increased from 1940-1970 but decreased between 1970-2000 in most regions in Mexico. A model projected a significant decrease in precipitation in the dry season at regions which receives high orographic precipitation (Karmalkar et al., 2011). Another climate model projected the highest warming in the wet season and at the Yucatan Peninsula. It also predicted a decrease in precipitation in the wet season at the Yucatan Peninsula. Combined with these changes in climatology and degradation of soil caused by overgrazing, deforestation, and urbanization, surface and groundwater availability has changed as well in Mexico (Murdoch et al., 2000). The flood becomes recurrent, the runoff reaches the watershed faster, and the streamflow drops more rapidly at the western Sierra Madre, which is the main water provider of northern Mexico (Viramontes and Descroix, 2003). At Yucatan Peninsula, groundwater is estimated to decrease from $118 \pm 33 mm/year$ to $92 \pm 40 mm/year$ in the next two decades under the intermediate scenario (RCP4.5) (Rodríguez-Huerta et al., 2020).

On top of these observed and expected climate changes, Mexico suffers from a geographic mismatch between water source and population. 7% of the land, lying in the southeast of the country, receives 40% of the rainfall. Only 12% of the nation's water is on the central plateau, where 60% of the population and 51% of the cropland is located (Liverman and O'Brien, 1991). Close to 30 % of the national population live in arid and semi-arid climates region in Mexico, which occupies about half of Mexico's land area (Verbist et al., 2010). 10% of the employment in Mexico is in the agricultural sector (OECD, 2015), and rain-fed agriculture and livestock production are predominant (Brauch et al., 2011). Thus, Mexico is vulnerable to land degradation and change in the temperature and precipitation pattern more than other countries.

Wheat is one of the major cereal crops grown in Mexico: the total production was 3.2 million tons, and the total area sown was 640,580 ha in 2017 (INEGI, 2017). This production is concentrated in Sonora, Baja California, Sinaloa, Guanajuato, and Michoacán states, which together represent about 86% of the total national production (INEGI, 2017), and these places have the arid and semi-arid climate, resulting in intensive use of irrigated water. Thus, climate change can be detrimental to wheat production. Hernandez-Ochoa et al. (2018) found that changes in rainfall can cause rain-fed wheat yields to decline by up to 32%, which exceeds a positive impact from the elevated atmospheric CO_2 concentration. Guarin et al. (2019) concluded that an increase in tropospheric ozone concentration could also lead to an extensive loss of wheat yields. Corn is another crucial crop harvested in Mexico. Murray-Tortarolo et al. (2018) showed a positive correlation between mean annual precipitation and rain-fed maize production and concluded that national maize production could decline by 10% by 2100 in Mexico. They also predicted an even larger regional decline up to 30%. Mexico, furthermore, captures nearly 1.3 million metric tons of marine products every year, which ranks 16th in the world in terms of total global marine products. Also, 240 thousand Mexicans rely directly on fishery for their livelihoods (FAO, 2012). Cisneros-Mata et al. (2019) states climate change will negatively affect every fishery in Mexico.

Reducing water availability would be problematic for other industries and lives in cities as well. For example, one-fifth of the electricity used in Mexico is from hydroelectric power generation. Also, water-supply infrastructure has not been able to keep up with rapid urban and industrial development, which consumes more than 80% of water supplies. If climate change were to result in higher temperatures and reduced precipitation, the displacement not only from rural to urban but also urban to urban or foreign countries would increase (Liverman and O'Brien, 1991).

With these potential risks of climate change, various empirical studies have looked at climate migration (Haeffner et al. (2018), Schmidt (2019), Schmidt-Verkerk (2009)). Some qualitative research has suggested a complex nexus between climate change and migration in Mexico. Haeffner et al. (2018) qualitatively investigated the association between household traits and drought adaptation strategies in two cities in Baja California Sur. Although they found most households picked in-situ adaptation strategies, such as changing farming practices and acquiring off-farm work, they concluded that a rancher's households were more likely to migrate out of the watershed during droughts. They also stated that not having close access to an urban water infrastructure during droughts made more people take some adaptation strategies. For the Mexico-U.S. migration flow, Schmidt (2019) examined qualitative empirical data from two rural communities in Zacatecas state in 2008 and 2018. They suggested some emigration from Mexico to the U.S. led by a decline in crop yields, they concluded that farmers would adapt mainly by switching jobs or doing internal circular migration if local employment was unavailable. With regards to the internal migration in Mexico, Schmidt-Verkerk (2009) described that internal migration was less costly than international migration and would increase because those who have not migrated before might become forced to do so when they cannot live off agriculture anymore. They also mentioned that some people who cannot migrate due to personal or financial reasons would most be affected by future climate change. Although the first two studies were reluctant to strongly assert an increase in climate migration, all three studies agreed on the difficulty of predicting climate migration.

Other authors investigated the relationship between climate and migration in Mexico quantitatively (Nawrotzki et al. (2015), Feng et al. (2010), Nawrotzki et al. (2013)). They employed econometrics or regression models where climate and other related socio-economic factors were dependent variables, and migration rates were independent variables. Nawrotzki et al. (2015) looked at an empirical relationship between warm and wet spell duration and US-bound migration from rural and urban Mexico. Their results revealed that temperature warming and excessive precipitation significantly increased international migration only for rural areas. They also found the interaction term between temperature and male labor in agriculture to be positive in a regression model. Thus, they hypothesized that a decline of the male labor in agriculture caused by further urbanization might possibly reduce temperature-related international migration. Feng et al. (2010) added agricultural yields as a variable in their regression to looked at the linkages among climate, crop production, and US-bound migration from Mexico. They found a 10% reduction in crop yields would increase emigrants by 2% of the state population. Based on this result, they estimated the number of Mexican adult migrants who move from Mexico to the U.S. by 2080 to be 1.4 to 6.7 million. Nawrotzki et al. (2013) also looked at the influence of climate change on US-bound migration from Mexico. More specifically, they scrutinized an association between rainfall and Mexico-U.S. migration pattern in Mexican rural regions. They found that a reduction in precipitation increased U.S.-bound migration in dry Mexican states. This statement conflicts with the result of Nawrotzki et al. (2015), which showed no significant difference between dry and wet states. Also, there is no full consensus on the magnitude of climate migration in Mexico. Further research has to be conducted to clarify its mechanism.

In addition to the international climate migration, an association between internal migration and climate change in Mexico has been studied based on quantitative empirical data (Nawrotzki et al. (2017), Leyk et al. (2017)). Nawrotzki et al. (2017) investigated a relationship between climate shocks and internal migration between rural and urban areas based on 2000 and 2010 Mexican censuses. Their results showed that each additional drought month increased the odds of rural-urban migration by 3.6%. In contrast, the relationship between heat months and rural-urban migration was nonlinear. Before the number of heat months exceeded a threshold, the relationship between heat months and rural-urban migration was negative. However, as it passed the threshold, this relationship became positive and progressively increased in strength. Another research conducted by Leyk et al. (2017) investigated how climate change impacted internal and international migration between 2005-2010 at the municipality level. Their findings suggested that municipal-level rainfall deficits are a significant predictor of both international and internal migration, especially in municipalities with predominantly rain-fed agriculture.

1.1 This research project's purpose

To address the ongoing uncertainties about the relationship between climate and migration in Mexico, as well as the appropriate data sources to most effectively explore questions about this topic, this thesis does three things. First, two climate indicator data sets are compared to understand how they differ in their characterization of hydrological shocks and changes in Mexico since drought and water availability have been linked to migration in previous studies. To this end, I compare University of Delaware Air Temperature & Precipitation and Global Surface Water (Section 4.1). Secondly, I compare two migration data sets to observe the differences in the characteristics and the usability for migration analysis (Section 4.2). Thirdly, I use regression analysis to empirically examine relationship between the different climate and migration indicators in the past to see what this may imply about migration and hydrological change in the future under climate change (Section 4.3).

2 Data

This study uses four spatio-temporal data sets: two for the climate and two for the migration metrics.

2.1 Migration Metrics

Integrated Public Use Microdata Series (IPUMS) International (MPC, 2020) and Global Estimated Net Migration Grids By Decade, v1 (De Sherbinin et al., 2012) (henceforth referred to as IPUMS-I and De.Sherbinin) were used to measure the migration among municipalities in Mexico.

IPUMS International

IPUMS-I collects more than 600 censuses and surveys from 103 countries worldwide, making it one of the largest collections of individual-level census data. After collecting them, IPUMS-I integrates them temporally and spatially, enabling cross-country and -period analysis. Mexican data is derived from the censuses collected by the National Institute of Statistics, Geography, and Informatics (INEGI), and each census involves about 10% of the total population. The censuses asked households and individuals a broad range of questions about dwelling location, dwelling characteristics, ownership of houses, income, work, and demography. Among these variables, IPUMS-I provides two kinds: source and harmonized variables. Source variables are raw censuses with unique codes for each sample, while harmonized variables are processed censuses by IPUMS-I that have the same codes or labels across all samples. In other words, harmonized variables are comparable among different censuses and countries without extra work, making it one of the most important advantages of IPUMS-I. Thus, various studies has employed IPUMS-I to compute migration over more than two periods (Sobek (2016), Esteve et al. (2012)).

Table 2.1 shows IPUMS variables used in this study. 'MX2000A_RESMUN', 'MX2010A_MIGMUNI5', and 'MX2015A_MIGMUN5' record second administrative units in which an individual resided five years before the survey year. For instance, the survey in Mexico in 2000 asked, "In what municipality did this person live in 1995?" (MPC, 2020). INEGI collected this information in 1995, 2000, 2010, and 2015, making it one of the countries with the largest migration records at the second administrative units level. The second administrative unit corresponds to Mexican municipalities, and Mexico consists of 2454 municipalities, which is much finer than 32 states. Also, the variable in 1995 was dropped due to the limitation of the compared climate metrics. A caveat is that they were the source variables, meaning the municipality codes were not harmonized by IPUMS-I. Thus, they had to be manually harmonized across the three time periods using a IPUMS-I's time-stable municipality code called "GEO2_MX" (Table 2.1).

After processing the unharmonized variables, the inter-municipality migration was cal-

Table 2.1: Description of IPUMS variables

IPUMS Variable Names	description	unit	type of variable	Availability
MX2000A_RESMUN	Municipality of residence in 1995	Municipality	Source	2000
MX2010A_MIGMUNI5	Municipality of residence in 2005	Municipality	Source	2010
MX2015A_MIGMUN5	Municipality of residence in 2010	Municipality	Source	2015
GEOLEV2	Municipality of current residence	Municipality	Harmonized	N/A
GEO2_MX	Municipality boundary	Municipality	Harmonized	N/A
URBAN	Locality of residence is urban or rural	Locality	Harmonized	1960, 1970, 1990, 1995, 2000, 2005, 2010, 2015

culated. GEOLEV2 showed the current residence of the municipality (destination), while MX2000A_RESMUN, MX2010A_MIGMUNI5, and MX2015A_MIGMUN5 showed the residence of the municipality five years prior (origin). Comparing these variables, I filtered out individuals with identical origin and destination municipalities. Then, the remaining individuals were aggregated based on the origins to compute out-migration and based on the destinations to compute in-migration of municipalities between 1995-2000, 2005-2010, and 2010-2015. One thing to be careful of was to use a variable called ”PERWT” while aggregating them. PERWT is the number of persons in the actual population represented by the person in the sample. Then, the net out-migration of a municipality was estimated by adding in- and out-migration (Fig. 2.1 a). Also, the population of the municipality in the start year was calculated by adding individuals with the same origin municipalities before filtering (Fig. 2.1 b). Lastly, a variable called ’URBAN’ was applied to measure rural-urban migration. IPUMS-I defined localities with more than 2,500 persons as urban. URBAN in 2000, 2010, and 2015 were used to select individuals whose destinations are urban localities. URBAN in 1995, 2005, and 2010 were used to find out origin municipalities were rural or urban. The origin municipality was defined as rural if the population in urban localities were zero. I also compared the rural population calculated from IPUMS-I and the World Bank for consistency (Fig. 7.1).

IPUMS-I is based on direct observations, such as surveys and censuses answered by citizens, so it is theoretically an accurate estimate of the migration flow within a country. However, IPUMS-I cannot estimate net international migration because it does not track people who migrate from Mexico to foreign countries. It only records people living inside Mexico in the survey year, so only internal migration and international in-migration can be estimated. One thing to note is that IPUMS-I records only origin and destination, meaning the circular and stepwise movements are not captured. For example, if an individual moved to a different municipality in 1997 and came back to the original municipality before 2000, this individual is counted as a non-migrant. Also, if a person moved from Municipality A to Municipality B to Municipality C between 1995-2000, this person is considered as a migrant from A to C. The information about Municipality B is dropped.

De.Sherbinin

The De.Sherbinin migration data is a gridded decadal net in-migration (in-migration minus out-migration) in the 1970s, 1980s, and 1990s with the spatial resolution of 30 arc-second (Fig. 2.1 d). To be consistent with IPUMS-I net out-migration, the net in-migration values of De.Sherbinin data were multiplied by -1 to obtain net out-migration. While IPUMS-I is a direct measurement of migration patterns, De.Sherbinin is a migration estimate based on population changes, births, and deaths in Mexico. Taking the population difference between start and end years and adjusting for the natural population increase, net migration was estimated (De Sherbinin et al., 2012). Thus, De.Sherbinin could potentially be a less accurate measure of migration.

De.Sherbinin data only provides migration information, unlike IPUMS-I that provides both migration and population information. Thus, a gridded population data called the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) data in 1970, 1980, and 1990 were used (10., 2020). ISIMIP has a spatial resolution of 5 arc-minute and an annual temporal resolution. The population of a municipality was calculated by adding all of the grid cells within a boundary of the municipality (Fig. 2.2 a,b).

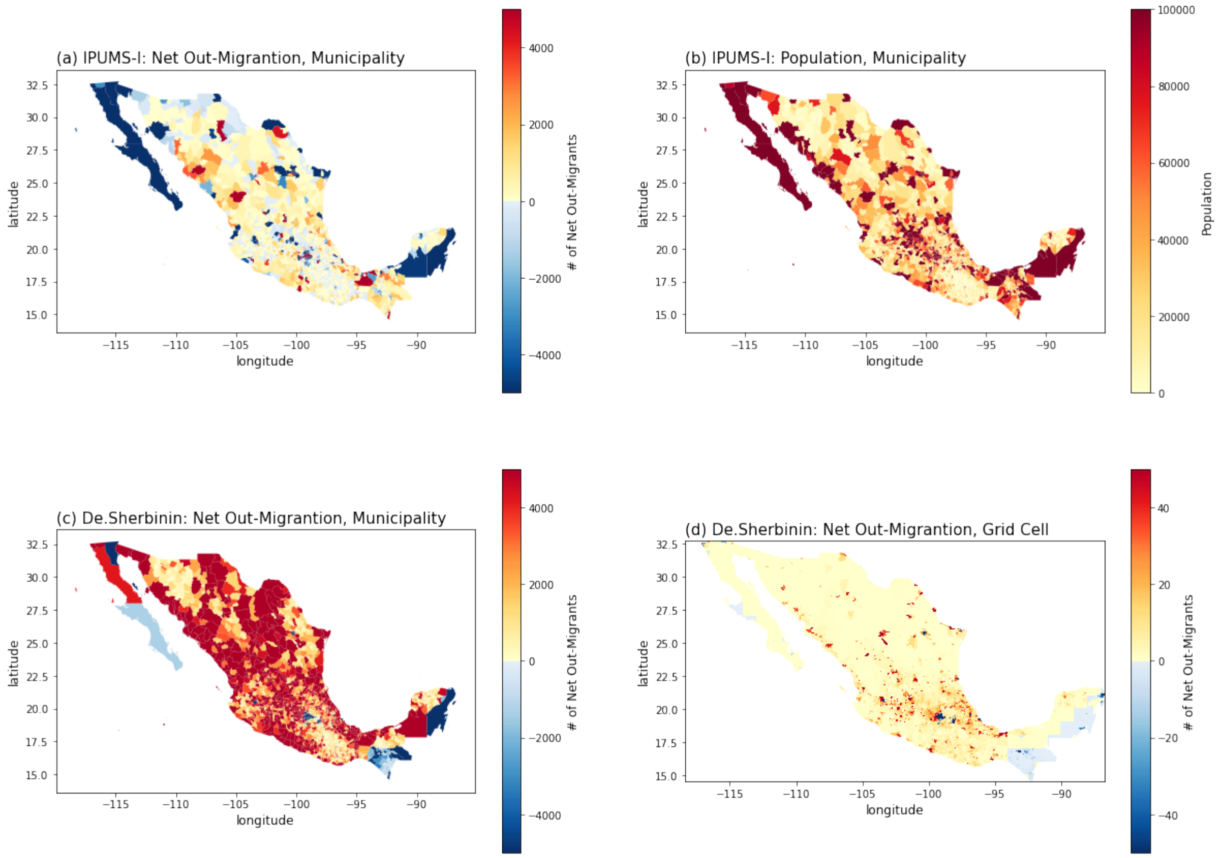

Figure 2.1: Color maps of (a) the number of IPUMS-I net out-migrants, (b) the IPUMS-I population of every municipality, (c) De.Sherbinin net out-migration at the municipality level, and (d) at the grid cell level

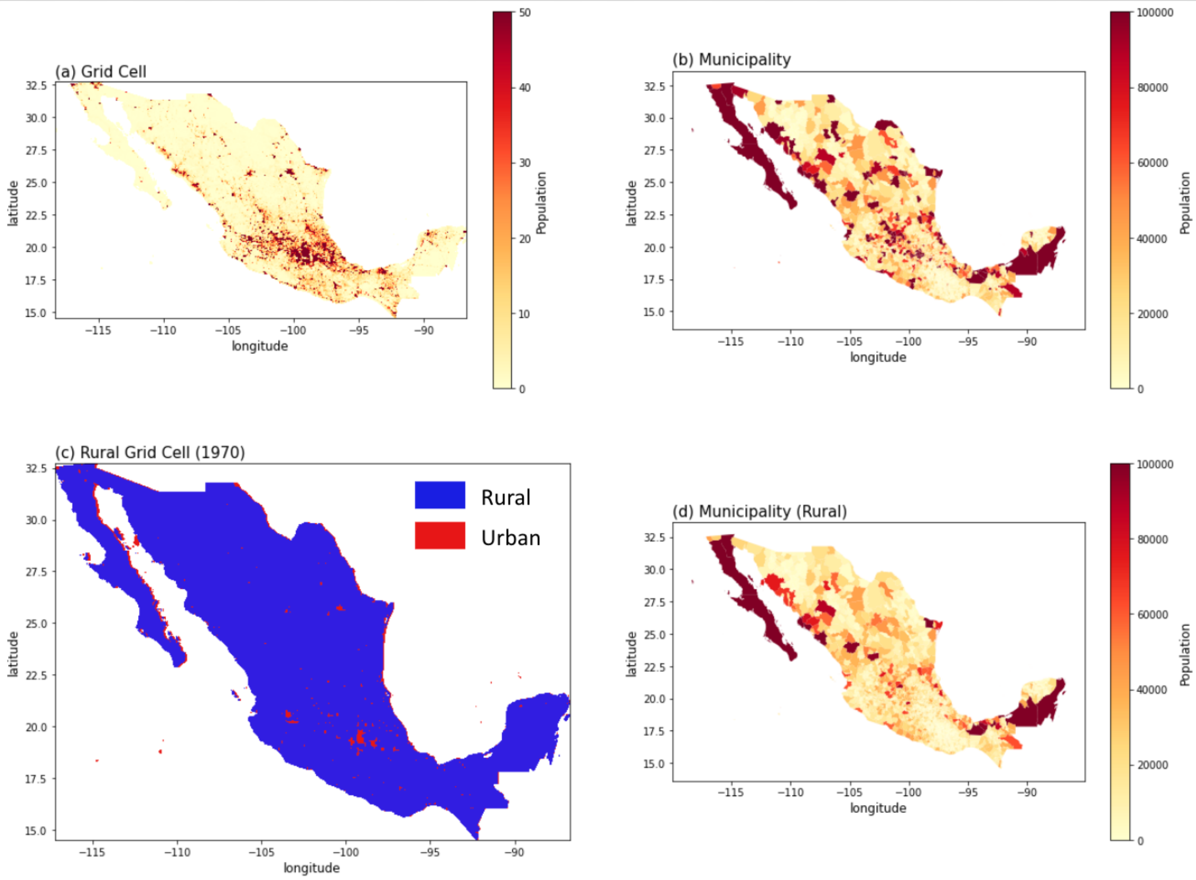

Figure 2.2: Color maps of ISIMIP in Mexico. (a) is the mean of ISIMIP in 1970, 1980, and 1990 at the grid level. (b) is the mean of ISIMIP in 1970, 1980, and 1990 at the municipality level. (c) shows the rural grids as blue and the urban grids as red. (d) is the mean of rural grids of ISIMIP in 1970, 1980, and 1990 aggregated at the municipality level.

2.2 Climate Metrics

Global Surface Water

The first climate data set is Global Surface Water (GSW) (Pekel et al., 2016). Surface water availability is essential for agriculture, farming, and other industries. Also, it is related to multiple climate variables, including temperature and precipitation. Therefore, global surface water is one of the crucial climate metrics to see how environmental factors relate to migration.

GSW is a gridded data set developed by the European Commission's Joint Research Centre and records the location and temporal distribution of surface waters from 1984 to 2020 with 30m resolution based on over three million images retrieved from Landsat5, 7, and 8. In Mexico, GSW covers about 2% of the total area. (Pekel et al., 2016) states that this data set can be used for tracking the expansion or shrink of lakes, rivers, delta, and sea-level rise. (Pekel et al., 2016) also provides various types of statistics about surface water based on GSW, such as "Water Occurrence", "Recurrence", "Occurrence Change Intensity", and "Yearly History".

Several studies have utilized GSW to map inundation area (Alfieri et al. (2018), Shen et al. (2019))."Water Occurrence" provides the frequency of surface water existence between 1984 and 2020 for every grid from 0 to 100. One hundred means that surface water has always existed in the grid between 1984 and 2020, while 0 means no surface water existed during this period. Thus, Water Occurrence could be suitable to capture the flood's frequency over 37 years. Similarly, "Recurrence" provides one value over the 37 years, which indicates how often surface water returns to a grid during the 37 years. "Occurrence Change Intensity" was also investigated. This value compares the water occurrence value between 1984-1999 and 2000-2020 and gives the difference, so it could be helpful to examine the change in the flood frequency before and after 2000. However, the provided statistics did not provide a yearly value needed to calculate a five-year trend of the changes in surface water. If time allowed, measuring the yearly water occurrence and the yearly recurrence based on the raw GSW data could have helped observe the intensity of floods during the five-year period.

One yearly data provided by Pekel et al. (2016) was ”Yearly History” (hereafter referred as to GSW Yearly). GSW Yearly was retrieved from Google Earth Engine, free google’s service for spatial analysis. GSW Yearly classifies each grid into three categories; nowater, seasonal, and permanent. Permanent pixels are covered by water for 12 months per year or for the number of months where valid observations were made in the year. Seasonal indicates pixels covered by water for less than 12 months or less than the number of months with valid observations. If these permanent or seasonal pixels are not covered by surface water in a particular year, they are classified as nowater (Fig. 2.3 b). Even though this yearly data let me calculate the five-year trends of each category, I found that GSW Yearly was not suitable for measuring flood events because the satellite images on which GSW are based upon were taken every eight days, but the flood events are often shorter than that. Therefore, just knowing the frequency of the time when surface water was present at that place might miss some flooding events. Thus, GSW Yearly was instead used to capture the general changes in surface water availability, not specific to the coastal area. In addition, I created a new variable called ’seaper’, which was the sum of seasonal and permanent grids. Then, to calculate the trend and level of GSW Yearly for every municipality in Mexico, the GSW Yearly’s grid cells were aggregated to municipality-level for each category.

The advantage of this data set is the fine resolution and the spatial and temporal availability. As far as I know, there are no other data sets that collect global surface water records finer than 30m resolution and have more [more? to describe data amount] than 37 years of data. Therefore, it is a great source to observe the trends of surface water dynamics. However, as stated before, the cycle of each snapshot is 8-day, so short events are potentially missing.

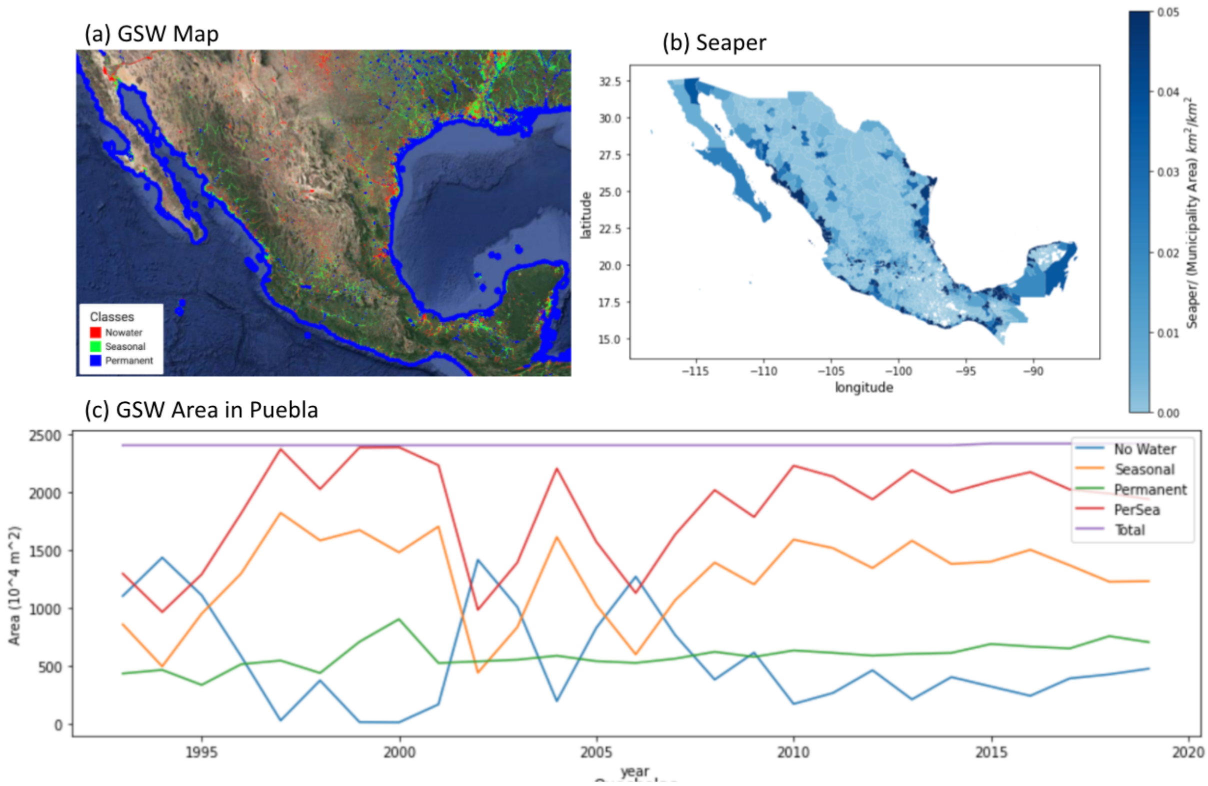

Figure 2.3: (a) An aerial photo of GSW's three categories. (b) Average area of Seaper normalized by the area of municipalities over 1993-2015 (c) The transition of the area of Nowater, Seasonal, and Permanent at Puebla municipality.

UDEL

The second data set, University of Delaware (UDEL) Air Temperature and Precipitation v5.01 (Willmott, 2000), is a monthly gridded temperature and precipitation data that are interpolated mainly from gauge information of land stations all over the world. It covers the period from 1900 to 2017 with a half-degree spatial resolution (Fig. 2.4). Four metrics were calculated from UDEL for 5-year (1996-2000, 2006-2010, 2011-2015) or 10-year (1971-1980, 1981-1990, 1991-2000) periods; temperature trend (Ttrend), temperature variability (Tvar), precipitation trend (Ptrend), and precipitation variability (Pvar). These trends and variabilities in precipitation and temperature were picked since various researchers used them to investigate climate migration (Bohra-Mishra et al. (2017),Gray and Wise (2016),Tayanç et al. (1997)). Ttrend and Ptrend are the least-squares of UDEL temperature and precipitation that are anchored from the preceding 30-year baseline period. The least-squares are multiplied by 10 to convert the unit from $degC/year$ and $cm/month/year$ to $degC/decade$ and $cm/month/decade$. Tvar and Pvar are defined as t e variance between residuals in the baseline period and the following 5 or 10 years from detrended UDEL. Positive Tvar or Pvar suggests that the temperature or precipitation varies more dramatically during the last 5 or 10 years than the preceding baseline period.

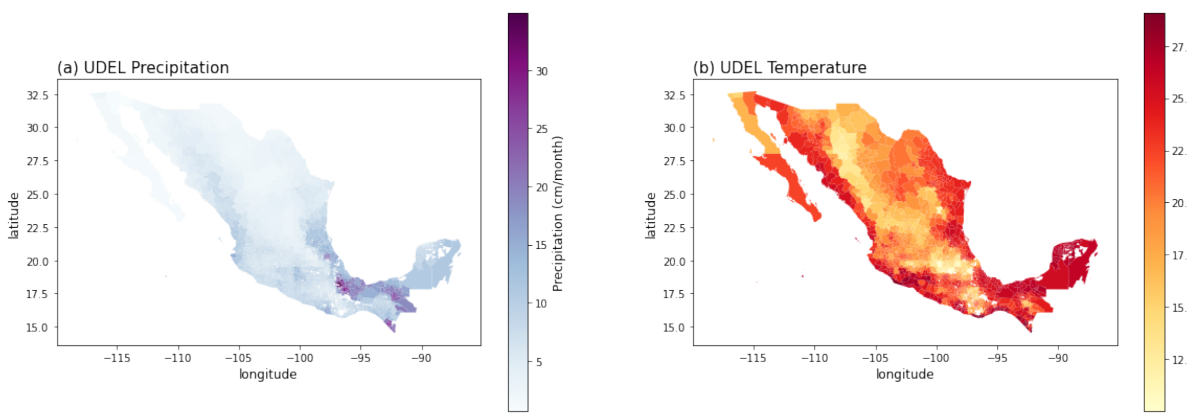

Figure 2.4: UDEL Climatology (1970-2015); (a) temperature and (b) precipitation

Highlight that Mexico is the largest collection of migration.

3 Method

3.1 GSW Metrics

Before computing GSW metrics, all pixels that had no observation in the past 37 years were excluded so that the total area of GSW is consistent throughout the years, as shown in Fig. 2.3 c. Moreover, the data before 1993 were filtered out due to an excessive amount of missing values. Then, each category's area was normalized by the total area of GSW for each municipality to account for the GSW's coverage difference among municipalities. After filtering and normalizing, the trends of nowater, seasonal, permanent, and seaper were calculated for a period, j, and a municipality, m, by taking a least-square. A subscript, i, represented the years within the period j (Eq. 3.1). Additional to the trends, levels of the four categories of GSW normalized by the area of municipalities were calculated with an equation 3.2 as a measure of the background condition. Furthermore, 1-, 2-, and 3-year lagged trends and levels were computed by adding one, two, and three preceding years respectively to the original 5-year interval. For example, if the original temporal coverage was 1996-2000, then 1-year lag, 2-year lag, and 3-year lag would cover 1995-2000, 1994-2000, and 1993-2000 respectively.

$$GSWTrend_{jm} = \frac{\Sigma(Year_i - \overline{Year})(\frac{Nowater_{im}}{TotalGSW_{im}} - \overline{\frac{Nowater_{im}}{TotalGSW_{im}}})}{\Sigma(Year_i - \overline{Year})^2} \tag{3.1}$$

$$GSWLevel_{jm} = \frac{\Sigma(\frac{Nowater_{im}}{AreaMunicipality_{im}}) - \overline{(\frac{Nowater_{m}}{AreaMunicipality_{m}})}}{5} \tag{3.2}$$

3.2 Migration Metrics

The environmental pressures are usually considered as a push factor, not a pull factor. Thus, the net out-migration (out-migration - in-migration) at origin municipality, which equals the number of people who migrated out of a municipality during the 5 or 10 years, was computed. The population density differed among municipalities, so the number of net out-migration during a period, t, of the municipality, m, was divided by the municipality's population at the first year of its period, t_0, as shown in Eq. 3.3 for IPUMS-I and 3.4 for De.Sherbinin data.

$$NetOutMigRate_{mt} = \frac{(OutMig_{mt} - InMing_{mt})}{Population_{mt_0}} \tag{3.3}$$

$$NetOutMigRate_{mt} = \frac{(-1) \times (NetInMig_{mt})}{Population_{mt_0}} \tag{3.4}$$

3.3 All Migration Moves

Firstly, I began by employing Ordinary Least Square (OLS) multivariate regression models (Eq. 3.5) on IPUMS-I's and De.Sherbinin's net out-migration rate with UDEL climate metrics (Model 1.1 and 6.1, Table 3.1). All regressions were run with R using the plm package (Croissant and Millo, 2018), and all result tables were generated using R's stargazer package (Hlavac, 2018). Building up these models, the background climatology, BasePrecip and BaseTemp, were added (Model 1.2, 6,2). Then to observe how climate change influences migration differently between wet and dry municipalities, the terms where UDEL climate metrics interacted with the background precipitation and temperature were added (Model 1.3, 6.3). Eq. 3.5 shows the fully built-up model. The background climatology is the 30-year average of UDEL precipitation and temperature preceding the start year of the migration.

All of the models in this study include both municipality and time fixed effects, δ and γ respectively. These fixed effects reduced the bias caused by omitted variables. In other words,

Table 3.1: Summary of all models

Models	Dependent Variable	Independent Variables	Weights	Type
1.1	IPUMS net out-migration rate	Ttrend, Tvar, Ptrend, Pvar	None	OLS
1.2		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip		
1.3		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip, Interaction terms		
1.4	IPUMS net out-migration rate	Ttrend, Tvar, Ptrend, Pvar	rural pop	WLS
1.5		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip		
1.6		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip, Interaction terms		
1.7	IPUMS rural-urban out-migration rate	Ttrend, Tvar, Ptrend, Pvar	None	OLS
1.8		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip		
1.9		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip, Interaction terms		
2.1	IPUMS net out-migration rate	Nowater Trend	None	OLS
2.2		Nowater Trend, BaseTemp, BasePrecip		
2.3		Nowater Trend, BaseTemp, BasePrecip, Interaction terms		
2.4	IPUMS net out-migration rate	Nowater Trend	rural pop	WLS
2.5		Nowater Trend, BaseTemp, BasePrecip		
2.6		Nowater Trend, BaseTemp, BasePrecip, Interaction terms		
2.7	IPUMS rural-urban out-migration rate	Nowater Trend	None	OLS
2.8		Nowater Trend, BaseTemp, BasePrecip		
2.9		Nowater Trend, BaseTemp, BasePrecip, Interaction terms		
3.1	IPUMS net out-migration rate	Seaper Trend	None	OLS
3.2		Seaper Trend, BaseTemp, BasePrecip		
3.3		Seaper Trend, BaseTemp, BasePrecip, Interaction terms		
3.4	IPUMS net out-migration rate	Seaper Trend	rural pop	WLS
3.5		Seaper Trend, BaseTemp, BasePrecip		
3.6		Seaper Trend, BaseTemp, BasePrecip, Interaction terms		
3.7	IPUMS rural-urban out-migration rate	Seaper Trend	None	OLS
3.8		Seaper Trend, BaseTemp, BasePrecip		
3.9		Seaper Trend, BaseTemp, BasePrecip, Interaction terms		
4.1	IPUMS net out-migration rate	Ttrend, Tvar, Ptrend, Pvar, Nowa Level	None	OLS
4.2		Ttrend, Tvar, Ptrend, Pvar, Nowa Level, Interaction terms		
4.3	IPUMS net out-migration rate	Ttrend, Tvar, Ptrend, Pvar, Nowa Level	rural pop	WLS
4.4		Ttrend, Tvar, Ptrend, Pvar, Nowa Level, Interaction terms		
4.5	IPUMS rural-urban out-migration rate	Ttrend, Tvar, Ptrend, Pvar, Nowa Level	None	OLS
4.6		Ttrend, Tvar, Ptrend, Pvar, Nowa Level, Interaction terms		
5.1	IPUMS net out-migration rate	Ttrend, Tvar, Ptrend, Pvar, Seaper Level	None	OLS
5.2		Ttrend, Tvar, Ptrend, Pvar, Seaper Level, Interaction terms		
5.3	IPUMS net out-migration rate	Ttrend, Tvar, Ptrend, Pvar, Seaper Level	rural pop	WLS
5.4		Ttrend, Tvar, Ptrend, Pvar, Seaper Level, Interaction terms		
5.5	IPUMS rural-urban out-migration rate	Ttrend, Tvar, Ptrend, Pvar, Seaper Level	None	OLS
5.6		Ttrend, Tvar, Ptrend, Pvar, Seaper Level, Interaction terms		
6.1	De.Sherbinin net out-migration rate	Ttrend, Tvar, Ptrend, Pvar	None	OLS
6.2		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip		
6.3		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip, Interaction terms		
6.4	De.Sherbinin net out-migration rate	Ttrend, Tvar, Ptrend, Pvar	rural pop	WLS
6.5		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip		
6.6		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip, Interaction terms		
6.7	De.Sherbinin rural-urban net out-migration rate	Ttrend, Pvar, Ptrend, Pvar	None	OLS
6.8		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip		
6.9		Ttrend, Tvar, Ptrend, Pvar, BaseTemp, BasePrecip, Interaction terms		

heterogeneity constant over municipality or time (entity- or time-invariant factors) that could affect the migration pattern was removed by applying fixed effects to the models.

$$\begin{aligned} NetOutMigRate_{mt} = {} & \beta_0 + \gamma_t + \delta_m + \alpha_1 Ttrend_{mt} + \alpha_2 Tvar_{mt} + \alpha_3 Ptrend_{mt} + \alpha_4 Pvar_{mt} \\ & + \xi_1 BaseTemp_{mt} + \xi_2 BasePrecip_{mt} \\ & + \beta_1 (Ttrend_{mt} \times BaseTemp_{mt}) + \beta_2 (Ttrend_{mt} \times BasePrecip_{mt}) \\ & + \beta_3 (Tvar_{mt} \times BaseTemp_{mt}) + \beta_4 (Tvar_{mt} \times BasePrecip_{mt}) \\ & + \beta_5 (Ptrend_{mt} \times BaseTemp_{mt}) + \beta_6 (Ptrend_{mt} \times BasePrecip_{mt}) \\ & + \beta_7 (Pvar_{mt} \times BaseTemp_{mt}) + \beta_8 (Pvar_{mt} \times BasePrecip_{mt}) \end{aligned} \tag{3.5}$$

Secondly, IPUMS-I's net out-migration rate was regressed on the trend of Nowater (Model 2.1). De.Sherbinin was not regressed in this model since its temporal coverage did not overlap with GSW. Similar to Model 1.2 and 1.3, BaseTemp, BasePrecip, and the interaction terms were added to Model 2.1 (Model 2.2, 2.3, Eq. 3.6). Likewise, the influence of Seaper trend on migration was investigated using Model 3.1, 3.2, and 3.3 (Eq. 3.7).

$$\begin{aligned} NetOutMigRate_{mt} = {} & \beta_0 + \gamma_t + \delta_m + \alpha_1 NowaterTrend_{mt} + \xi_1 BaseTemp_{mt} + \xi_2 BasePrecip_{mt} \\ & + \beta_1 (NowaterTrend_{mt} \times BaseTemp_{mt}) + \beta_2 (NowaterTrend_{mt} \times BasePrecip_{mt}) \end{aligned} \tag{3.6}$$

$$\begin{aligned} NetOutMigRate_{mt} = {} & \beta_0 + \gamma_t + \delta_m + \alpha_1 SeaperTrend_{mt} + \xi_1 BaseTemp_{mt} + \xi_2 BasePrecip_{mt} \\ & + \beta_1 (SeaperTrend_{mt} \times BaseTemp_{mt}) + \beta_2 (SeaperTrend_{mt} \times BasePrecip_{mt}) \end{aligned} \tag{3.7}$$

Lastly, IPUMS-I's net out-migration rate was regressed on the UDEL climate metrics with GSW level as a background condition (Model 4.1-5.6). De.Sherbinin was not regressed since the temporal coverage did not overlap. The equations are shown in Eq.3.8 and Eq.3.9.

$$\begin{aligned} NetOutMigRate_{mt} = {} & \beta_0 + \gamma_t + \delta_m + \alpha_1 Ttrend_{mt} + \alpha_2 Tvar_{mt} + \alpha_3 Ptrend_{mt} + \alpha_4 Pvar_{mt} \\ & + \xi_1 NowaterLevel_{mt} \\ & + \beta_1 (Ttrend_{mt} \times NowaterLevel_{mt}) + \beta_2 (Tvar_{mt} \times NowaterLevel_{mt}) \\ & + \beta_3 (Ptrend_{mt} \times NowaterLevel_{mt}) + \beta_4 (Pvar_{mt} \times NowaterLevel_{mt}) \end{aligned} \tag{3.8}$$

$$\begin{aligned} NetOutMigRate_{mt} = {} & \beta_0 + \gamma_t + \delta_m + \alpha_1 Ttrend_{mt} + \alpha_2 Tvar_{mt} + \alpha_3 Ptrend_{mt} + \alpha_4 Pvar_{mt} \\ & + \xi_1 SeaperLevel_{mt} \\ & + \beta_1 (Ttrend_{mt} \times SeaperLevel_{mt}) + \beta_2 (Tvar_{mt} \times SeaperLevel_{mt}) \\ & + \beta_3 (Ptrend_{mt} \times SeaperLevel_{mt}) + \beta_4 (Pvar_{mt} \times SeaperLevel_{mt}) \end{aligned} \tag{3.9}$$

3.4 Rural-Urban Moves

I employed two methods to estimate the impacts of environmental stressors on rural-urban migration. The first one estimated it by weighting the models based on the fraction of the rural population. Thus, instead of OLS, the weights ($w = RuralPopulation_{mt}/Population_{mt}$) were added to run weighted least square (WLS) regression models (Model 1.4, 1.5, 1.6, 2.4, 2.5, 2.6, 3.4, 3.5, 3.6, 4.3, 4.4, 5.3, 5.4, 6.4, 6.5, and 6.6). This method did not require any filtering of migrants, so the implementation was simpler. However, whether these weights correctly represented the fraction of rural-urban migration out of all migration was uncertain.

Therefore, the second method estimated rural-urban moves more directly by picking migrants who have rural origin and urban destination. To do so, the IPUMS-I's variable, 'URBAN' in 1995, 2000, 2005, 2010, and 2015, was used. 'URBAN' records whether a household lived at an urban or rural locality in the survey year. Thus, an individuals' destination was determined as urban or rural based on URBAN in 2000, 2010, and 2015. Nonetheless, no variable told whether the origin, a place of residence five years prior, was urban or rural. Therefore, I defined every municipality as urban or rural based on each municipality's population in urban localities in 1995, 2005, and 2010. If a municipality did not have any urban localities, then the municipality was defined as rural. After that, individuals with rural origin (rural municipality) and urban destination (urban locality) were selected. Finally, these individuals were summed along with the origin municipalities. Then, the sum equaled the number of out-migrants at a municipality who moved from the rural municipalities to urban localities. One thing to note is that in-migration could not be computed here. Thus, out-migration was used instead of net out-migration.

Similarly, the rural-urban migration flow of De.Sherbinin data was estimated based on ISIMIP instead of URBAN. The calculation steps were as follows. First, the rural population in Mexico in 1970 was obtained from the World Bank Rural Population data (Bank). Secondly, the values of ISIMIP grids in 1970 were summed until the sum reached the World Bank's rural population. Thirdly, the summed grids were labeled as rural, and the rest was labeled as urban (Fig. 2.2(c)). Fourthly, De.Sherbinin data was re-gridded to match the spatial resolution of the labeled ISIMIP. Fifthly, every De.Sherbinin's grid was labeled identically as the labeled ISIMIP. Lastly, the rural De.Sherbinin grids were aggregated to estimate rural-urban migration (Fig. 2.1 c). These six steps were repeated for the data in 1980 and 1990. Additionally, the the values of ISIMIP rural grid cells were aggregated to the municipality level to obtain the rural population of each municipality (Fig. 2.2 d).

As described above, the rural-urban migration flow was estimated with both IPUMS-I and De.Sherbinin. However, they represented different flows. Whereas IPUMS-I captured people moving from rural municipalities to urban localities, De.Sherbinin captured people moving out of or into rural areas. Consequently, De.Sherbinin includes rural-rural migration between two municipalities. Also, De.Sherbinin's one contains movement within a municipality and international migration, unlike IPUMS-I. If a person moves from a rural grid to an urban grid within the same municipality, this person is counted towards De.Sherbinin's rural-urban migration. These differences made the magnitude of De.Sherbinin's rural-urban flow to be bigger than IPUMS-I, which was undesirable but was inevitable in this scheme.

On top of interpreting each model's result, two comparative analyses were implemented. First one compared the results of all migration moves with and without the rural population weights. Then, the second one compared the results of all migration moves with weights and the results of filtered rural-urban migration moves without weights. Moreover, to check if climate variation had a delayed effect on rural-urban migration, climate variables were lagged by 1, 2, and 3 years.

4 Result

Before discussing the regression results, three comparative analyses were done between UDEL and GSW Yearly, IPUMS-I and ISIMIP, and IPUMS-I and De.Sherbinin.

4.1 Comparative Analysis of UDEL and GSW

To understand the connection between precipitation/temperature and surface water, a comparative analysis of UDEL and GSW Yearly was carried out. Both UDEL and GSW Yearly are the spatio-temporal gridded data indicating water availability, but UDEL is temperature and precipitation data based on ground stations' measurements, while GSW Yearly is surface water data based on satellite measurements. To check the correlation between these two data sets, I computed Pearson's correlation coefficients between the 5-year trend of GSW (Nowater and Seaper) against UDEL 5-year trend (Ttrend and Ptrend) at the state and municipality levels for three periods (1996-2000, 2006-2010, 2011-2015) (Fig. 4.1). Ttrend showed no significant correlation between Nowater trend and Seaper trend at both state and municipality levels. These uncorrelations might be because the temperature was related to both evaporation and precipitation. Evaporation simply increases as temperature increases (Baier and Robertson, 1965). However, the relationship between precipitation and temperature differs depending on the season, moisture, background temperature, atmospheric circulation, and ocean circulation (Trenberth and Shea, 2005). Due to this complication, the correlation between temperature and global surface water might have been lost.

On the other hand, Ptrend and GSW Yearly trends were positively correlated at the state level, with $r_{seaper} = 0.305$ and $r_{nowater} = -0.305$. This positive correlation was consistent with previous research stating a positive correlation between precipitation and surface water (Prathumratana et al., 2008). However, despite this positive relationship at the state level, Ptrend and GSW Yearly were not correlated at the municipality level. The absence of their correlation suggested that the municipality's area is too small to capture the change in surface water dynamics.

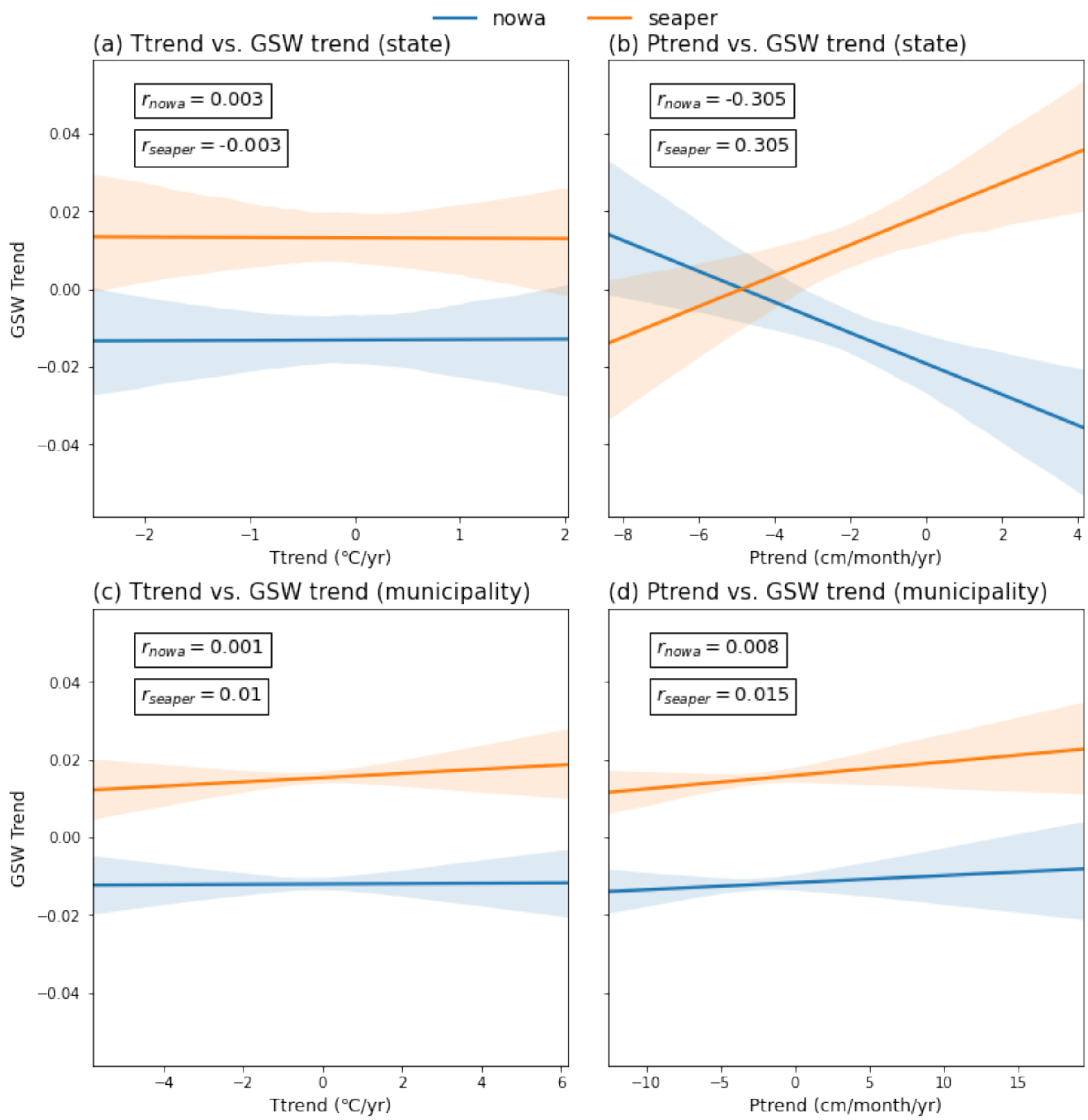

Figure 4.1: Comparison of UDEL and GSW Trends

4.2 Comparative Analysis of IPUMS and ISIMIP

I compared the municipalities' population derived from IPUMS in 1995 and ISIMIP in 1990. They matched well for most of the municipalities with the correlation coefficient of $r = 0.98$ (Fig. 4.2 a). In addition, the rural population was compared. IPUMS-I rural population is the number of people in the rural localities in 1995, while ISIMIP rural population is the number of people in the rural grids in 1990. Even though they correlate weaker than the total population, they match nicely with $r = 0.86$ (Fig. 4.2 b).

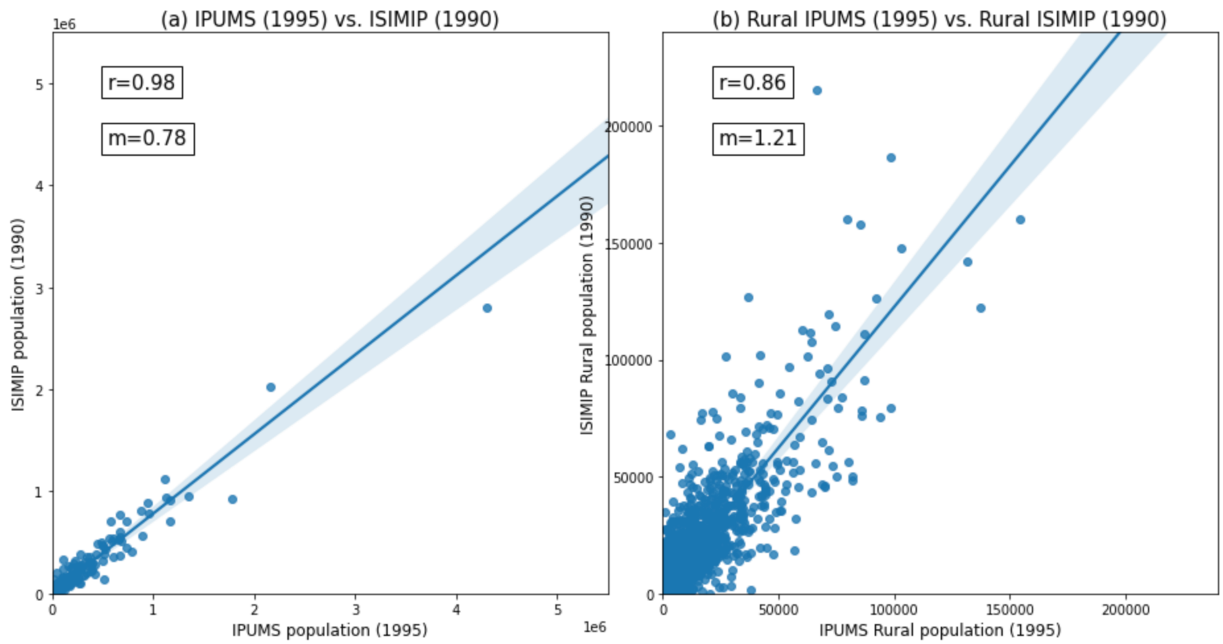

Figure 4.2: Comparison of IPUMS and ISIMIP

4.3 Comparative Analysis of IPUMS-I and De.Sherbinin

While IPUMS-I's net out-migration is solely from the census data (direct observation of migration), De.Sherbinin data was indirectly estimated migration from population data and the natural population increase (birth - death). Another difference is that while IPUMS-I includes only internal migration, De.Sherbinin data includes both internal and international migration. Therefore, I investigated how these differences were reflected in the outcome. The only overlapping period was 1995-2000, so net out-migration, in-migration, and out-migration derived from IPUMS-I (1995-2000) and De.Sherbinin data (1990's) were juxtaposed (Fig. 4.4). IPUMS-I's in-migration was calculated by counting the number of people who moved into a municipality, and out-migration was the number of individuals who moved out of a municipality during 1995-2000. On the other hand, De.Sherbinin data only provide the value of the net in-migration of each grid, so it was impossible to separate in-migration and out-migration flow. Thus, I assumed that the positive grids (in-migration¿out-migration) represented only in-migration and the negative grids (out-migration¿in-migration) represented only out-migration.

The net out-migration of IPUMS-I and De.Sherbinin showed a negative correlation ($r = -0.384$) with large uncertainty, indicating the inconsistency between the migration pattern of IPUMS-I and De.Sherbinin. This discrepancy was attributed to the two differences explained above. One is the difference in measurements (direct and indirect estimation), and the second is the involved migration pattern (international and internal). The number of international net out-migrants in the 1990s was estimated as 2583450 by summing all De.Sherbinin's grids in Mexico (Table 4.1). Thus, De.Sherbinin's estimate of the total out-migration (internal+international) was 12748863. Thus, more than 20% of the out-migration in Mexico must have consisted of the international migration in the 1990s. This significance of international migration matched with the conclusion of (Azose and Raftery, 2019). Compared to international out-migration, the international in-migration was much smaller 4.1, which made the correlation between IPUMS-I in-migration and De.Sherbinin in-migration stronger ($r = 0.793$), as shown in Fig. 4.4 b.

The 4.3 (a) and (c) show the net out-migration rate of IPUMS-I and De.Sherbinin respectively. As discussed above, the magnitude of De.Sherbinin's migration is larger, so (c) indicates higher migration rate in magnitude, which is likely due to international migration flow. Therefore, in the 4.3 (b) the country-level international migration rate was subtracted from the De.Sherbinin's net out-migration rate in all municipalities to obtain a rough approximate of internal migration rate. Since the average country-level international migration rate in 1970s, 1980s, and 1990s was 0.0041, (b) and (c) do not show significant difference. However, for some municipalities, such as the ones in Baja California, the migration rate became similar to the IPUMS-I values (a).

IPUMS was also used to calculate the international migration. IPUMS-I in 2000 records individuals who moved from foreign countries to Mexico during 1995-2000. The sum of these individuals' PERWT was 387902, which corresponded to the number of international in-migrants. However, Mexico's IPUMS-I did not provide information about international out-migration. Thus, IPUMS USA, another data collection IPUMS publishes, was used to count U.S.-bound out-migration. Based on IPUMS USA, 1961564 of people emigrated from Mexico to the U.S during 1995-2000. Since migration with U.S. destination composed more than 95% of the total international out-migration in Mexico in the 1990s (Azose and Raftery (2019)), I assumed the U.S.-bound migration equaled the total international out-migration from Mexico. As a result, the international net out-migration during 1995-2000 was $1961564 - 387902 = 1573662$ based on IPUMS. Thus, IPUMS's international net out-migration between 1995-2000 was about 60% of the De.Sherbinin's international net out-migration in the 1990s. Azose and Raftery (2019) showed that the international net out-migration increased from 1990-1995 to 1995-2000 by 40%, meaning about 58% of the total net out-migration in the 1990s was attributed to the second half period. This was consistent with my result, making these two data set more creditable measure of international migration flow.

Table 4.1: Comparison amoung three migration data sets: IPUMS-I, De.Sherbinin, and Azose and Raffery. Mexico-U.S. outmigration in 1995-2000 was calculated using IPUMS-USA.

		1970s	1980s	1990s	1995-2000	2005-2010	2010-2015
IPUMS-I	Mexico-U.S. outmig (IPUMS-USA)				1,961,564		
	International inmig				387,902	1,076,761	699,376
	Internal outmig				5,497,057	6,069,746	5,530,804
	Internal inmig				5,497,057	6,069,746	5,530,804
De.Sherbinin	International net outmig	1,785,713	3,872,914	2,583,450			
	Internal + International outmig	4,704,393	7,258,694	12,748,863			
	Internal + International inmig	2,918,680	3,385,779	10,165,413			
Azose and Raffery	Internaional net outmig			3,155,638	1,848,227	408,996	523,842
	International outmig			4,993,328	2,892,328	2,076,169	2,250,019
	International inmig			1,837,690	1,044,101	1,667,173	1,726,177

4.4 All Migration, OLS and WLS

UDEL Climate Metrics, UDEL Climatology

I began by estimating a model for UDEL climate metrics that influences all migration movement in Mexico. Then, the models were built up by adding background conditions, UDEL Climatology, and interaction terms. To explore the timing of the climate migration, four kinds of lags (lag 0, lag 1, lag 2, lag 3) were compared. For most of the models, climate variables lagged by two years showed the largest coefficients and the smallest standard deviations. Thus, in this section, only the models with lag 2 are presented. All the other lags' results are shown in the appendix.

Table 4.4 shows the results of Model 1.1 that includes four UDEL climate metrics as dependent variables with the 2-year lag. Building up to this model, Table 4.4 also shows the results of Model 1.2 and 1.3 with background climatology and the interaction terms. As a comparison, the right side of Table 4.4 shows the results of Model 1.4, 1.5, and 1.6, which are the WLS regression models where the weights are the proportions of the rural population. No significant coefficient was found in both unweighted and weighted models except Model 1.6. The interaction term between BasePrecip and Pvar, -0.003, was significant at 1% level. The 25 percentile of BasePrecip is 6.2401 cm/month and 75 percentile is 10.641 cm/month. Thus, the coefficient of Pvar would be $\alpha_4 + \beta_8 \times BasePrecip_{25\%} = 0.017 + -0.003 \times 6.240 = -0.0017$ for

Table 4.2: Descriptive statistics of IPUMS, UDEL, GSW with 2-year lag

	unit	count	mean	std	min	25%	50%	75%	max
IPUMS Net Out-migration rate (All Moves)		6993.0	-0.0019	0.1410	-6.7296	-0.0134	0.0024	0.0193	0.7081
IPUMS Net Out-migration rate (Rural-Urban)		5555.0	0.4065	0.5383	-9.2857	0.0043	0.0695	1.0000	1.0000
Ttrend	deg C/5-yr	6774.0	-0.0040	0.8174	-4.9352	-0.4680	-0.0588	0.3464	4.7891
Tvar		6774.0	-0.0400	0.1336	-0.5255	-0.1367	-0.0504	0.0424	0.3978
Ptrend	cm/month/5-yr	6774.0	-1.5333	1.9403	-10.1211	-2.7634	-1.3457	-0.2840	13.4648
Pvar		6774.0	-0.1293	0.2002	-0.6379	-0.2504	-0.1396	-0.0155	0.8222
BasePrecip	cm/month	6981.0	9.1912	5.1354	0.7062	6.2401	7.8944	10.6413	34.7773
BaseTemp	deg C	6981.0	19.9312	4.0909	9.6839	16.7826	19.8647	23.0628	29.2244
Nowater Level		6993.0	0.3151	0.2817	0.0000	0.0639	0.2647	0.4931	1.0000
Seaper Level		6993.0	0.4888	0.3364	0.0000	0.1417	0.5656	0.7811	1.0000
Nowater Trend		6993.0	-0.0095	0.0421	-0.2143	-0.0229	-0.0003	0.0010	0.2143
Seaper Trend		6993.0	0.0113	0.0419	-0.2143	-0.0005	0.0008	0.0244	0.2143

Table 4.3: Descriptive statistics of De.Sherbinin and UDEL at with 2-year lag

1970's, 1980's 1990's	**unit**	count	mean	std	min	25%	50%	75%	max
De.Sherbinin Net out-migration rate		6993.0	0.1806	0.2308	-1.5841	0.0977	0.1715	0.2556	7.4448
De.Sherbinin Net out-migration rate (Rural Grids)		6788.0	0.2315	1.1341	-46.2841	0.1186	0.1956	0.2999	35.1978
Ttrend	deg C/decade	6774.0	0.1287	0.4907	-3.6022	-0.1773	0.0984	0.3989	3.1718
Tvar		6774.0	-0.0030	0.1202	-0.4226	-0.0803	-0.0162	0.0621	1.1905
Ptrend	cm/month/decade	6774.0	-0.4067	1.8603	-14.1732	-1.1517	-0.4338	0.2136	17.4620
Pvar		6774.0	0.0224	0.2815	-0.6639	-0.1185	-0.0188	0.1006	3.5071
BasePrecip	cm/month	6981.0	9.1902	5.3043	0.6355	6.1416	7.8892	10.6625	36.0459
BaseTemp	deg C	6981.0	19.8842	4.0651	9.6506	16.6758	19.8548	23.0556	28.9992

dry municipalities, and $\alpha_4 + \beta_8 \times BasePrecip_{75\%} = 0.017 + -0.003 \times 10.641 = -0.015$ for wet municipalities. This means that at wetter municipalities, 1 unit change in Pvar would induce a decrease in net out-migration rate by 1.66 % more than at drier municipalities. The precipitation variability has almost no effect at drier municipalities. Since this significance was only seen in the weighted model, 1.6, not in the unweighted model, 1.3, the difference of Pvar's influence on net out-migration rate between dry and wet municipalities was likely more prominent for rural municipalities.

Table 4.5 shows the results of the same models, 6.1, 6.2, 6.3, 6.4, 6.5 and 6.6, where the De.Sherbinin's net out-migration rate is the independent variable and UDEL is the dependent variable. Model 6.1 showed a positive effect of the temperature trend. This positive relationship between temperature and net out-migration rate was found by Nawrotzki et al. (2013) as well. Model 6.1 also showed a negative effect of the precipitation variability on the De.Sherbinin's net out-migration rate. Previous research, however, have proposed that the drought or excessive precipitation causes the net out-migration to increase (Nawrotzki et al. (2013), Nawrotzki et al.

Table 4.4: Results of the models estimating the influence of the UDEL metrics and climatology on all IPUMS-I net out-migration, Lag2

	Lag 2					
	All Moves			Rural-Urban (weighted)		
	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 1.5	Model 1.6
	b std					
Ttrend	0.001 (0.001)	0.0005 (0.001)	−0.003 (0.006)	0.001 (0.001)	0.001 (0.001)	−0.006 (0.006)
Ptrend	0.0001 (0.0005)	0.0001 (0.0005)	0.00004 (0.002)	−0.0004 (0.0004)	−0.0003 (0.0004)	−0.0004 (0.002)
Tvar	−0.005 (0.007)	−0.005 (0.007)	−0.030 (0.036)	0.0002 (0.007)	−0.00001 (0.007)	0.005 (0.034)
Pvar	−0.003 (0.005)	−0.002 (0.006)	0.003 (0.029)	0.002 (0.005)	0.003 (0.005)	0.017 (0.027)
BaseTemp		−0.002 (0.011)	−0.002 (0.012)		0.003 (0.011)	0.006 (0.011)
BasePrecip		0.002 (0.002)	0.001 (0.003)		0.002 (0.002)	0.002 (0.002)
BaseTemp:Ttrend			0.0002 (0.0003)			0.001* (0.0003)
BasePrecip:Ttrend			−0.0001 (0.0003)			−0.0004* (0.0002)
BaseTemp:Ptrend			0.00003 (0.0001)			−0.00004 (0.0001)
BasePrecip:Ptrend			−0.00005 (0.0001)			0.0001 (0.0001)
BaseTemp:Tvar			0.001 (0.002)			−0.0001 (0.002)
BasePrecip:Tvar			0.001 (0.001)			0.0005 (0.001)
BaseTemp:Pvar			0.001 (0.001)			0.001 (0.001)
BasePrecip:Pvar			−0.002 (0.001)			−0.003*** (0.001)
Observations	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.0003	0.0005	0.001	0.0001	0.0002	0.001
Adjusted R^2	-0.501	-0.502	-0.503	-0.502	-0.502	-0.504
F Statistic	0.356 (df = 4; 4510)	0.355 (df = 6; 4508)	0.463 (df = 14; 4500)	0.564 (df = 4; 4510)	0.611 (df = 6; 4508)	1.229 (df = 14; 4500)
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

(2017)), which is opposite of what the Pvar coefficient implied.

In Model 6.3, the interaction term between Tvar and BasePrecip was $0.020, p < 0.01$. Thus, Tvar's coefficient is $\alpha_2 + \beta_4 \times BasePrecip_{25\%} = 0.222 + 0.020 \times 6.240 = 0.347$ at dry municipalities, and $\alpha_2 + \beta_4 \times BasePrecip_{75\%} = 0.222 + 0.020 \times 10.641 = 0.435$ at wet municipalities. Net out-migration induced by the temperature variability is higher by about 9% at wet municipalities than dry municipalities. Similarly, the interaction term between Tvar and BaseTemp was significant at 1% level, suggesting the differences in the temperature variability's impact on migration between hotter and colder municipalities. The weighted models, 6.4, 6.5, and 6.6 gave almost the same results as the unweighted models. Therefore, the degree of urbanization in a municipality was either unassociated with the extent of climate migration or inaccurate measure of rural-urban migration flow.

It was surprising how De.Sherbinin net out-migration rate were much more closely correlated with UDEL climate metrics than IPUMS-I net out-migration rate. Most of the parameters in Table 4.5 were significant at 5% level, while only one parameter was significant in Table 4.4. The reason behind this difference was unclear, but one possible cause was the difference in how environmental stressors were related to internal and international migration. As explained in the data section, IPUMS-I captures solely internal migration, while De.Sherbinin data captures both internal and international migration. Thus, the climate migration could have more prominent for the cross-boarder displacement. The comparison of IPUMS-I and De.Sherbinin is further discussed in the discussion section. However, further investigation must be carried out to find out the cause of this unexpected differences in results.

GSW Trend, UDEL Climatology

Secondly I looked at the influence of GSW trend on IPUMS-I migration, not De.Sherbinin data because its temporal coverage does not overlap with GSW. Table 4.6 shows the results of Model 2.1-2.8. Model 2.1, 2.2, 2.4, and 2.5 had no significant parameters, meaning the trend of

Table 4.5: Results of the models estimating the influence of UDEL climate metrics on all De.Sherbinin net out-migration, Lag2

	Lag 2					
		All Moves			Rural-Urban (Weighted)	
	Model 6.1	Model 6.2	Model 6.3	Model 6.4	Model 6.5	Model 6.6
	b std					
Ttrend	0.036*** (0.004)	0.019*** (0.006)	−0.0003 (0.025)	0.038*** (0.005)	0.022*** (0.006)	−0.009 (0.026)
Tvar	0.036* (0.020)	0.028 (0.021)	0.222** (0.104)	0.018 (0.021)	0.047** (0.020)	0.216* (0.122)
Ptrend	0.014*** (0.002)	0.017*** (0.002)	0.049*** (0.010)	0.012*** (0.002)	0.018*** (0.002)	0.044*** (0.010)
Pvar	−0.050*** (0.013)	−0.032** (0.014)	−0.058 (0.071)	−0.046*** (0.014)	−0.040*** (0.013)	−0.024 (0.074)
BaseTemp		−0.115*** (0.021)	−0.095*** (0.021)		−0.079*** (0.020)	−0.130*** (0.022)
BasePrecip		0.031*** (0.010)	0.035*** (0.010)		0.028*** (0.010)	0.036*** (0.011)
BaseTemp:Ttrend			0.001 (0.001)			0.001 (0.001)
BasePrecip:Ttrend			0.0001 (0.001)			0.00002 (0.001)
BaseTemp:Ptrend			−0.001** (0.001)			−0.001* (0.001)
BasePrecip:Ptrend			−0.0004 (0.0004)			−0.0003 (0.0004)
BaseTemp:Tvar			−0.017*** (0.005)			−0.016** (0.006)
BasePrecip:Tvar			0.020*** (0.005)			0.016*** (0.005)
BaseTemp:Pvar			0.001 (0.004)			−0.001 (0.004)
BasePrecip:Pvar			−0.003 (0.002)			−0.001 (0.002)
Observations	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.032	0.038	0.049	0.032	0.040	0.048
Adjusted R^2	-0.454	-0.445	-0.431	-0.454	-0.443	-0.433
F Statistic	30.783*** (df = 4; 4510)	29.603*** (df = 6; 4508)	16.620*** (df = 14; 4500)	30.783*** (df = 4; 4510)	31.023*** (df = 6; 4508)	15.004*** (df = 14; 4500)

Note: *p<0.1; **p<0.05; ***p<0.01

nowater areas did not have any significant effect on IPUMS-I migration rate.

Nonetheless, in Model 2.3, the interaction term between nowater trend and background precipitation had a significance at 5% level ($\beta_2 = -0.008, p < 0.05$), meaning that the difference of nowater trend's impact on migration between dry and wet municipality was significant. Nowater trend affect net out-migration rate by $\alpha_1 + \beta_2 \times BasePrecip_{25\%} = -0.052 - 0.008 \times 6.240 = -0.102$ at drier municipalities, while it affects migration rate by $\alpha_1 + \beta_2 \times BasePrecip_{75\%} = -0.052 - 0.008 \times 10.641 = -0.137$ at wetter municipalities. Thus, the wetter municipalities experience larger in-migration flow than the drier municipalities when nowater area increased. However, the signs and the magnitude of these coefficient were not robust. Nowater Trend was estimated to have a positive effect on out-migration in Model 2.1, but it was negative in Model 2.3 for both dry and wet municipalities, which hindered to make a conclusive answer.

The weighted models 2.6 suggested significance of both interaction terms ($\beta_1 = 0.009, \beta_2 = -0.006, p < 0.05$). At colder municipalities, nowater trends' impact on net out-migration rate is $\alpha_1 + \beta_2 \times BaseTemp_{25\%} = -0.106 - 0.009 \times 16.78 = -0.257$. At hotter municipalities, nowater trends' impact on net out-migration rate is $\alpha_1 + \beta_2 \times BaseTemp_{75\%} = -0.106 - 0.009 \times 23.06 = -0.314$. Thus, for hotter municipalities, one unit increase in nowater trends causes about 5% more in-migration than colder municipalities. This interaction term between nowater trend and BaseTemp was only significant with the rural population weights, insisting that an association of background temperature with the linkage between nowater areas and migration is stronger at rural municipalities. Nonetheless, similar to the interaction terms in Model 2.3, these coefficients' magnitude and signs were not robust. Thus, I would only conclude that how nowater trend affects the migration at rural municipalities depends on the background temperature of the municipalities.

Table 4.6: Results of the models estimating the influence of Nowater Trend and the UDEL climatology on all IPUMS-I net out-migration, Lag2

	Lag 2					
	All Moves			Rural-Urban (weighted)		
	Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 2.5	Model 2.6
	b std					
tre_nowa	0.015 (0.018)	0.015 (0.018)	−0.052 (0.088)	0.009 (0.017)	0.009 (0.017)	−0.106 (0.084)
BaseTemp		−0.003 (0.009)	−0.003 (0.009)		−0.001 (0.008)	−0.001 (0.008)
BasePrecip		0.003 (0.002)	0.003 (0.002)		0.003 (0.002)	0.003 (0.002)
tre_nowa:BaseTemp			0.007 (0.005)			0.009** (0.004)
tre_nowa:BasePrecip			−0.008** (0.004)			−0.006** (0.003)
Observations	6,993	6,981	6,981	6,993	6,981	6,981
R^2	0.0001	0.0005	0.002	0.0001	0.0004	0.001
Adjusted R^2	-0.501	-0.501	-0.500	-0.501	-0.501	-0.500
F Statistic	0.639 (df = 1; 4659)	0.719 (df = 3; 4649)	1.449 (df = 5; 4647)	0.278 (df = 1; 4659)	0.879 (df = 3; 4649)	1.828 (df = 5; 4647)
Note:						*p<0.1; **p<0.05; ***p<0.01

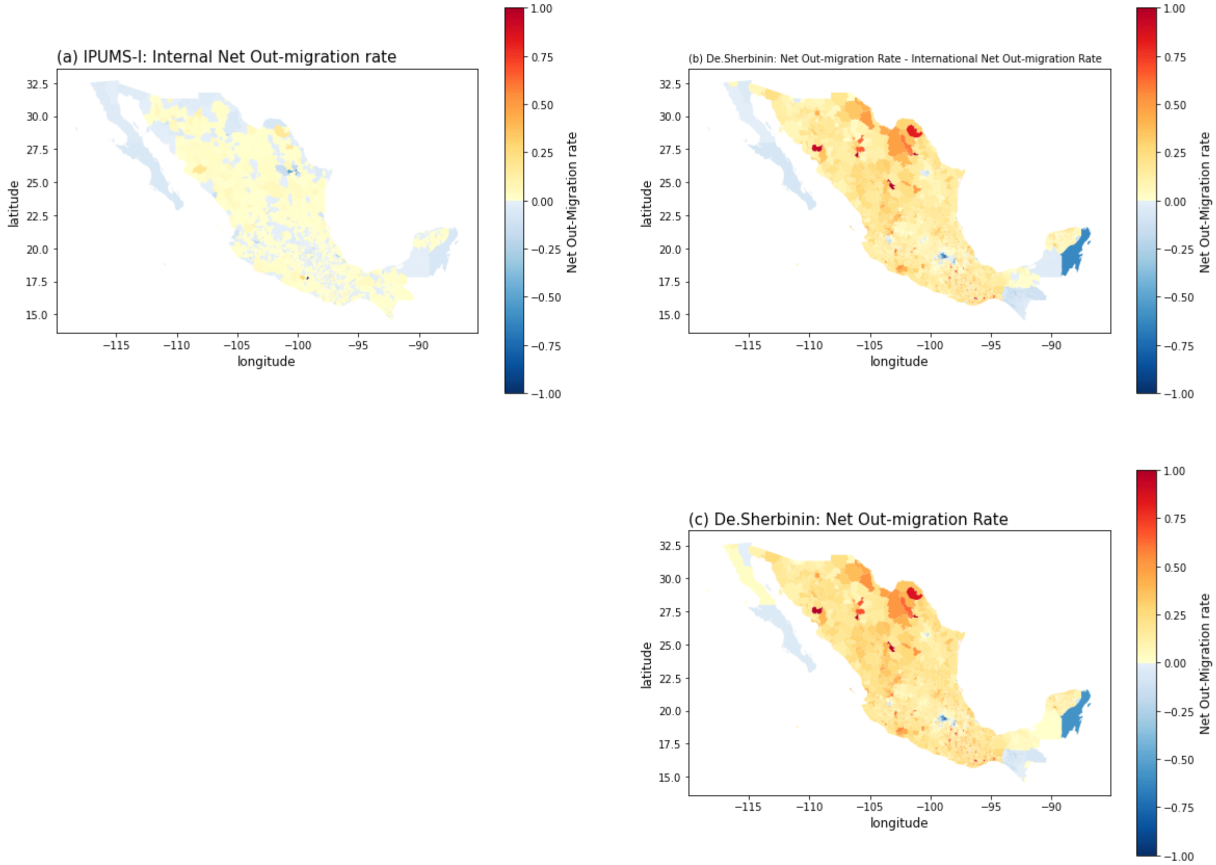

Figure 4.3: IPUMS and De.Sherbinin-International Migration Rate

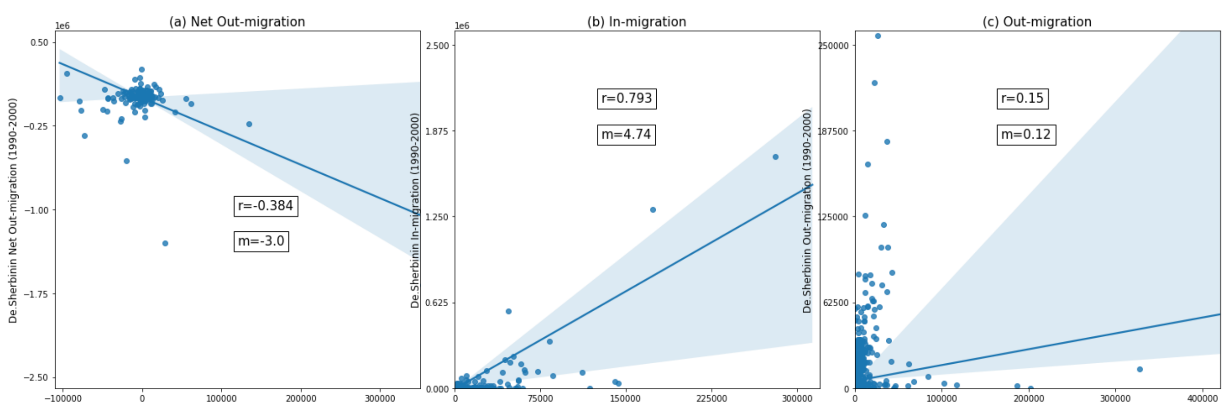

Figure 4.4: Comparison of IPUMS and De.Sherbinin

Table 4.7 shows the results of Model 3.1-3.8. All of the models had no significant parametrs at 5% level except Model 3.6. Model 3.6's result had one significant variable at 5% level, the interaction terms between Seaper Trend and BasePrecip ($\beta_2 = 0.007$). Seaper Trend influenced net out-migration rate significantly differently between wet and dry rural municipalities. The impact of Seaper Trend on migration rate at dry municipalities is $\alpha_1 + \beta_2 \times BasePrecip_{25\%} = 0.080 + 0.007 \times 6.240 = 0.124$ and at wet municipalities is $\alpha_1 + \beta_2 \times BasePrecip_{75\%} = 0.080 + 0.007 \times 10.641 = 0.154$, so the difference is 0.031. Seaper Trend has higher impact on net out-migration rate by 0.031 at wetter municipalities. These results should be common with the nowater trend since seaper is a counterpart of nowater.

Table 4.7: Results of the models estimating the influence of Seaper Trend and the UDEL climatology on all IPUMS-I net out-migration, Lag2

	Lag 2					
	All Moves			Rural-Urban (weighted)		
	Model 3.1	Model 3.2	Model 3.3	Model 3.4	Model 3.5	Model 3.6
tre_seaper	−0.018	−0.018	0.043	−0.016	−0.016	0.080
	(0.018)	(0.018)	(0.087)	(0.017)	(0.017)	(0.083)
BaseTemp		−0.003	−0.003		−0.001	−0.001
		(0.009)	(0.009)		(0.008)	(0.008)
BasePrecip		0.003	0.003		0.003	0.003
		(0.002)	(0.002)		(0.002)	(0.002)
tre_seaper:BaseTemp			−0.007			−0.008*
			(0.005)			(0.004)
tre_seaper:BasePrecip			0.007*			0.007**
			(0.004)			(0.003)
Observations	6,993	6,981	6,981	6,993	6,981	6,981
R^2	0.0002	0.001	0.002	0.0002	0.001	0.001
Adjusted R^2	-0.500	-0.501	-0.500	-0.500	-0.501	-0.500
F Statistic	0.960 (df = 1; 4659)	0.829 (df = 3; 4649)	1.412 (df = 5; 4647)	0.939 (df = 1; 4659)	1.099 (df = 3; 4649)	1.983* (df = 5; 4647)
Note:						*p<0.1; **p<0.05; ***p<0.01

UDEL Climate Metrics, GSW Level

I employed Nowater and Seaper level as a background condition of each municipality instead of UDEL climatology (Model 4.1-4.6 and Model 5.1-5.6). Table 4.8 and 4.9 show the results of the models when nowater level and seaper level were added relatively. Unfortunately none of the variables showed significance. Thus, the relationship between the amount of surface water in each municipality and how temperature and precipitation affected the net out-migration rate was not captured in the models.

Table 4.8: Results of the models estimating the influence of the UDEL metrics and Nowater Level on all IPUMS-I net out-migration, Lag2

	Lag 2					
	All Moves			Rural-Urban (weighted)		
	Model 1.1	Model 4.1	Model 4.2	Model 1.4	Model 4.3	Model 4.4
	b std					
Ttrend	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Tvar	−0.005 (0.007)	−0.005 (0.007)	−0.005 (0.008)	0.0002 (0.007)	0.0001 (0.007)	0.001 (0.007)
Ptrend	0.0001 (0.0005)	0.00005 (0.0005)	0.0001 (0.0005)	−0.0004 (0.0004)	−0.0004 (0.0004)	−0.0003 (0.0004)
Pvar	−0.003 (0.005)	−0.003 (0.005)	−0.004 (0.006)	0.002 (0.005)	0.002 (0.005)	0.002 (0.005)
nowa		−0.407 (0.264)	−0.354 (0.313)		−0.200 (0.318)	−0.250 (0.387)
Ttrend:nowa			−0.182* (0.108)			−0.110 (0.126)
nowa:Tvar			−0.220 (0.790)			−0.366 (0.917)
nowa:Ptrend			−0.031 (0.058)			−0.019 (0.067)
nowa:Pvar			0.234 (0.780)			−0.282 (0.960)
Observations	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.0003	0.001	0.002	0.0001	0.0003	0.001
Adjusted R^2	-0.501	-0.501	-0.501	-0.502	-0.502	-0.502
F Statistic	0.356 (df = 4; 4510)	0.760 (df = 5; 4509)	0.822 (df = 9; 4505)	0.564 (df = 4; 4510)	0.531 (df = 5; 4509)	0.471 (df = 9; 4505)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 4.9: Results of the models estimating the influence of the UDEL metrics and Seaper Level on all IPUMS-I net out-migration, Lag2

	Lag 2					
	All Moves			Rural-Urban (weighted)		
	Model 1.4	Model 4.3	Model 4.4	Model 1.7	Model 4.5	Model 4.6
	b std					
Ttrend	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Tvar	−0.005 (0.007)	−0.005 (0.007)	−0.004 (0.007)	0.0002 (0.007)	0.0001 (0.007)	0.001 (0.007)
Ptrend	0.0001 (0.0005)	0.00005 (0.0005)	0.0001 (0.0005)	−0.0004 (0.0004)	−0.0004 (0.0004)	−0.0003 (0.0004)
Pvar	−0.003 (0.005)	−0.003 (0.005)	−0.004 (0.006)	0.002 (0.005)	0.002 (0.005)	0.002 (0.005)
seaper		0.399 (0.263)	0.276 (0.273)		0.193 (0.316)	0.083 (0.330)
Ttrend:seaper			−0.028 (0.023)			−0.019 (0.025)
seaper:Tvar			−0.070 (0.114)			−0.117 (0.168)
seaper:Ptrend			−0.005 (0.013)			−0.007 (0.014)
seaper:Pvar			0.067 (0.179)			0.024 (0.186)
Observations	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.0003	0.001	0.002	0.0001	0.0003	0.001
Adjusted R^2	-0.501	-0.501	-0.501	-0.502	-0.502	-0.502
F Statistic	0.356 (df = 4; 4510)	0.743 (df = 5; 4509)	0.785 (df = 9; 4505)	0.564 (df = 4; 4510)	0.526 (df = 5; 4509)	0.538 (df = 9; 4505)
Note:						*p<0.1; **p<0.05; ***p<0.01

4.5 Rural-Urban Migration, WLS and OLS

I compared two methods to capture the characteristics of rural-urban migration flow: (1) using the proportion of the rural population in each municipality as weights to run the WLS regression models (Model 1.4-1.6, 2.4-2.6, 3.4-3.6, 4.3, 4.4, 5.3, 5.4 6.4-6.6), and (2) selecting migrants who migrated from rural to urban regions (Model 1.7-1.9, 2.7-2.9, 3.7-3.9, 4.5, 4.6, 5.5, 5.6, 6.7-6.9). The WLS regression models were simpler to implement, but it was uncertain whether the proportion of the rural population accurately represented the size of rural-urban migration flow. Therefore, in the second method, migrants were selected based upon whether the residence was rural or urban before running a regression to observe how climate affects rural-urban migration directly. This method required an extra step to filter and did not filter perfectly but can be a more accurate measure.

Table 4.10 shows the results of Model 1.4-1.9. There was no significant difference between Model 1.4 and 1.7, and between 1.5 and 1.8, although the coefficients' signs differed for some parameters. The interaction term between Ttrend and BasePrecip became significant at 1% level when rural-urban migration was selected in Model 1.9, but the interaction term between Pvar and BasePrecip lost its significance compared to Model 1.6. Since they were not consistent, it was difficult to say which is a better way to investigate rural-urban climate migration based on the results.

Although the results are less creditable due to inconsistency, the significance of the interaction term between Ttrend and BasePrecip might indicate the risk of humid heat. This term's coefficient was 0.003, the 25 percentile of the precipitation was 6.2401, and the 75 percentile of the precipitation was 10.6413. Therefore, the difference of Ttrend's impact on migration between wet and dry municipalities is $(10.6413 - 6.2401) \times 0.003 = 0.013203$, which means that one unit increase in temperature trend causes 1.32% more out-migration at the wetter municipalities. When humidity is high, the difference between wet bulb and dry bulb temperature becomes small, meaning less water can evaporate into the air and can harm human health. Sherwood and Huber

(2010) warmed that humans suffer from hyperthermia when the wet-bulb temperature exceeds 35 °C for an extended time. Therefore, an increase in temperature at wetter municipalities might have caused more out-migration due to humid heat.

Table 4.10: Results of the models estimating the influence of the UDEL metrics and climatology on Rural-Urban IPUMS-I net out-migration, Lag2

	Lag 2					
	Rural-Urban (weighted)			Rural-Urban (filtered)		
	Model 1.4	Model 1.5	Model 1.6	Model 1.7	Model 1.8	Model 1.9
	b std					
Ttrend	0.001 (0.001)	0.001 (0.001)	−0.006 (0.006)	0.002 (0.004)	−0.0001 (0.005)	−0.012 (0.025)
Ptrend	−0.0004 (0.0004)	−0.0003 (0.0004)	−0.0004 (0.002)	0.001 (0.002)	0.001 (0.002)	0.004 (0.010)
Tvar	0.0002 (0.007)	−0.00001 (0.007)	0.005 (0.034)	−0.042 (0.031)	−0.041 (0.032)	−0.040 (0.155)
Pvar	0.002 (0.005)	0.003 (0.005)	0.017 (0.027)	−0.013 (0.023)	−0.008 (0.024)	0.054 (0.128)
BaseTemp		0.003 (0.011)	0.006 (0.011)		−0.030 (0.050)	−0.049 (0.052)
BasePrecip		0.002 (0.002)	0.002 (0.002)		0.007 (0.010)	0.008 (0.011)
Ttrend:BaseTemp			0.001* (0.0003)			−0.001 (0.001)
Ttrend:BasePrecip			−0.0004* (0.0002)			0.003*** (0.001)
BaseTemp:Ptrend			−0.00004 (0.0001)			0.00000 (0.0005)
BasePrecip:Ptrend			0.0001 (0.0001)			−0.0002 (0.0005)
BaseTemp:Tvar			−0.0001 (0.002)			0.0001 (0.008)
BasePrecip:Tvar			0.0005 (0.001)			−0.004 (0.006)
BaseTemp:Pvar			0.001 (0.001)			−0.007 (0.006)
BasePrecip:Pvar			−0.003*** (0.001)			0.010 (0.006)
Observations	6,774	6,774	6,774	5,378	5,378	5,378
R^2	0.0001	0.0002	0.001	0.001	0.001	0.004
Adjusted R^2	-0.502	-0.502	-0.504	-0.538	-0.538	-0.537
F Statistic	0.564 (df = 4; 4510)	0.611 (df = 6; 4508)	1.229 (df = 14; 4500)	0.657 (df = 4; 3494)	0.552 (df = 6; 3492)	1.029 (df = 14; 3484)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 4.11, 4.12, 4.13, and 4.14 compare the results of two kinds of the regressions on rural-urban out-migration rate and GSW (Model 2.4-2.9, 3.4-3.9, 4.3-4.6, 5.3-5.6). In general,

when an independent variable was the selected rural-urban migrants, the standard deviation got larger, resulting in losing statistical significance. For example, in Model 2.9, the interaction term between Nowater trend and BaseTemp had the same coefficients as the one in Model 2.6, but the standard deviation was 0.022, which was much larger than the one in Model 2.6, 0.004. As a result, the statistical significance was lost. Thus, using weights can be useful to identify the climate effect on migration when the sample size is small since filtering rural-urban migration might reduce the sample size too much. Another possibility of losing importance was that other types of movement than rural-urban migration were more closely related to climate change. These types of displacement have to be separately investigated to identify the most important type of displacement in terms of climate migration.

Table 4.11: Results of the models estimating the influence of Nowater Trend and the UDEL climatology on Rural-Urban IPUMS-I net out-migration, Lag2

	Lag 2					
	Rural-Urban (weighted)			Rural-Urban (filtered)		
	Model 2.4	Model 2.5	Model 2.6	Model 2.7	Model 2.8	Model 2.9
	b std					
tre_nowa	0.009 (0.017)	0.009 (0.017)	−0.106 (0.084)	0.051 (0.087)	0.050 (0.087)	0.129 (0.418)
BaseTemp		−0.001 (0.008)	−0.001 (0.008)		−0.023 (0.043)	−0.022 (0.043)
BasePrecip		0.003 (0.002)	0.003 (0.002)		0.006 (0.010)	0.007 (0.010)
tre_nowa:BaseTemp			0.009^{**} (0.004)			0.009 (0.022)
tre_nowa:BasePrecip			-0.006^{**} (0.003)			−0.025 (0.017)
Observations	6,993	6,981	6,981	5,555	5,549	5,549
R^2	0.0001	0.0004	0.001	0.0001	0.0003	0.001
Adjusted R^2	-0.501	-0.501	-0.500	-0.536	-0.537	-0.537
F Statistic	0.278 (df = 1; 4659)	0.879 (df = 3; 4649)	1.828 (df = 5; 4647)	0.346 (df = 1; 3615)	0.316 (df = 3; 3609)	0.615 (df = 5; 3607)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 4.12: Results of the models estimating the influence of Seaper Trend and the UDEL climatology on Rural-Urban IPUMS-I net out-migration, Lag2

	Lag 2					
	Rural-Urban (weighted)			Rural-Urban (filtered)		
	Model 3.4	Model 3.5	Model 3.6	Model 3.7	Model 3.8	Model 3.9
	b std					
tre_seaper	−0.016 (0.017)	−0.016 (0.017)	0.080 (0.083)	−0.018 (0.087)	−0.016 (0.088)	−0.080 (0.416)
BaseTemp		−0.001 (0.008)	−0.001 (0.008)		−0.023 (0.043)	−0.022 (0.043)
BasePrecip		0.003 (0.002)	0.003 (0.002)		0.006 (0.010)	0.007 (0.010)
tre_seaper:BaseTemp			-0.008^{*} (0.004)			−0.009 (0.022)
tre_seaper:BasePrecip			0.007^{**} (0.003)			0.024 (0.017)
Observations	6,993	6,981	6,981	5,555	5,549	5,549
R^2	0.0002	0.001	0.001	0.00001	0.0002	0.001
Adjusted R^2	-0.500	-0.501	-0.500	-0.536	-0.537	-0.537
F Statistic	0.939 (df = 1; 4659)	1.099 (df = 3; 4649)	1.983^{*} (df = 5; 4647)	0.040 (df = 1; 3615)	0.218 (df = 3; 3609)	0.519 (df = 5; 3607)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 4.13: Results of the models estimating the influence of the UDEL metrics and Nowater Level on Rural-Urban IPUMS-I net out-migration, Lag2

	Lag 2					
	Rural-Urban (weighted)			Rural-Urban (filtered)		
	Model 1.4	Model 4.3	Model 4.4	Model 1.7	Model 4.5	Model 4.6
	b std					
Ttrend	0.001	0.001	0.001	0.002	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.005)
Ptrend	−0.0004	−0.0004	−0.0003	0.001	0.001	0.002
	(0.0004)	(0.0004)	(0.0004)	(0.002)	(0.002)	(0.002)
Tvar	0.0002	0.0001	0.001	−0.042	−0.043	−0.044
	(0.007)	(0.007)	(0.007)	(0.031)	(0.031)	(0.033)
Pvar	0.002	0.002	0.002	−0.013	−0.013	−0.016
	(0.005)	(0.005)	(0.005)	(0.023)	(0.023)	(0.024)
nowa		−0.200	−0.250		−0.990	−1.272
		(0.318)	(0.387)		(1.052)	(1.376)
Ttrend:nowa			−0.110			−0.234
			(0.126)			(0.476)
nowa:Tvar			−0.366			0.530
			(0.917)			(3.894)
nowa:Ptrend			−0.019			−0.227
			(0.067)			(0.303)
nowa:Pvar			−0.282			2.006
			(0.960)			(4.217)
Observations	6,774	6,774	6,774	5,378	5,378	5,378
R^2	0.0001	0.0003	0.001	0.001	0.001	0.001
Adjusted R^2	-0.502	-0.502	-0.502	-0.538	-0.538	-0.539
F Statistic	0.564 (df = 4; 4510)	0.531 (df = 5; 4509)	0.471 (df = 9; 4505)	0.657 (df = 4; 3494)	0.703 (df = 5; 3493)	0.496 (df = 9; 3489)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 4.14: Results of the models estimating the influence of the UDEL metrics and Nowater Level on Rural-Urban IPUMS-I net out-migration, Lag2

	Lag 2					
	Rural-Urban (weighted)			Rural-Urban (filtered)		
	Model 1.4	Model 5.3	Model 5.4	Model 1.7	Model 5.5	Model 5.6
	b std					
Ttrend	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.004)	0.002 (0.004)	0.003 (0.004)
Ptrend	−0.0004 (0.0004)	−0.0004 (0.0004)	−0.0003 (0.0004)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Tvar	0.0002 (0.007)	0.0001 (0.007)	0.001 (0.007)	−0.042 (0.031)	−0.043 (0.031)	−0.042 (0.032)
Pvar	0.002 (0.005)	0.002 (0.005)	0.002 (0.005)	−0.013 (0.023)	−0.014 (0.023)	−0.014 (0.024)
seaper		0.193 (0.316)	0.083 (0.330)		0.990 (1.050)	0.840 (1.086)
Ttrend:seaper			−0.019 (0.025)			−0.069 (0.114)
seaper_lev:Tvar			−0.117 (0.168)			−0.108 (0.451)
seaper_lev:Ptrend			−0.007 (0.014)			−0.033 (0.055)
seaper_lev:Pvar			0.024 (0.186)			0.047 (0.777)
Observations	6,774	6,774	6,774	5,378	5,378	5,378
R^2	0.0001	0.0003	0.001	0.001	0.001	0.001
Adjusted R^2	-0.502	-0.502	-0.502	-0.538	-0.538	-0.539
F Statistic	0.564 (df = 4; 4510)	0.526 (df = 5; 4509)	0.538 (df = 9; 4505)	0.657 (df = 4; 3494)	0.703 (df = 5; 3493)	0.482 (df = 9; 3489)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 4.15 shows the results of Model 6.4-6.9. To be clear, the difference between Model 6.4-6.6 and Model 6.7-6.9 are the independent variable and the regression models. Model 6.4-6.6 should show how climate change impacts internal and international net out-migration from rural to urban areas. On the other hand, Model 6.7-6.9 should show how climate change impacts internal, international, and intra-municipal net out-migration from rural to urban areas.

Both Model 6.4 and 6.7 results showed that Ttrend and Ptrend are both positive and statistically significant at 5% level. Therefore, increasing temperature or precipitation likely induce more international, internal, and intra-municipality out-migration from rural to urban areas. Tvar and Pvar, on the other hand, were different between Model 6.4 and 6.7. In Model 6.4, Tvar gained significance, but Pvar lost its significance. Thus, Tvar might have influenced intra-municipal migration strongly, but Pvar might have not influenced intra-municipality migration as much as international and internal migration. Regarding with the comparison between Model 6.6 and 6.9, their results were similar but the magnitude. The characteristic of humid heat-induced migration seen in Model 1.9 was not observed in Model 6.6 nor 6.9.

Table 4.15: Results of the models estimating the influence of UDEL climate metrics on Rural-Urban De.Sherbinin net out-migration, Lag2

	Lag 2					
	All Moves, Weighted (WLS)			Rural-Urban, Unweighted (OLS)		
	Model 6.4	Model 6.5	Model 6.6	Model 6.7	Model 6.8	Model 6.9
	b std					
Ttrend	0.038***	0.019***	−0.009	0.073**	0.004	0.073
	(0.005)	(0.006)	(0.026)	(0.033)	(0.043)	(0.186)
Tvar	0.018	0.028	0.216*	0.299**	0.323**	2.563***
	(0.021)	(0.021)	(0.122)	(0.147)	(0.149)	(0.795)
Ptrend	0.012***	0.017***	0.044***	0.032**	0.042***	0.178**
	(0.002)	(0.002)	(0.010)	(0.013)	(0.016)	(0.073)
Pvar	−0.046***	−0.032**	−0.024	−0.076	−0.051	−0.600
	(0.014)	(0.014)	(0.074)	(0.098)	(0.099)	(0.528)
BaseTemp		−0.115***	−0.130***		−0.375**	−0.466***
		(0.021)	(0.022)		(0.147)	(0.157)
BasePrecip		0.031***	0.036***		0.052	0.066
		(0.010)	(0.011)		(0.072)	(0.078)
Ttrend:BaseTemp			0.001			−0.007
			(0.001)			(0.010)
Ttrend:BasePrecip			0.00002			0.004
			(0.001)			(0.007)
Tvar:BaseTemp			−0.016**			−0.148***
			(0.006)			(0.041)
Tvar:BasePrecip			0.016***			0.082**
			(0.005)			(0.037)
Ptrend:BaseTemp			−0.001*			−0.006
			(0.001)			(0.004)
Ptrend:BasePrecip			−0.0003			−0.001
			(0.0004)			(0.003)
Pvar:BaseTemp			−0.001			0.024
			(0.004)			(0.027)
Pvar:BasePrecip			−0.001			−0.007
			(0.002)			(0.014)
Observations	6,774	6,774	6,774	6,575	6,575	6,575
R^2	0.032	0.038	0.048	0.004	0.006	0.010
Adjusted R^2	-0.454	-0.445	-0.433	-0.499	-0.496	-0.493
F Statistic	30.783*** (df = 4; 4510)	29.603*** (df = 6; 4508)	15.004*** (df = 14; 4500)	4.181*** (df = 4; 4370)	4.256*** (df = 6; 4368)	3.094*** (df = 14; 4360)
Note:						*p<0.1; **p<0.05; ***p<0.01

5 Discussion

5.1 IPUMS-I and De.Sherbinin

Both IPUMS-I and De.Sherbinin were creditable migration data that could be accessed without a fee for academic purposes. Pros and cons of IPUMS-I and De.Sherbinin data were investigated through this research. As mentioned in the result section, IPUMS-I measured the internal migration, while De.Sherbinin did not. Therefore, IPUMS-I is a reliable measure of internal migration for every country, but whether De.Sherbinin is a good measure of internal migration depends on countries. If the country's international migration is negligible compared to internal migration, De.Sherbinin can also estimate internal migration accurately. If not, the interpretation of De.Sherbinin becomes complex since it reflects both internal and international migration. Thus, Mexico, where international migration flow is considerable, was not the best place to practice De.Sherbinin data.

Another advantage of IPUMS-I was its information about individuals' origins and destinations. The information about the origins and the destinations enabled a more precise selection of the rural-urban migration flow. Given only the net out-migrants' number of each grid cell from De.Sherbinin data, I could only select individuals with rural origin, meaning the destinations could be either rural or urban. Moreover, IPUMS-I's information about origin and destination allowed computing in- and out-migration separately. Furthermore, it also enabled a practice of a gravity model, analysis of migration by paring an origin and a destination and treating environmental stressors as both push and pull factors, as a next step.

IPUMS-I has one more important advantage, the details about numerous socio-economics and other related variables. In this study, for instance, "URBAN" was used to filter the rural-urban displacement. It also provides current job types, income, and gender, which can help find key characteristics of the internal migration. De.Sherbinin data allows a similar process by incorporating a new data set. For example, ISIMIP, the population data, was overlapped to calculate the net out-migration rate and to define rural grids in this study. A gridded income data can also be combined to understand the relationship between income and migration. However, different data often have different spatial and temporal resolutions and specifications, resulting in more potential errors.

Despite these inconveniences, De.Sherbinin possesses a few advantages. Firstly, it is suitable for measuring a country's international net migration, while IPUMS-I cannot measure it. Also, De.Sherbinin is the gridded data covering the entire world, so the harmonization processes are unnecessary. Also, it allows analysis on various scales, such as grid-level, municipality-level, state-level, and country-level. I, for example, applied a municipality boundary to obtain the municipality-level migration. If a state boundary was applied instead, the state-level migration could be estimated. More unique geographical units can be employed as well; for instance, dividing Mexico into metropolitan areas, cities, and small cities could help capture unique migration patterns.

Also, an issue was found on the IPUMS-I's time-stable second administrative unit boundary, GEO2_MX. This boundary is flawed because harmonization sometimes puts multiple municipalities into one boundary, resulting in masked migration among combined municipalities. In addition, Mexico unevenly divides the states into municipalities. For example, the state of Oaxaca has 570 municipalities when the average number of municipalities in a state is 78, and the area of Oaxaca is less than 5% of Mexico. As a result, GEO2_MX might produce biased migration estimate. De.Sherbinin data can avoid these issues by utilizing an appropriate geographical boundary. In this study, however, GEO2_MX was used for De.Sherbinin as well to be consistent.

5.2 UDEL and GSW

Both UDEL and GSW are global monthly gridded data about water availability, but each has pros and cons. Firstly, GSW has a fine spatial resolution of 30 arc-second, covering both land and ocean. Also, GSW contains processed satellite images that capture surface water and processed statistics, such as ”Water Occurrence” and ”Yearly History” Pekel et al. (2016). All statistics are freely accessible on Google Earth Engine, making it convenient to interpret surface water dynamics. However, GSW records observations only where surface water has existed during the past 37 years. Consequently, Most lands are identified as no data. Compared to GSW, UDEL is much coarser with half-degree spatial resolution, but it covers everywhere on land, and its temporal coverage extends from 1900-2017, which is much longer than GSW.

The GSW trend and level of a municipality were calculated based solely on the grids within the municipality boundary. However, as described in the result section’s comparative analysis of UDEL and GSW, the municipality scale was not large enough to observe surface water dynamics. Thus, using a larger boundary or altering the calculation process is necessary. For example, I could have buffered the GSW’s grids or the municipality boundary to include the surface water’s influence on the surroundings. Also, checking the correlation between GSW and agricultural productivity is necessary to figure out if changes in GSW are related to the insecurity of agricultural livelihood. In addition to improving the GSW’s interpretation, including other metrics related to surface water could be helpful. For example, surface water quality and quantity, groundwater, agriculturally available water, sea-level rise might help understand the linkage between surface water and migration. The atmospheric gases’ concentration, such as pCO_2 and pN_2, might also clue us about climate migration. In short, improvements on both migration and climate metrics are necessary.

5.3 Findings from Regression

The regression results showed that the climate metrics were more significant when De.Sherbinin net out-migration rate was the dependent variable. This result suggested that international migration was more closely related to climate change. However, research conducted by Pew Hispanic Center insisted that the migration flow from Mexico to the U.S. might reach zero or might be even reversed (Passel et al., 2012). They explained that this decline is induced by a decrease in the appearance of the U.S. job market, an increase in risk associated with illegal crossing, and a decrease in the fertility rate in Mexico. (Passel et al., 2012). This conclusion contradicts my result, the increasing trend of international climate migration.

Regarding the rural-urban migration, I employed two methods to analyze it; weighting the proportion of the rural population and filtering migrants whose origin is rural and destination is urban. When the filtered migration rate was used, the coefficients of the models' parameters became up to ten times larger than the one with the weights for both IPUMS-I and De.Sherbinin. This enhancement, however, was likely because of the difference in the magnitude of the net out-migration rate. While the IPUMS-I's weighted rural-urban migration represented rural-urban net out-migration, the filtered one disregarded urban-rural in-migration and represented only rural-urban out-migration. As a result, the magnitude of the filtered migration rate became larger. This difference between the weighted and filtered rural-urban migration rates made it harder to compare them.

Similarly, the magnitude of the weighted and the filtered rural-urban migration rate differed for De.Sherbinin data. Aggregating De.Sherbinin's rural grid cells to filter rural-urban migration was not ideal because the sum contained three kinds of migration: international, inter-municipality, and intra-municipality. Therefore, to estimate rural-urban flow from De.Sherbinin data, the weighting is preferable than filtering. In this study, each municipality's proportion of the rural population was used as a weight, but other measures, which distinguish rural/urban, can be applied, such as the area of farmland or the number of farmers. Alternatively, these measures can be added as independent variables to the regression models. For example, Nawrotzki et al. (2015) added male agricultural labor as an independent variable and found that an increase in the male agricultural labor intensified the influence of temperature rise on migration.

Although I did not reach a definitive answer in terms of rural-urban climate migration, a consistent lagging of 2-3 years between climate change and migration was found in Mexico, and this result matches Nawrotzki and DeWaard (2016). Another finding was that the background temperature and precipitation seemed to affect the magnitude of climate change's influence on migration in Mexico. Since climate in Mexico is either temperate or tropical, the temperature difference is small. Therefore, it is important to consider climate migration differently between dry and wet more than between colder and hotter municipalities.

Above all, some suggestions for the following steps are listed below. Redesigning rural-urban climate migration analysis, improving the GSW metrics, and including drought metrics, such as the standard precipitation index. Also, an updated version of De.Sherbinin data for the 21st century can be produced with new population and natural increase data, such as LandScan. Furthermore, more censuses on migration is necessary for a sophisticated and robust study. Currently, Mexican Migration Project (MMP) and IPUMS-I are two main censuses used for migration analysis in Mexico due to their detailed information. However, both of them suffer from a lack of data. For example, MMP contains various social and economic measure of individuals, but it tracks only Mexico-U.S. migration (no international migration) at certain parts of Mexico. Although IPUMS-I records entire Mexico's internal migration associated with various social and economic measures, it only contains information after migration, not before migration. Consequently, the change in social and economic status through migration cannot be observed. Thus, more resources have to be allocated to collect censuses that cover the entire Mexico and collect individuals' socioeconomic factors before and after migration. Furthermore, the similar effort should be implemented for the countries where climate migration is expected to increase, such as Sub-Saharan Africa, South America, Southeast Asia, and small Pacific islands. In addition, an empirical orthogonal function analysis (EOF analysis) can be employed to investigate the relationship between migration and climate change. The EOF analysis is often used in climate science to detect a spatial and temporal relationships within a set of time-series variables. For example, the EOF analysis is employed to identify the influence of El Nino-Southern Oscillation on Pacific sea surface temperature. Similarly, the EOF analysis might enable to detect some undetected climate migration's relationship with the regression models.

6 Conclusion

This thesis has examined three things. First, UDEL and GSW were compared. This comparative analysis revealed that precipitation and surface water were correlated at the state level but not at the municipality level. It also showed no correlation between surface water and temperature. Secondly, I compared two migration data sets: IPUMS-I and De.Sherbinin. IPUMS-I captured internal migration and allowed to choose more accurate rural-urban migration flow. On the other hand, De.Sherbinin data only provides the total of international and internal migration, inhibited internal climate migration analysis in Mexico, where international migration size was considerable. Lastly, the relationship between climate and migration was investigated with multiple regression models. The results showed that De.Sherbinin data was more closely related to climate metrics than IPUMS-I, which potentially indicates the close linkage between environmental stressors and international migration in Mexico. Moreover, the climate metrics had consistently delayed influence on migration by about two years, implying the lag between the timing of the environmental change and the migration decision. I was not able to observe any climate migration characteristics specific to rural-urban movement. However, I learned that capturing rural-urban migration flow requires more than simply applying rural population weights to the regression or selecting individuals who moved from rural to urban areas.

7 Appendix

7.1 Rural Population

IPUMS-I's and the World Bank's rural and total population were compared. Both of them use the Mexican censuses and define rural as localities with less than 2,500 inhabitants (MPC (2020),Desa (2018)). Therefore, both rural and total populations match between IPUMS-I and the World Bank. After 2005, however, their rural populations deviate, although their total populations stay close. This deviation is because the World Bank's data after 2005 is a projection, not an observation. World Bank estimated the rural population to decline more than the reality. I used this World Bank's data to identify the De.Sherbinin's rural grids from 1970-1990, so the inaccurate projection did not affect my research. Also, World Bank computes the percentages of the rural population differently among countries, so this inconsistency might not be true for other countries. Furthermore, since World Bank summarizes 223 countries' rural population percentages, its data is convenient for a global analysis. However, for a country-level analysis, the latest censuses should be used to calculate the rural population instead of this World Bank's data.

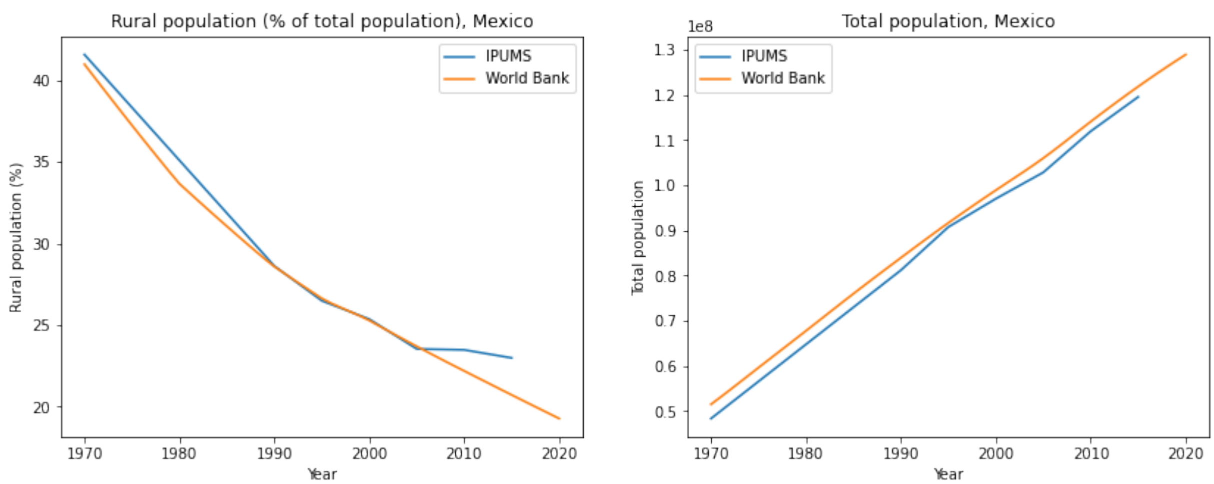

Figure 7.1: Comparison between IPUMS-I's and the World Bank's rural and total population

7.2 More Regression Results

Here are the tables of all regression results with different lags. For most models, the magnitude of coefficients was the largest at lag 2, resulting in more significant parameters in the models with 2 years of lags.

Table 7.1: Results of Model 6.1 and 6.4, De.Sherbinin and UDEL metrics, No background climate, No interaction terms

	Model 6.1				Model 6.4			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	0.030^{***}	0.032^{***}	0.036^{***}	0.038^{***}	0.049^{*}	0.060^{**}	0.073^{**}	0.084^{**}
	(0.004)	(0.004)	(0.004)	(0.005)	(0.028)	(0.030)	(0.033)	(0.036)
Ptrend	0.013^{***}	0.013^{***}	0.014^{***}	0.017^{***}	0.029^{**}	0.028^{**}	0.032^{**}	0.037^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.011)	(0.012)	(0.013)	(0.013)
Tvar	0.058^{***}	0.057^{***}	0.036^{*}	0.035^{*}	0.352^{**}	0.318^{**}	0.299^{**}	0.287^{*}
	(0.018)	(0.019)	(0.020)	(0.020)	(0.138)	(0.140)	(0.147)	(0.151)
Pvar	-0.056^{***}	-0.053^{***}	-0.050^{***}	-0.078^{***}	-0.050	-0.043	-0.076	-0.112
	(0.012)	(0.013)	(0.013)	(0.013)	(0.091)	(0.095)	(0.098)	(0.098)
Observations	6,774	6,774	6,774	6,774	6,575	6,575	6,575	6,575
R^2	0.039	0.035	0.032	0.037	0.004	0.004	0.004	0.004
Adjusted R^2	-0.443	-0.450	-0.453	-0.446	-0.498	-0.498	-0.499	-0.498
F Statistic	45.598^{***} (df = 4; 4510)	40.633^{***} (df = 4; 4510)	37.721^{***} (df = 4; 4510)	43.388^{***} (df = 4; 4510)	4.817^{***} (df = 4; 4370)	4.314^{***} (df = 4; 4370)	4.181^{***} (df = 4; 4370)	4.377^{***} (df = 4; 4370)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.2: Results of Model 6.2 and 6.5, De.Sherbinin, UDEL metrics, and UDEL climatology, With background climate, No Interaction terms

	Model 6.2				Model 6.5			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	0.020^{***}	0.020^{***}	0.022^{***}	0.023^{***}	-0.003	0.002	0.004	0.011
	(0.005)	(0.005)	(0.006)	(0.007)	(0.035)	(0.038)	(0.043)	(0.049)
Ptrend	0.015^{***}	0.016^{***}	0.018^{***}	0.023^{***}	0.036^{***}	0.036^{***}	0.042^{***}	0.049^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.012)	(0.014)	(0.016)	(0.017)
Tvar	0.066^{***}	0.068^{***}	0.047^{**}	0.042^{**}	0.373^{***}	0.345^{**}	0.323^{**}	0.293^{*}
	(0.019)	(0.019)	(0.020)	(0.020)	(0.141)	(0.143)	(0.149)	(0.152)
Pvar	-0.048^{***}	-0.045^{***}	-0.040^{***}	-0.067^{***}	-0.028	-0.020	-0.051	-0.083
	(0.013)	(0.013)	(0.013)	(0.013)	(0.095)	(0.098)	(0.099)	(0.099)
BasePrecip	0.020^{**}	0.021^{**}	0.028^{***}	0.036^{***}	0.054	0.049	0.052	0.058
	(0.009)	(0.009)	(0.010)	(0.010)	(0.068)	(0.069)	(0.072)	(0.075)
BaseTemp	-0.075^{***}	-0.079^{***}	-0.079^{***}	-0.073^{***}	-0.366^{***}	-0.373^{***}	-0.375^{**}	-0.352^{**}
	(0.019)	(0.019)	(0.020)	(0.020)	(0.140)	(0.142)	(0.147)	(0.152)
Observations	6,774	6,774	6,774	6,774	6,575	6,575	6,575	6,575
R^2	0.045	0.041	0.040	0.045	0.007	0.006	0.006	0.006
Adjusted R^2	-0.435	-0.440	-0.443	-0.435	-0.495	-0.496	-0.496	-0.496
F Statistic	35.384^{***} (df = 6; 4508)	32.392^{***} (df = 6; 4508)	31.023^{***} (df = 6; 4508)	35.278^{***} (df = 6; 4508)	4.798^{***} (df = 6; 4368)	4.420^{***} (df = 6; 4368)	4.256^{***} (df = 6; 4368)	4.205^{***} (df = 6; 4368)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.3: Results of Model 6.3 and 6.6, De.Sherbinin, UDEL metrics, and UDEL climatology, With background climate and Interaction terms

	Model 6.3				Model 6.6			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	−0.008	−0.002	−0.0003	0.025	−0.144	−0.019	0.073	0.264
	(0.021)	(0.022)	(0.025)	(0.027)	(0.156)	(0.168)	(0.186)	(0.202)
Ptrend	0.055***	0.053***	0.049***	0.045***	0.185***	0.172**	0.178**	0.159**
	(0.009)	(0.010)	(0.010)	(0.010)	(0.069)	(0.073)	(0.073)	(0.073)
Tvar	0.272***	0.245**	0.222**	0.191*	2.915***	2.638***	2.563***	2.435***
	(0.099)	(0.106)	(0.104)	(0.103)	(0.758)	(0.807)	(0.795)	(0.801)
Pvar	−0.137*	−0.109	−0.058	−0.004	−0.414	−0.392	−0.600	−0.446
	(0.073)	(0.075)	(0.071)	(0.067)	(0.550)	(0.561)	(0.528)	(0.500)
BaseTemp	−0.093***	−0.099***	−0.095***	−0.083***	−0.492***	−0.493***	−0.466***	−0.405**
	(0.020)	(0.020)	(0.021)	(0.022)	(0.148)	(0.152)	(0.157)	(0.163)
BasePrecip	0.032***	0.028***	0.035***	0.042***	0.068	0.048	0.066	0.070
	(0.009)	(0.010)	(0.010)	(0.011)	(0.071)	(0.072)	(0.078)	(0.081)
Ttrend:BaseTemp	0.001	0.001	0.001	−0.0003	0.006	−0.002	−0.007	−0.017
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.009)	(0.010)	(0.011)
Ttrend:BasePrecip	−0.00001	0.0002	0.0001	0.001	−0.001	0.002	0.004	0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.006)	(0.007)	(0.007)
BaseTemp:Ptrend	−0.002***	−0.002***	−0.001**	−0.001	−0.006	−0.006	−0.006	−0.004
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
BasePrecip:Ptrend	−0.0002	0.00001	−0.0004	−0.001	−0.001	−0.0003	−0.001	−0.001
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.003)	(0.003)	(0.003)	(0.003)
BaseTemp:Tvar	−0.019***	−0.021***	−0.017***	−0.022***	−0.157***	−0.148***	−0.148***	−0.158***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.040)	(0.042)	(0.041)	(0.042)
BasePrecip:Tvar	0.022***	0.029***	0.020***	0.035***	0.069**	0.081**	0.082**	0.113***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.032)	(0.035)	(0.037)	(0.039)
BaseTemp:Pvar	0.004	0.004	0.001	−0.003	0.011	0.014	0.024	0.016
	(0.004)	(0.004)	(0.004)	(0.003)	(0.028)	(0.028)	(0.027)	(0.025)
BasePrecip:Pvar	−0.002	−0.006***	−0.003	−0.004**	0.003	−0.005	−0.007	−0.009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.015)	(0.015)	(0.014)	(0.014)
Observations	6,774	6,774	6,774	6,774	6,575	6,575	6,575	6,575
R^2	0.059	0.056	0.049	0.061	0.012	0.010	0.010	0.011
Adjusted R^2	-0.417	-0.420	-0.431	-0.414	-0.490	-0.493	-0.493	-0.492
F Statistic	20.023*** (df = 14; 4500)	19.233*** (df = 14; 4500)	16.620*** (df = 14; 4500)	20.731*** (df = 14; 4500)	3.685*** (df = 14; 4360)	3.179*** (df = 14; 4360)	3.094*** (df = 14; 4360)	3.353*** (df = 14; 4360)
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 7.4: Results of Model 6.7, De.Sherbinin, UDEL metrics, and UDEL climatology, No background climate, No Interaction terms

	Model 6.7			
	lag 0	lag 1	lag 2	lag 3
Ttrend	0.049*	0.060**	0.073**	0.084**
	(0.028)	(0.030)	(0.033)	(0.036)
Ptrend	0.029**	0.028**	0.032**	0.037***
	(0.011)	(0.012)	(0.013)	(0.013)
Tvar	0.352**	0.318**	0.299**	0.287*
	(0.138)	(0.140)	(0.147)	(0.151)
Pvar	−0.050	−0.043	−0.076	−0.112
	(0.091)	(0.095)	(0.098)	(0.098)
Observations	6,575	6,575	6,575	6,575
R^2	0.004	0.004	0.004	0.004
Adjusted R^2	-0.498	-0.498	-0.499	-0.498
F Statistic (df = 4; 4370)	4.817***	4.314***	4.181***	4.377***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.5: Results of Model 6.8, De.Sherbinin, UDEL metrics, and UDEL climatology, With background climate, No Interaction terms

	Model 6.8			
	lag 0	lag 1	lag 2	lag 3
	b std			
Ttrend	−0.003	0.002	0.004	0.011
	(0.035)	(0.038)	(0.043)	(0.049)
Ptrend	0.036***	0.036***	0.042***	0.049***
	(0.012)	(0.014)	(0.016)	(0.017)
Tvar	0.373***	0.345**	0.323**	0.293*
	(0.141)	(0.143)	(0.149)	(0.152)
Pvar	−0.028	−0.020	−0.051	−0.083
	(0.095)	(0.098)	(0.099)	(0.099)
BasePrecip	0.054	0.049	0.052	0.058
	(0.068)	(0.069)	(0.072)	(0.075)
BaseTemp	−0.366***	−0.373***	−0.375**	−0.352**
	(0.140)	(0.142)	(0.147)	(0.152)
Observations	6,575	6,575	6,575	6,575
R^2	0.007	0.006	0.006	0.006
Adjusted R^2	-0.495	-0.496	-0.496	-0.496
F Statistic (df = 6; 4368)	4.798***	4.420***	4.256***	4.205***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.6: Results of Model 6.9, De.Sherbinin, UDEL metrics, and UDEL climatology, With background climate, With Interaction terms

	Model 6.9			
	lag 0	lag 1	lag 2	lag 3
Ttrend	−0.144	−0.019	0.073	0.264
	(0.156)	(0.168)	(0.186)	(0.202)
Tvar	2.915***	2.638***	2.563***	2.435***
	(0.758)	(0.807)	(0.795)	(0.801)
Ptrend	0.185***	0.172**	0.178**	0.159**
	(0.069)	(0.073)	(0.073)	(0.073)
Pvar	−0.414	−0.392	−0.600	−0.446
	(0.550)	(0.561)	(0.528)	(0.500)
BaseTemp	−0.492***	−0.493***	−0.466***	−0.405**
	(0.148)	(0.152)	(0.157)	(0.163)
BasePrecip	0.068	0.048	0.066	0.070
	(0.071)	(0.072)	(0.078)	(0.081)
BaseTemp:Ttrend	0.006	−0.002	−0.007	−0.017
	(0.008)	(0.009)	(0.010)	(0.011)
BasePrecip:Ttrend	−0.001	0.002	0.004	0.008
	(0.006)	(0.006)	(0.007)	(0.007)
BaseTemp:Ptrend	−0.006	−0.006	−0.006	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)
BasePrecip:Ptrend	−0.001	−0.0003	−0.001	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)
BaseTemp:Tvar	−0.157***	−0.148***	−0.148***	−0.158***
	(0.040)	(0.042)	(0.041)	(0.042)
BasePrecip:Tvar	0.069**	0.081**	0.082**	0.113***
	(0.032)	(0.035)	(0.037)	(0.039)
BaseTemp:Pvar	0.011	0.014	0.024	0.016
	(0.028)	(0.028)	(0.027)	(0.025)
BasePrecip:Pvar	0.003	−0.005	−0.007	−0.009
	(0.015)	(0.015)	(0.014)	(0.014)
Observations	6,575	6,575	6,575	6,575
R^2	0.012	0.010	0.010	0.011
Adjusted R^2	-0.490	-0.493	-0.493	-0.492
F Statistic (df = 14; 4360)	3.685***	3.179***	3.094***	3.353***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.7: Results of Model 1.1 and 1.4, IPUMS-I, UDEL metrics, and UDEL climatology, With background climate and Interaction terms

	Model 1.1				Model 1.4			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	0.0004 (0.001)	0.0005 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Tvar	0.004 (0.007)	−0.001 (0.007)	−0.005 (0.007)	−0.004 (0.008)	0.008 (0.006)	0.005 (0.006)	0.0002 (0.007)	0.002 (0.007)
Ptrend	−0.0001 (0.0003)	0.00004 (0.0004)	0.0001 (0.0005)	0.00002 (0.001)	−0.0003 (0.0003)	−0.0003 (0.0004)	−0.0004 (0.0004)	−0.0005 (0.0005)
Pvar	−0.008 (0.006)	−0.006 (0.005)	−0.003 (0.005)	0.003 (0.004)	−0.001 (0.006)	−0.001 (0.005)	0.002 (0.005)	0.006 (0.004)
Observations	6,774	6,774	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.001	0.0005	0.0003	0.0003	0.0001	0.0001	0.0001	0.0001
Adjusted R^2	-0.501	-0.501	-0.501	-0.501	-0.502	-0.502	-0.502	-0.502
F Statistic (df = 4; 4510)	0.580	0.510	0.356	0.335	0.909	0.705	0.564	0.980

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7.8: Results of Model 1.2 and 1.5, IPUMS-I, UDEL metrics, and UDEL climatology, With background climate and Interaction terms

	Model 1.2				Model 1.5			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	0.0002 (0.001)	0.0003 (0.001)	0.0005 (0.001)	0.0005 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Tvar	0.004 (0.007)	−0.002 (0.007)	−0.005 (0.007)	−0.005 (0.008)	0.007 (0.006)	0.004 (0.006)	−0.00001 (0.007)	0.002 (0.007)
Ptrend	−0.0001 (0.0003)	0.00003 (0.0004)	0.0001 (0.0005)	0.0002 (0.001)	−0.0003 (0.0003)	−0.0003 (0.0004)	−0.0003 (0.0004)	−0.0004 (0.001)
Pvar	−0.006 (0.006)	−0.005 (0.006)	−0.002 (0.006)	0.003 (0.005)	0.001 (0.006)	−0.0003 (0.005)	0.003 (0.005)	0.006 (0.004)
BaseTemp	−0.001 (0.011)	−0.001 (0.011)	−0.002 (0.011)	−0.004 (0.012)	0.001 (0.010)	0.003 (0.011)	0.003 (0.011)	0.0003 (0.011)
BasePrecip	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.003 (0.002)	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)
Observations	6,774	6,774	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.001	0.001	0.0005	0.001	0.0002	0.0002	0.0002	0.0003
Adjusted R^2	-0.502	-0.502	-0.502	-0.502	-0.502	-0.502	-0.502	-0.502
F Statistic (df = 6; 4508)	0.450	0.414	0.355	0.417	0.862	0.677	0.611	0.814

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7.9: Results of Model 1.3 and 1.6, IPUMS-I, UDEL metrics, and UDEL climatology, With background climate and Interaction terms

	Model 1.3				Model 1.6			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	−0.002 (0.004)	−0.002 (0.005)	−0.003 (0.006)	−0.006 (0.006)	−0.004 (0.004)	−0.005 (0.005)	−0.006 (0.006)	−0.009 (0.006)
Tvar	−0.018 (0.032)	−0.021 (0.035)	−0.030 (0.036)	−0.024 (0.035)	−0.0001 (0.031)	0.008 (0.033)	0.005 (0.034)	0.007 (0.033)
Ptrend	0.0002 (0.002)	0.0004 (0.002)	0.00004 (0.002)	0.001 (0.003)	0.0002 (0.002)	0.0001 (0.002)	−0.0004 (0.002)	−0.0004 (0.003)
Pvar	−0.041 (0.034)	−0.023 (0.029)	0.003 (0.029)	0.021 (0.019)	−0.015 (0.033)	−0.005 (0.027)	0.017 (0.027)	0.021 (0.019)
BaseTemp	−0.004 (0.011)	−0.003 (0.011)	−0.002 (0.012)	−0.003 (0.012)	0.002 (0.011)	0.004 (0.011)	0.006 (0.011)	0.004 (0.011)
BasePrecip	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.002 (0.003)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)
BaseTemp:Ttrend	0.0001 (0.0002)	0.0002 (0.0002)	0.0002 (0.0003)	0.0004 (0.0003)	0.0003 (0.0002)	0.0005* (0.0002)	0.001* (0.0003)	0.001** (0.0003)
BasePrecip:Ttrend	0.00001 (0.0002)	−0.0001 (0.0002)	−0.0001 (0.0003)	−0.0001 (0.0003)	−0.0002 (0.0002)	−0.0003 (0.0002)	−0.0004* (0.0002)	−0.0003 (0.0002)
BaseTemp:Ptrend	−0.00001 (0.0001)	−0.00001 (0.0001)	0.00003 (0.0001)	0.00003 (0.0001)	−0.0001 (0.0001)	−0.0001 (0.0001)	−0.00004 (0.0001)	−0.00003 (0.0001)
BasePrecip:Ptrend	−0.00001 (0.0001)	−0.00000 (0.0001)	−0.00005 (0.0001)	−0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
BaseTemp:Tvar	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	−0.00001 (0.002)	−0.0001 (0.002)	0.0002 (0.002)
BasePrecip:Tvar	−0.0004 (0.001)	0.001 (0.001)	0.001 (0.001)	−0.0001 (0.001)	−0.001 (0.001)	0.0002 (0.001)	0.0005 (0.001)	−0.0004 (0.001)
BaseTemp:Pvar	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	−0.0004 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.0004 (0.001)
BasePrecip:Pvar	−0.001 (0.002)	−0.002 (0.002)	−0.002 (0.001)	−0.001 (0.001)	−0.002 (0.001)	−0.002* (0.001)	−0.003*** (0.001)	−0.003*** (0.001)
Observations	6,774	6,774	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.002	0.002	0.001	0.002	0.001	0.001	0.001	0.001
Adjusted R^2	-0.502	-0.503	-0.503	-0.503	-0.504	-0.504	-0.504	-0.504
F Statistic (df = 14; 4500)	0.592	0.507	0.463	0.529	1.011	0.998	1.229	1.315

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.10: Results of Model 1.7, IPUMS-I, UDEL metrics, and UDEL climatology, No background climate, No Interaction terms

	Model 1.7			
	lag 0	lag 1	lag 2	lag 3
	b std			
Ttrend	−0.00004	0.001	0.002	0.003
	(0.003)	(0.004)	(0.004)	(0.005)
Tvar	−0.003	−0.025	−0.042	−0.047
	(0.030)	(0.030)	(0.031)	(0.032)
Ptrend	0.001	0.002	0.001	0.0005
	(0.001)	(0.002)	(0.002)	(0.002)
Pvar	−0.037	−0.022	−0.013	0.004
	(0.026)	(0.024)	(0.023)	(0.019)
Observations	5,378	5,378	5,378	5,378
R^2	0.001	0.001	0.001	0.001
Adjusted R^2	-0.538	-0.538	-0.538	-0.538
F Statistic (df = 4; 3494)	0.752	0.629	0.657	0.592
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.11: Results of Model 1.8, IPUMS-I, UDEL metrics, and UDEL climatology, With background climate, No Interaction terms

	Model 1.8			
	lag 0	lag 1	lag 2	lag 3
	b std			
Ttrend	−0.002	−0.001	−0.0001	−0.0001
	(0.004)	(0.005)	(0.005)	(0.006)
Tvar	−0.003	−0.025	−0.041	−0.046
	(0.030)	(0.030)	(0.032)	(0.033)
Ptrend	0.001	0.002	0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.002)
Pvar	−0.031	−0.017	−0.008	0.005
	(0.027)	(0.025)	(0.024)	(0.020)
BaseTemp	−0.038	−0.033	−0.030	−0.030
	(0.048)	(0.049)	(0.050)	(0.051)
BasePrecip	0.005	0.006	0.007	0.009
	(0.011)	(0.011)	(0.010)	(0.011)
Observations	5,378	5,378	5,378	5,378
R^2	0.001	0.001	0.001	0.001
Adjusted R^2	-0.538	-0.538	-0.538	-0.538
F Statistic (df = 6; 3492)	0.617	0.532	0.552	0.550
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.12: Results of Model 1.9, IPUMS-I, UDEL metrics, and UDEL climatology, With background climate, With Interaction terms

	Model 1.9			
	lag 0	lag 1	lag 2	lag 3
	b std			
Ttrend	−0.002 (0.017)	−0.010 (0.022)	−0.012 (0.025)	−0.020 (0.028)
Ptrend	0.004 (0.007)	0.003 (0.008)	0.004 (0.010)	0.008 (0.012)
Tvar	0.005 (0.137)	0.020 (0.154)	−0.040 (0.155)	0.040 (0.153)
Pvar	0.013 (0.147)	−0.019 (0.128)	0.054 (0.128)	0.069 (0.081)
BaseTemp	−0.046 (0.049)	−0.048 (0.051)	−0.049 (0.052)	−0.047 (0.052)
BasePrecip	0.003 (0.011)	0.007 (0.011)	0.008 (0.011)	0.012 (0.011)
BaseTemp:Ttrend	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.0004 (0.001)
BasePrecip:Ttrend	0.002^{*} (0.001)	0.003^{***} (0.001)	0.003^{***} (0.001)	0.003^{***} (0.001)
BaseTemp:Ptrend	−0.0001 (0.0003)	−0.00000 (0.0004)	0.00000 (0.0005)	−0.0001 (0.001)
BasePrecip:Ptrend	−0.0002 (0.0003)	−0.0001 (0.0004)	−0.0002 (0.0005)	−0.0003 (0.001)
BaseTemp:Tvar	−0.002 (0.007)	−0.001 (0.008)	0.0001 (0.008)	−0.005 (0.008)
BasePrecip:Tvar	0.003 (0.006)	−0.004 (0.006)	−0.004 (0.006)	−0.002 (0.006)
BaseTemp:Pvar	−0.004 (0.007)	−0.003 (0.006)	−0.007 (0.006)	-0.007^{*} (0.004)
BasePrecip:Pvar	0.002 (0.007)	0.007 (0.007)	0.010 (0.006)	0.009^{*} (0.005)
Observations	5,378	5,378	5,378	5,378
R^2	0.003	0.003	0.004	0.005
Adjusted R^2	-0.539	-0.538	-0.537	-0.536
F Statistic (df = 14; 3484)	0.730	0.809	1.029	1.199

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.13: Results of Model 2.1 and 2.4, IPUMS-I, Nowater Trend, and UDEL climatology, No background climate, No Interaction terms

	Model 2.1				Model 2.4			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
tre_nowa	0.002 (0.012)	0.007 (0.015)	0.015 (0.018)	0.011 (0.021)	−0.001 (0.011)	0.0004 (0.013)	0.009 (0.017)	0.007 (0.019)
Observations	6,993	6,993	6,993	6,993	6,993	6,993	6,993	6,993
R^2	0.00000	0.00005	0.0001	0.0001	0.00000	0.00005	0.0001	0.0001
Adjusted R^2	-0.501	-0.501	-0.501	-0.501	-0.501	-0.501	-0.501	-0.501
F Statistic (df = 1; 4659)	0.017	0.219	0.639	0.257	0.016	0.001	0.278	0.143

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.14: Results of Model 2.2 and 2.5, IPUMS-I, Nowater Trend, and UDEL climatology, With background climate, No Interaction terms

	Model 2.2				Model 2.5			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
tre_nowa	0.002	0.007	0.015	0.012	−0.001	0.001	0.009	0.007
	(0.012)	(0.015)	(0.018)	(0.021)	(0.011)	(0.013)	(0.017)	(0.019)
BaseTemp	−0.003	−0.003	−0.003	−0.003	−0.001	−0.001	−0.001	−0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
BasePrecip	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	6,981	6,981	6,981	6,981	6,981	6,981	6,981	6,981
R^2	0.0003	0.0004	0.0005	0.0004	0.0003	0.0003	0.0004	0.0004
Adjusted R^2	-0.501	-0.501	-0.501	-0.501	-0.501	-0.501	-0.501	-0.501
F Statistic (df = 3; 4649)	0.500	0.565	0.719	0.596	0.792	0.789	0.879	0.836

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7.15: Results of Model 2.3 and 2.6, IPUMS-I, Nowater Trend, and UDEL climatology, With background climate and Interaction terms

	Model 2.3				Model 2.6			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
tre_nowa	−0.027	−0.022	−0.052	−0.045	−0.037	−0.060	−0.106	−0.089
	(0.057)	(0.071)	(0.088)	(0.100)	(0.053)	(0.066)	(0.084)	(0.095)
BaseTemp	−0.003	−0.003	−0.003	−0.003	−0.001	−0.001	−0.001	−0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
BasePrecip	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
tre_nowa:BaseTemp	0.003	0.004	0.007	0.006	0.003	0.006	0.009^{**}	0.008
	(0.003)	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)
tre_nowa:BasePrecip	−0.004	-0.006^{**}	-0.008^{**}	−0.007	−0.003	-0.005^{*}	-0.006^{**}	−0.006
	(0.002)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)
Observations	6,981	6,981	6,981	6,981	6,981	6,981	6,981	6,981
R^2	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001
Adjusted R^2	-0.501	-0.500	-0.500	-0.501	-0.501	-0.500	-0.500	-0.501
F Statistic (df = 5; 4647)	0.875	1.207	1.449	0.910	1.036	1.462	1.828	1.229

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7.16: Results of Model 2.7, IPUMS-I, Nowater Trend, and UDEL climatology, No background climate, No Interaction terms

	Model 2.7			
	lag 0	lag 1	lag 2	lag 3
	b std			
tre_nowa	0.024 (0.057)	0.039 (0.071)	0.051 (0.087)	0.025 (0.099)
Observations	5,555	5,555	5,555	5,555
R^2	0.00005	0.0001	0.0001	0.00002
Adjusted R^2	-0.536	-0.536	-0.536	-0.536
F Statistic (df = 1; 3615)	0.174	0.301	0.346	0.064
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.17: Results of Model 2.8, IPUMS-I, Nowater Trend, and UDEL climatology, With background climate, No Interaction terms

	Model 2.8			
	lag 0	lag 1	lag 2	lag 3
	b std			
tre_nowa	0.024 (0.057)	0.038 (0.071)	0.050 (0.087)	0.024 (0.099)
BaseTemp	−0.023 (0.043)	−0.023 (0.043)	−0.023 (0.043)	−0.023 (0.043)
BasePrecip	0.006 (0.010)	0.006 (0.010)	0.006 (0.010)	0.006 (0.010)
Observations	5,549	5,549	5,549	5,549
R^2	0.0002	0.0003	0.0003	0.0002
Adjusted R^2	-0.537	-0.537	-0.537	-0.537
F Statistic (df = 3; 3609)	0.263	0.302	0.316	0.227
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.18: Results of Model 2.9, IPUMS-I, Nowater Trend, and UDEL climatology, With background climate, With Interaction terms

	Model 2.9			
	lag 0	lag 1	lag 2	lag 3
	b std			
tre_nowa	0.168 (0.274)	0.209 (0.339)	0.129 (0.418)	0.074 (0.471)
BaseTemp	−0.022 (0.043)	−0.022 (0.043)	−0.022 (0.043)	−0.023 (0.043)
BasePrecip	0.007 (0.010)	0.007 (0.010)	0.007 (0.010)	0.007 (0.010)
tre_nowa:BaseTemp	−0.002 (0.014)	−0.001 (0.018)	0.009 (0.022)	0.009 (0.025)
tre_nowa:BasePrecip	−0.010 (0.011)	−0.016 (0.014)	−0.025 (0.017)	−0.024 (0.020)
Observations	5,549	5,549	5,549	5,549
R^2	0.001	0.001	0.001	0.001
Adjusted R^2	-0.537	-0.537	-0.537	-0.537
F Statistic (df = 5; 3607)	0.371	0.476	0.615	0.428

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.19: Results of Model 3.1 and 3.4, IPUMS-I, Seaper Trend, and UDEL climatology, No background climate, no Interaction terms

	Model 3.1				Model 3.4			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
tre_seaper	−0.004 (0.012)	−0.010 (0.015)	−0.018 (0.018)	−0.014 (0.021)	−0.005 (0.011)	−0.007 (0.013)	−0.016 (0.017)	−0.015 (0.019)
Observations	6,993	6,993	6,993	6,993	6,993	6,993	6,993	6,993
R^2	0.00003	0.0001	0.0002	0.0001	0.00003	0.0001	0.0002	0.0001
Adjusted R^2	-0.501	-0.501	-0.500	-0.501	-0.501	-0.501	-0.500	-0.501
F Statistic (df = 1; 4659)	0.134	0.445	0.960	0.461	0.180	0.257	0.939	0.606

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.20: Results of Model 3.2 and 3.5, IPUMS-I, Seaper Trend, and UDEL climatology, With background climate, No Interaction terms

	Model 3.2				Model 3.5			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
tre_seaper	−0.004	−0.010	−0.018	−0.015	−0.005	−0.007	−0.016	−0.015
	(0.012)	(0.015)	(0.018)	(0.021)	(0.011)	(0.013)	(0.017)	(0.019)
BaseTemp	−0.003	−0.003	−0.003	−0.003	−0.001	−0.001	−0.001	−0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
BasePrecip	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	6,981	6,981	6,981	6,981	6,981	6,981	6,981	6,981
R^2	0.0003	0.0004	0.001	0.0004	0.0003	0.0004	0.001	0.0004
Adjusted R^2	-0.501	-0.501	-0.501	-0.501	-0.501	-0.501	-0.501	-0.501
F Statistic (df = 3; 4649)	0.540	0.640	0.829	0.669	0.855	0.879	1.099	0.992
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 7.21: Results of Model 2.3 and 2.6, IPUMS-I, Seaper Trend, and UDEL climatology, With background climate and Interaction terms

	Model 2.3				Model 2.6			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
tre_seaper	0.020	0.014	0.043	0.037	0.019	0.039	0.080	0.064
	(0.056)	(0.070)	(0.087)	(0.099)	(0.053)	(0.066)	(0.083)	(0.094)
BaseTemp	−0.003	−0.003	−0.003	−0.003	−0.001	−0.001	−0.001	−0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
BasePrecip	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
tre_seaper:BaseTemp	−0.003	−0.004	−0.007	−0.006	−0.003	−0.005	−0.008*	−0.007
	(0.003)	(0.004)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)
tre_seaper:BasePrecip	0.003	0.006*	0.007*	0.006	0.003*	0.005**	0.007**	0.006*
	(0.002)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.004)
Observations	6,981	6,981	6,981	6,981	6,981	6,981	6,981	6,981
R^2	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001
Adjusted R^2	-0.501	-0.500	-0.500	-0.501	-0.501	-0.500	-0.500	-0.501
F Statistic (df = 5; 4647)	0.807	1.157	1.412	0.888	1.136	1.588	1.983*	1.340
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 7.22: Results of Model 3.7, IPUMS-I, Seaper Trend, and UDEL climatology, No background climate, No Interaction terms

	Model 3.7			
	lag 0	lag 1	lag 2	lag 3
	b std			
tre_seaper	0.003 (0.058)	−0.009 (0.071)	−0.018 (0.087)	0.008 (0.099)
Observations	5,555	5,555	5,555	5,555
R^2	0.00000	0.00000	0.00001	0.00000
Adjusted R^2	-0.536	-0.536	-0.536	-0.536
F Statistic (df = 1; 3615)	0.003	0.016	0.040	0.006
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.23: Results of Model 3.8, IPUMS-I, Seaper Trend, and UDEL climatology, With background climate, No Interaction terms

	Model 3.8			
	lag 0	lag 1	lag 2	lag 3
	b std			
tre_seaper	0.004 (0.058)	−0.008 (0.071)	−0.016 (0.088)	0.009 (0.099)
BaseTemp	−0.023 (0.043)	−0.023 (0.043)	−0.023 (0.043)	−0.023 (0.043)
BasePrecip	0.006 (0.010)	0.006 (0.010)	0.006 (0.010)	0.006 (0.010)
Observations	5,549	5,549	5,549	5,549
R^2	0.0002	0.0002	0.0002	0.0002
Adjusted R^2	-0.537	-0.537	-0.537	-0.537
F Statistic (df = 3; 3609)	0.209	0.211	0.218	0.210
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.24: Results of Model 3.9, IPUMS-I, Seaper Trend, and UDEL climatology, With background climate, With Interaction terms

	Model 3.9			
	lag 0	lag 1	lag 2	lag 3
	b std			
tre_seaper	−0.131	−0.165	−0.080	−0.019
	(0.271)	(0.337)	(0.416)	(0.469)
BaseTemp	−0.022	−0.022	−0.022	−0.022
	(0.043)	(0.043)	(0.043)	(0.043)
BasePrecip	0.007	0.007	0.007	0.007
	(0.010)	(0.010)	(0.010)	(0.010)
tre_seaper:BaseTemp	0.002	0.001	−0.009	−0.010
	(0.014)	(0.018)	(0.022)	(0.024)
tre_seaper:BasePrecip	0.009	0.015	0.024	0.023
	(0.011)	(0.014)	(0.017)	(0.020)
Observations	5,549	5,549	5,549	5,549
R^2	0.0004	0.001	0.001	0.001
Adjusted R^2	-0.537	-0.537	-0.537	-0.537
F Statistic (df = 5; 3607)	0.310	0.384	0.519	0.395
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.25: Results of Model 4.1 and 4.3, IPUMS-I, UDEL metrics, and Nowater Level, With background climate, No Interaction terms

	Model 4.1				Model 4.3			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	0.0004	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tvar	0.004	−0.001	−0.005	−0.004	0.008	0.005	0.0001	0.002
	(0.007)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)
Ptrend	−0.0001	0.00001	0.00005	−0.00001	−0.0003	−0.0003	−0.0004	−0.0005
	(0.0003)	(0.0004)	(0.0005)	(0.001)	(0.0003)	(0.0004)	(0.0004)	(0.0005)
Pvar	−0.008	−0.006	−0.003	0.003	−0.001	−0.001	0.002	0.006
	(0.006)	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.004)
nowa_lev	−0.381	−0.396	−0.407	−0.396	−0.191	−0.180	−0.200	−0.204
	(0.236)	(0.249)	(0.264)	(0.284)	(0.287)	(0.303)	(0.318)	(0.341)
Observations	6,774	6,774	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.001	0.001	0.001	0.001	0.0004	0.0004	0.0003	0.0003
Adjusted R^2	-0.500	-0.501	-0.501	-0.501	-0.501	-0.502	-0.502	-0.502
F Statistic (df = 5; 4509)	0.984	0.912	0.760	0.659	0.815	0.634	0.531	0.855
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 7.26: Results of Model 4.2 and 4.4, IPUMS-I, UDEL metrics, and Nowater Level, With background climate and Interaction terms

	Model 4.2				Model 4.4			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)
Tvar	0.005 (0.007)	−0.001 (0.007)	−0.005 (0.008)	−0.005 (0.008)	0.008 (0.006)	0.005 (0.007)	0.001 (0.007)	0.003 (0.007)
Ptrend	−0.0001 (0.0004)	0.00005 (0.0004)	0.0001 (0.0005)	0.00005 (0.001)	−0.0003 (0.0003)	−0.0003 (0.0004)	−0.0003 (0.0004)	−0.0004 (0.001)
Pvar	−0.009 (0.006)	−0.007 (0.006)	−0.004 (0.006)	0.002 (0.005)	0.0001 (0.006)	−0.001 (0.005)	0.002 (0.005)	0.006 (0.004)
nowa_lev	−0.345 (0.306)	−0.343 (0.305)	−0.354 (0.313)	−0.291 (0.336)	−0.239 (0.371)	−0.212 (0.381)	−0.250 (0.387)	−0.248 (0.430)
nowa_lev:Ttrend	−0.104 (0.074)	−0.144 (0.093)	−0.182* (0.108)	−0.213* (0.127)	−0.056 (0.089)	−0.079 (0.110)	−0.110 (0.126)	−0.145 (0.145)
nowa_lev:Tvar	−0.417 (0.796)	−0.504 (0.802)	−0.220 (0.790)	0.190 (0.900)	−0.445 (0.887)	−0.614 (0.943)	−0.366 (0.917)	−0.122 (1.051)
nowa_lev:Ptrend	−0.023 (0.044)	−0.022 (0.050)	−0.031 (0.058)	−0.029 (0.072)	−0.006 (0.049)	0.002 (0.058)	−0.019 (0.067)	−0.045 (0.087)
nowa_lev:Pvar	0.332 (0.907)	0.239 (0.813)	0.234 (0.780)	0.380 (0.695)	−0.747 (1.189)	−0.673 (1.044)	−0.282 (0.960)	0.065 (0.821)
Observations	6,774	6,774	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.002	0.002	0.002	0.002	0.001	0.001	0.001	0.001
Adjusted R^2	-0.501	-0.501	-0.501	-0.501	-0.502	-0.502	-0.502	-0.502
F Statistic (df = 9; 4505)	0.865	0.868	0.822	0.807	0.611	0.568	0.471	0.644

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7.27: Results of Model 4.5, IPUMS-I, UDEL metrics, and Nowater Level, With background climate, No Interaction terms

	Model 4.5			
	lag 0	lag 1	lag 2	lag 3
	b std			
Ttrend	0.0001	0.001	0.002	0.003
	(0.003)	(0.004)	(0.004)	(0.005)
Tvar	−0.003	−0.025	−0.043	−0.047
	(0.030)	(0.030)	(0.031)	(0.032)
Ptrend	0.001	0.002	0.001	0.0004
	(0.001)	(0.002)	(0.002)	(0.002)
Pvar	−0.037	−0.022	−0.013	0.003
	(0.026)	(0.024)	(0.023)	(0.019)
nowa_lev	−0.832	−0.927	−0.990	−0.973
	(0.958)	(1.000)	(1.052)	(1.126)
Observations	5,378	5,378	5,378	5,378
R^2	0.001	0.001	0.001	0.001
Adjusted R^2	-0.538	-0.538	-0.538	-0.538
F Statistic (df = 5; 3493)	0.753	0.675	0.703	0.623
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.28: Results of Model 4.6, IPUMS-I, UDEL metrics, and Nowater Level, With background climate, With Interaction terms

	Model 4.6			
	lag 0	lag 1	lag 2	lag 3
	b std			
Ttrend	0.0003	0.002	0.003	0.004
	(0.003)	(0.004)	(0.005)	(0.005)
Tvar	0.00002	−0.025	−0.044	−0.049
	(0.031)	(0.031)	(0.033)	(0.033)
Ptrend	0.002	0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Pvar	−0.041	−0.026	−0.016	0.002
	(0.027)	(0.024)	(0.024)	(0.020)
nowa_lev	−0.927	−1.286	−1.272	−1.235
	(1.362)	(1.384)	(1.376)	(1.529)
nowa_lev:Ttrend	−0.097	−0.168	−0.234	−0.330
	(0.340)	(0.416)	(0.476)	(0.550)
nowa_lev:Tvar	−1.461	0.035	0.530	1.043
	(3.526)	(3.883)	(3.894)	(4.448)
nowa_lev:Ptrend	−0.136	−0.209	−0.227	−0.232
	(0.215)	(0.258)	(0.303)	(0.381)
nowa_lev:Pvar	2.578	2.515	2.006	0.786
	(5.060)	(4.447)	(4.217)	(3.447)
Observations	5,378	5,378	5,378	5,378
R^2	0.001	0.001	0.001	0.001
Adjusted R^2	-0.539	-0.539	-0.539	-0.539
F Statistic (df = 9; 3489)	0.538	0.490	0.496	0.431
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.29: Results of Model 5.1 and 5.3, IPUMS-I, UDEL metrics, and Seaper Level, With background climate, No Interaction terms

	Model 5.1				Model 5.3			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	0.0004 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Tvar	0.004 (0.007)	−0.001 (0.007)	−0.005 (0.007)	−0.004 (0.008)	0.008 (0.006)	0.005 (0.006)	0.0001 (0.007)	0.002 (0.007)
Ptrend	−0.0001 (0.0003)	0.00001 (0.0004)	0.00005 (0.0005)	−0.00001 (0.001)	−0.0003 (0.0003)	−0.0003 (0.0004)	−0.0004 (0.0004)	−0.0005 (0.0005)
Pvar	−0.008 (0.006)	−0.006 (0.005)	−0.003 (0.005)	0.003 (0.004)	−0.001 (0.006)	−0.001 (0.005)	0.002 (0.005)	0.006 (0.004)
seaper_lev	0.372 (0.236)	0.387 (0.249)	0.399 (0.263)	0.388 (0.283)	0.182 (0.286)	0.172 (0.302)	0.193 (0.316)	0.196 (0.340)
Observations	6,774	6,774	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.001	0.001	0.001	0.001	0.0004	0.0004	0.0003	0.0003
Adjusted R^2	-0.501	-0.501	-0.501	-0.501	-0.501	-0.502	-0.502	-0.502
F Statistic (df = 5; 4509)	0.963	0.893	0.743	0.644	0.808	0.629	0.526	0.850

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.30: Results of Model 5.2 and 5.4, IPUMS-I, UDEL metrics, and Seaper Level, With background climate and Interaction terms

	Model 5.2				Model 5.4			
	lag 0	lag 1	lag 2	lag 3	lag 0	lag 1	lag 2	lag 3
	b std							
Ttrend	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tvar	0.005	−0.0002	−0.004	−0.004	0.009	0.005	0.001	0.003
	(0.007)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)
Ptrend	−0.0001	0.00002	0.0001	0.00004	−0.0003	−0.0003	−0.0003	−0.0004
	(0.0003)	(0.0004)	(0.0005)	(0.001)	(0.0003)	(0.0004)	(0.0004)	(0.001)
Pvar	−0.008	−0.006	−0.004	0.001	−0.0003	−0.001	0.002	0.005
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)
seaper_lev	0.230	0.254	0.276	0.246	0.005	0.040	0.083	0.087
	(0.251)	(0.258)	(0.273)	(0.290)	(0.307)	(0.315)	(0.330)	(0.349)
seaper_lev:Ttrend	−0.024	−0.027	−0.028	−0.015	−0.020	−0.021	−0.019	−0.009
	(0.016)	(0.019)	(0.023)	(0.028)	(0.017)	(0.021)	(0.025)	(0.029)
seaper_lev:Tvar	−0.129	−0.129	−0.070	0.035	−0.189	−0.166	−0.117	−0.035
	(0.125)	(0.110)	(0.114)	(0.132)	(0.179)	(0.163)	(0.168)	(0.179)
seaper_lev:Ptrend	−0.002	−0.002	−0.005	−0.010	−0.002	−0.004	−0.007	−0.009
	(0.009)	(0.010)	(0.013)	(0.014)	(0.010)	(0.011)	(0.014)	(0.017)
seaper_lev:Pvar	0.011	0.016	0.067	0.247	−0.074	−0.012	0.024	0.156
	(0.161)	(0.153)	(0.179)	(0.164)	(0.178)	(0.168)	(0.186)	(0.160)
Observations	6,774	6,774	6,774	6,774	6,774	6,774	6,774	6,774
R^2	0.002	0.002	0.002	0.002	0.001	0.001	0.001	0.001
Adjusted R^2	-0.501	-0.501	-0.501	-0.501	-0.502	-0.502	-0.502	-0.502
F Statistic (df = 9; 4505)	0.877	0.910	0.785	0.950	0.771	0.679	0.538	0.739
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 7.31: Results of Model 5.5, IPUMS-I, UDEL metrics, and Seaper Level, With background climate, No Interaction terms

	Model 5.5			
	lag 0	lag 1	lag 2	lag 3
	b std			
Ttrend	0.0001 (0.003)	0.001 (0.004)	0.002 (0.004)	0.003 (0.005)
Tvar	−0.003 (0.030)	−0.025 (0.030)	−0.043 (0.031)	−0.047 (0.032)
Ptrend	0.001 (0.001)	0.002 (0.002)	0.001 (0.002)	0.0004 (0.002)
Pvar	−0.037 (0.026)	−0.022 (0.024)	−0.014 (0.023)	0.003 (0.019)
seaper_lev	0.835 (0.957)	0.928 (0.998)	0.990 (1.050)	0.973 (1.125)
Observations	5,378	5,378	5,378	5,378
R^2	0.001	0.001	0.001	0.001
Adjusted R^2	-0.538	-0.538	-0.538	-0.538
F Statistic (df = 5; 3493)	0.754	0.676	0.703	0.623
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7.32: Results of Model 5.6, IPUMS-I, UDEL metrics, and Seaper Level, With background climate, With Interaction terms

	Model 5.6			
	lag 0	lag 1	lag 2	lag 3
	b std			
Ttrend	0.0003 (0.003)	0.002 (0.004)	0.003 (0.004)	0.003 (0.005)
Tvar	−0.001 (0.030)	−0.024 (0.030)	−0.042 (0.032)	−0.046 (0.033)
Ptrend	0.001 (0.001)	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)
Pvar	−0.039 (0.027)	−0.024 (0.024)	−0.014 (0.024)	0.002 (0.020)
seaper_lev	0.636 (0.998)	0.784 (1.025)	0.840 (1.086)	0.869 (1.162)
seaper_lev:Ttrend	−0.039 (0.075)	−0.049 (0.091)	−0.069 (0.114)	−0.092 (0.146)
seaper_lev:Tvar	−0.315 (0.496)	−0.146 (0.427)	−0.108 (0.451)	−0.034 (0.529)
seaper_lev:Ptrend	−0.020 (0.037)	−0.030 (0.045)	−0.033 (0.055)	−0.039 (0.062)
seaper_lev:Pvar	0.105 (0.690)	0.125 (0.642)	0.047 (0.777)	0.037 (0.716)
Observations	5,378	5,378	5,378	5,378
R^2	0.001	0.001	0.001	0.001
Adjusted R^2	-0.539	-0.539	-0.539	-0.539
F Statistic (df = 9; 3489)	0.518	0.462	0.482	0.430
Note:				*p<0.1; **p<0.05; ***p<0.01

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