Exploring the dynamics of rural-urban migration, armed conflict, urbanization and anthropogenic change in Colombia

Guibor Camargo*, Andrés Miguel Sampayo*, Andrés Peña Galindo*, Francisco J. Escobedo[1], Fernando Carriazo*, Alejandro Feged-Rivadeneira*[æ]

*Faculty of International, Political and Urban Studies, Universidad del Rosario (Bogota, Colombia)

[1]Faculty of Natural Sciences, Universidad del Rosario (Bogotá, Colombia)

[æ]alejandro.feged@urosario.edu.co +57 3112376732

Abstract

Anthropogenic change is associated with population growth, land use change, and changing economies. However, internal migration patterns and armed conflicts are also key drivers behind anthropogenic and demographic processes. To better understand this sort of change, we explore the spatial relationship between forced migration due to armed conflict and changing demographic factors in Colombia, a country which has a recent history of 7 million internal migrants. In addition, we use remote sensing, Google Earth Engine, as well as spatial statistical analyses of demographic data in order to measure anthropogenic change between 1984 and 2008; and we look into spatiotemporal relationships between both demographic and anthropogenic changes, which are caused by forced migration. We find, thus, that the latter is significantly and positively related to an increasing rural-urban kind of migration which originates in armed conflict, and results show that it is also negatively associated with interregional expulsion. Indeed, anthropogenic prints (term hereafter used to denote changes in nighttime satellite imagery) pertaining to different regions have had different sensitivities towards forced migration, and across different time periods. Finally we discuss how social and political phenomena such as Colombia's armed conflict can have significant effects on the dynamics and motions of humans and territories in countries of the Global South.

Keywords: Demographic growth, Displacement, Remote Sensing, Forced Migration, Urban sprawl, Mobility

1. Introduction

Growth of urban population in the world is one of the most influential phenomena affecting earth's sustainability as it is associated with global change, which is affecting not only the environment but climate as well (Kalnay and Cai, 2003; Creutzig *et al.*, 2015; Kasman and Duman, 2015). One of these anthropogenic changes is urbanization which has been documented as being one of the most influential forces in creating novel ecosystem as well as plant and animal assemblages (McKinney, 2002; Aronson Myla F. J. *et al.*, 2014). Socioeconomically, anthropogenic change is the main cause of several contemporary epidemiological transitions (Ogden, 2018) and has been a result of, and influenced by, changes in land use and economic systems (Gollin *et al.*, 2016; Soja, 2016). Indeed, the transition of a society, as part of the industrialization and post-industrialization processes, has driven these modern globalized economic shifts into the dynamics of labor, land, and capital and into the eventual reduction in the demand for agricultural labor (Ibáñez, Ana María *et al.*, 2006; He *et al.*, 2016).

The above literature describing this urbanization and global change phenomena has been well published in North America and Europe; however, there is less information explaining urbanization and industrialization phenomena in other regions of the world; particularly in the Global South (Gollin et al., 2016; Chauvin et al., 2017). Additionally, socioeconomic factors are often core reasons for the migration of people across regions and boundaries, a fact which affects these phenomena as well. Furthermore social and political instability, and particularly armed conflicts of a state, both internal and external, can also cause a breakdown in its governability and subsequently can trigger rural-urban migrations (Raleigh, 2011). However, other factors such as environmental or political realities have been reported to play a lesser role in urbanization in many regions(Hamdani, 2014, p. 19).

The recent and current socio-political contexts in a country such as Colombia present a unique opportunity to explore these effects of migration on urbanization in a country which has one of the world's largest documented population of Internally Displaced People (IDP). Accordingly, by using the evolution of Colombia´s armed conflict and its influence on rural-urban migration and urbanization patterns, we canbetter understand these dynamics in countries of the Global South. The availability of remote sensing techniques, geospatial data, and other information on the migration and violence caused by armed conflict in Colombia can, therefore, be used to explore the association between anthropogenic change and internal migration. Below, we propose, then, how the Colombian context and this approach can be used to study the drivers of urbanization and rural-urban migration of people in a novel manner (Bertinelli and Black, 2004; Tao and Xu, 2007; Abu-Lughod and Hay, 2013)

Colombia and its armed conflict.

Colombia is located in Northern South America and has a population of around 50.000.000 inhabitants, concentrated mostly in the western and northeastern areas of the country. Six of its metropolitan areas exceed 1.000.000 inhabitants, and over 70% of its population lives in urban areas. Its geographical extension is 1,142,748 km2 (more than 4 times the size of the United Kingdom), which means a population density of 44 inhabitants per square kilometer (Departamento Administrativo Nacional Estadística (DANE), 2018).

Over a span of 50 years, violence Colombia experienced dramatic shifts and social phenomena, including: significant changes in national security policies, influenced by illegal trade agents, and different impacts upon civilians, among many other factors

(Aguilera Peña, 2016). As an instance we find that between 1968 and 1982, the Armed Revolutionary Forces of Colombia (FARC) were one of the most relevant guerilla groups. But by the end of the 1980s, Colombia had an active and complex armed conflict on multiple fronts, and by this time the FARC had progressively became one of the most important insurgencies (1,200 combatants) due to several reasons (Aguilera Peña, 2016). First, the end of peace dialogues in 1986 strengthened FARC as an armed insurgence and triggered the creation of other guerrilla groups. In a second instance the rise of several drug cartels coupled with political violence led to a crisis marked by the murders of political candidates, judges and members of the government, causing retaliation by government. Both factors increased forced displacement, which peaked in 2002. Similarly, during this same time period, paramilitary groups increased their military power, reaching 8,000 men between 1998 and 2002. This year represented a turning point in Colombia's armed conflict beginning with the election of Álvaro Uribe, whose main strategy was "Democratic Security"; a government policy focused on defeating the insurgent groups through increased military pressure, and the increasing of defense expenditures as opposed to other ODCE countries (Sierra, 2019). This increase in the conflict resulted in numerous human rights violations and displacement of peoples (Cinep, 2010)

Internally Displaced People (IDP) in Colombia.

Studies of intraregional, or within nation, human migration caused by armed conflicts generally consider the status of such migrants as refugees while others refer to them as Internally Displaced People (IDPs; Bakewell, 2011), however Hathaway (2007) argues that such definitions differ according to different sources of information. For example, Bennett (1998) defines these IDPs as, "Persons or groups of persons who have been forced to flee homes or places of habitual residence as a result of, or to avoid, in particular, the effects of the armed conflict, situations of generalized violence, violations of human rights or natural disasters". The author's definition also refers to migrants who do not cross internationally recognized borders. In fact, by 1982 there were 10 refugees for every displaced person, and in 2006 there were 5 displaced persons for every 2 refugees (Weiss and Korn, 2006). Zetter (2007) also highlights the cases of Darfur, Nepal and Colombia as examples of intra-state wars that have caused notable increases in IDPs. Since 1990, the number of victims of forced displacement - within the States - has been higher than that of refugees, but the gap has increased in the second decade of the 21st century (Internal Displacement Monitoring Center, 2015). Castles (2003) points out that displacement -forced or not- shapes the structure of relationships between the Global North and South.

In Colombia, displacement of people due to violence has affected 90 percent of the countries' municipalities either by expelling or by receiving populations (Ibáñez, Ana María *et al.*, 2006). Overall, IDPs are in a greater degree of vulnerability due to loss of land, homes, and employment opportunities (Corte Constitucional de Colombia, 2014). By the middle of the 20th century, Colombian municipalities such as Quibdo, Sincelejo, and Florencia had IDP rates between 20-26%, and it was medium-sized cities that received these IDPs, the equivalent to 20% of their population in just a few years (Ibáñez, Ana María and Velásquez, 2008). Conversely, some of Colombia's municipalities lost more than 50% of their population due to the forced migration and 10% lost nearly 25% of their population (Ibáñez, Ana María, 2008).

At this point, the main causes for IDPs to be a part of these numbers are exposure to most types of violent events, in and the expulsion of rural population from areas of conflict, which is carried out as a recurring tactic among armed groups in order to achieve multiple objectives such as acquiring land tenure and resources(Kalyvas, 2010; Balcells and Steele, 2016). In such manner, Colombian paramilitary forces such as the AUC alone caused between 57% and 63% of recent IDPs, while Guerrilla groups caused 12 to13%, and the remaining was caused by other unidentified groups as well as the State (Escobar, 2004). The lack of governability, for instance, or the absence of the state, its institutions, services, and security they provide, are factors that also contribute to the migrations of IDPs (Ibáñez, Ana María, 2004).

Remote sensing

As indicated above, the dynamics between armed conflict and IDP dynamics across space and time are complex phenomena that can be very difficult to analyze. However, the advent of remote sensing technologies and availability of socio-political data can now provide the opportunity to monitor land use and cover changes such as urbanization and can also be used to better understand the spatial dynamics of anthropogenic phenomena across spatio-temporal scales (Patino and Duque, 2013). For example, anthropogenic change has been described using the interaction between greenness and multiple socio-demographic variables including: (Lo and Faber, 1997; Patino and Duque, 2013), residential desirability and social structure (Green, N. E., 1957; Monier and Green, 1957), poverty and inequality (Mumbower and Donoghue, 1967; Metivier and McCoy, 1971), well-being (Weber and Hirsch, 1992; Patino and Duque, 2013), and socio-demographic spatial distributions (Mullens Jr and Senger, 1969; Miller and Winer, 1984). Such use of remote sensing and empirical models can also be used to describe demographic and socio-economic phenomena (Phinn *et al.*, 2002; Patino and Duque, 2013). Specifically, the increased availability of sensors, satellite imagery and increased resolution has facilitated the study of processes such as urbanization, land-use and land-cover change, population densities, crime, housing markets, and many other problems associated with urban and regional planning (Rashed *et al.*, 2001; Lu and Weng, 2004; Yin *et al.*, 2005; Taubenböck *et al.*, 2009; Griffiths *et al.*, 2010; Patino and Duque, 2013).

For example, high resolution images have been used to detect temporal urban changes at the sale of individual buildings, while combinations of Landsat, SPOT-5 and Synthetic Aperture Radar images have been used for single and comparative studies of urban growth (Taubenböck *et al.*, 2009; Patino and Duque, 2013; Ma *et al.*, 2015; Xie and Weng, 2016; Xiao *et al.*, 2018)). Night-time satellite imagery is also being used to study urban and peri-urban growth and its dynamics with human densities, economic activities and pollution (Sutton, 1997; Patino and Duque, 2013; Ma *et al.*, 2015; Mellander *et al.*, 2015; Xie and Weng, 2016; Xiao *et al.*, 2018). Thus, remote sensing can be used to better measure, verify and understand armed conflict and the movement of IDPs particularly in inaccessible, dangerous areas lacking data (Witmer, 2015).

Study Aims and Objectives

Given the context of the armed conflict and IDP dynamics in Colombia as well as the potential of using remote sensing to understand these phenomena in the Global South, we lay out an approach which uses available data and technologies to better understand how conflict, economies, and demographics drive the movement of IDP to cities (Alix-Garcia *et al.*, 2013). In this study, we aim to explore the relationship and dynamics among armed conflict, forced displacement, and anthropogenic as well as demographic changes. Accordingly, using Colombia as a case study, our objectives are two-fold. First, we use remote sensing to measure national-level anthropogenic change over a period of 20 years marked by armed conflict. Second, we analyze how the spatial dynamics between anthropogenic change and forced displacement are driven by conflict and other demographic factors. Such approach can be used to better understand the political, demographic and economic drivers of anthropogenic changes on land cover and their influence on forced migration and demographic changes in countries experiencing armed conflict.

2. Materials and Methods

Past and current socio-political contexts in Colombia present a unique opportunity to explore the effects of migration on urbanization in a country which has one of the world's largest documented population of IDPs. Accordingly, we study urban growth, via measurement of anthropogenic change, by taking into account the proximity between municipalities and fluctuations along time in the armed conflict. We also combine different remote sensing data, Google Earth Engine, migration and armed conflict victim data, and spatial and statistical analyses to explore the relationships between anthropogenic change and internal migration. By using the Colombian socio-political context and this integrated quantitative approach we can better study the drivers of urbanization and rural-urban migration of people in the Global South in a more novel manner as we will detail below (Bertinelli and Black, 2004; Tao and Xu, 2007; Abu-Lughod and Hay, 2013)

2.1 Study area

According to Ocampo (2015) between 1993 and 2005, the population of Colombia´s municipal capitals grew at a rate of 2% per year, while the rural population decreased at the rate of 0.09%. The causes for this reduction in the population are associated with a fall in fertility rates with some particularities regarding adolescent fertility and an increase in migration to cities by the youngest population. The influence of the armed conflict against the influence of employment opportunities on this growth is however unknown (Ocampo, 2015). Figure 1 summarizes the relevant background information in our introduction section regarding the recent history and key dates associated with Colombia's armed conflict and displacement of peoples.

Figure 1. Brief history of Forced Migration Flows in Colombia.

2.2 Remote sensing analyses

We used remote sensing to address our objectives in multiple phases as shown in Figure 2. In the first phase of our analysis we used twelve different nightlight rasters from the Defense Meteorological Program Operational Linescan System (DMSP OLS - Nighttime Lights Time Series Version 4 raster data set), as well as image and data processing by NOAA's National Geophysical Data Center. In addition, the rasters selected from DMSP OLS where taken from spectral band containing unfiltered mean values of visible light. Figure 2 also shows the data processing which was implemented to generate the following variables used in our analyses: Average Anthropogenic Change (AAC), the Anthropogenic Print Spatial Expansion (ApSE) and the Anthropogenic Print Spatial Contraction (ApSC) for Colombia from 1991 to 2013.

Figure 2. Data processes. This figure shows the workflow of converting different raster files of satellite imagery into datasets that adequately described our main variable of interest: anthropogenic change over specific time-periods.

We measured anthropogenic change by using Nighttime Lights Time Series (Nighttime hereafter) for two reasons. First nighttime imagery has been used to appropriately describe population flows, as opposed to land-use change measured by classification of multi-spectral satellite imagery (Sutton, 1997; Patino and Duque, 2013; Ma *et al.*, 2015; Mellander *et al.*, 2015; Xie and Weng, 2016; Xiao *et al.*, 2018). Second, it was available for the whole study period, unlike other satellite imagery used to analyze urbanization processes. Thus, we use the term "anthropogenic print" hereafter to denote changes in nighttime satellite imagery, where one such common anthropogenic change is urbanization.

For our second analysis, we used Google Earth Engine and created six new corrected raster files (RC) from the average of two consecutive DMPS OLS files (raster process 1). Raster process 2 consisted of calculating the AAC using Google Earth Engine for three time periods of interest: 1991-1998, 1999-2006 and 2006-2013. With the calculated AAC raster using Equation 1, we extracted several municipal level statistics including: AAC's average, AAC's standard deviation, and AAC's maximum and minimum values.

$$AAC = \Delta RC = RC_{T+1} - RC_T = \frac{\sum_{t+5}^{t+8} \; avg\_vis}{4} - \frac{\sum_{t}^{t+4} \; avg\_vis}{4} \; (1)$$

Raster process 4, consisted of reclassifying positive and the negative values for each raster into quartiles and transforming them into a shapefile. As shown in raster process 5, we obtained a final database which classified all the national territory into 9 different categories. The resulting datasets are shown in Figure 3.

Figure 3. Visual representation of the spatial dataset used for the econometric analysis.

For each of the three time periods and municipalities, we calculated the total area covered by each of the nine AAC categories. Anthropogenic Print Spatial Expansion (ApSE) was calculated by dividing the total area (in hectares) for the greatest quartiles of AAC (areas that in a specific time period experienced either significant AAC increases, or very significant AAC increases) by the total hectares of each municipality. Equations 2 and 3 summarize both spatial indexes. Overall, AAC depicts changes in nightlight intensity levels, but it does not reflect the geographic expansion of anthropogenic activity (such as urban expansion).

$$ApSC_T = \frac{Ha_i \,||\, (-Q1)_T + (-Q2)_T}{Total\ Ha} \quad (2)$$

$$ApSE_T = \frac{Ha_i \,||\, (+Q3)_T + (+Q4)_T}{Total\ Ha} \quad (3)$$

These different measurements were implemented because there are some places with large variations in AAC levels where no significant changes related to the size of the anthropogenic print were observed, thus, increments in nightlight intensity could be related to densification process, electrification programs, or increases in electricity consumption. Then, we estimated the relationship between forced migration and urban expansion using the “forced migration flow” (FMF) index (Equation 4), that represents the percentage of population growth or the percentage of its decrease due to forced migration for each municipality. Because we were limited to 3 different time periods in our analysis, the opportunity to run panel base regression models is restricted, as described in Figure 4.

$$FMF_T = \frac{\sum_{t=1}^{8} Received\ population - \sum_{t=1}^{8} Expulsed\ population}{Total\ population_{t8}} \quad (4)$$

Figure 4. Study´s time lags representation

Thus, the distance from each municipality to the department's capital was calculated using ArcGIS's Euclidian analysis. The following table contains the summary statistics for the described variables and controls used in our study:

Table 1: Summary statistics of all the variables used in the statistical analysis.

Overall, we used four different models to capture and analyze the relation between forced migration flow (FMF) and anthropogenic print expansion (ApSE): Ordinary Least Squares (OLS), Durbin spatial error model (Kelejian, H., and Piras, G. 2017), Durbin model for spatial lag, and a Geographically Weighted Regression (GWR). From the first three models, we ran the GWR with one lag over the FMF for every time period studied, because it was the one that better described the effect of FMF over ApSE. The only difference with the other models is that the GWR excluded the squared demographic bonus to avoid multicollinearity.

We used cross sectional models that assume that the process of Anthropogenic Spatial Expansion does not occur simultaneously with the Forced Migration process, but rather that it takes some time for the Urban Expansion to occur, once a municipality is exposed to migration flows. Thus, the temporal lag of one period encompasses an eight-year period. After assessing the goodness of fit among models, we selected the cross sectional method with best goodness of fit. We then explored different temporal lags for the Migration Flow variable for the selected model. The following Figure 5 shows the regions used for the analysis, and their correspondent AAC and ApSE values for each time period. Our regression models also included the Demographic Bonus variable to explore how the Labor Force composition may affect urban expansion and assumed that the relationship between the Demographic Bonus and Urban expansion was not linear.

Figure 5: Regions of Colombia used in the Geographically Weighted Regression analysis.

3. Results

We found that the percentage of Urban Population variable is positive and statistically significant in all estimated models. This result indicates that as the urban area - that is to say a percentage of the total area of the municipality- increases in the initial period the urban expansion increases too. This effect was stronger for the regression models that encompassed the period 1992-1999. A one percent increase in the urban area at the beginning of this period, brings as a result an increase of 0.18% in the urban expansion. The negative coefficient of the variable Distance to a Capital City indicates that the proximity to a large urban center induces to a larger urban expansion. This can be explained by the strong economic interactions that may occur between large urban nuclei and the surrounding municipalities that may trigger urban growth. In a different regard, the percentage of municipal area with deforestation was not significant.

We also found that the coefficient for the variable FMF, our variable of interest, was positively and statistically significant in relation to anthropogenic urban expansion and forced migration flows. These coefficients are positive in all model specifications. However, the coefficients that accompany this variable are significant at all conventional levels in the OLS and Spatial Lag specifications, but not for the Spatial Error Model (Table 2). Overall, the magnitude of parameter estimates is larger in the OLS model than in the Spatial Lag version. It is interesting to find that the magnitude of the coefficients decreases as the Time Period for the estimation increases. For example, in the Spatial Lag model, the coefficient of the forced migration variable for the estimation that cover the period 1992-1999 is 0.650 while the value of this coefficient in the period 2007-2014 is 0.086.

Table 2. Anthropogenic Print Spatial Expansion (ApSE) regression analysis with one lag over FMF

The goodness of fit of all our models suggested that the Spatial Lag model best fit our data. Overall, the R2 statistic is higher in the spatial lag (i.e 0.757 for T3 in Spatial Lag) model compared to R2 of the OLS (0.259) or the Spatial Error models (0.137). The best goodness of fit of the Spatial Lag model is also supported by the higher values of the Log-likelihood for this specification compared to the Log-likelihood of the OLS and Spatial Error models (Table 2). Using the selected Spatial Lag model as a reference, we explored the effect of Flow Migration using different temporal lags, namely, one lag, half a lag and no lag. (Table 3).

Table 3. Anthropogenic Print Spatial Expansion (ApSE) Spatial lag regression output

For these set of models, we estimated the Spatial Lag for the periods T1, T2 and T3. Overall, the results of these models corroborate that the Spatial Lag model with a temporal lag of one period presents the strongest effect of FMF. For the period 1992-1999, the positive coefficient of 0.650 that accompanies the variable FMF indicates that a 10% increase in the migration flow brings as a result a 6.5% increase in the urban expansion variable. When we reduce the temporal lags to half lag and no lag, the effect of forced migration on urban expansion dissipates with the exception of the period T3=2007-2014, where the instantaneous effect of Flow Migration seems stronger (0.26 vs 0.19 in the half lag model and 0.086 in the one lag model). In all cases, the coefficient Rho for the Spatial Lag variable is positive and statistically significant at all conventional levels.

Table 4. Average AAC and ApSE per time period (T)

3.2 Relationship between forced migration and anthropogenic expansion (ApSE)

All the GWR models were analyzed by using a sample of 1,041 municipalities. Figure 6 shows the distribution of the coefficient of the FMF between 1984 and 1991 over the ApSE from 1992 to 1999. The graph shows the relationship between FMF from the

1980's and the ApSE in the 1990's, differentiated by region. Note that the effect violence from the 80's, had significant effect over the configuration of the anthropogenic print in the 90's in all the regions (p-value < 0.1). Some of these regions' anthropogenic prints had a much higher sensitivity towards violence than others. For example, in the Eastern Plains and the Great Tolima regions, the effect of violence on the ApSE was almost 2,2 times higher than in the Antioquia region (where cities like Medellin, Pereira or Armenia are located). We note that these estimates correspond to the independent variable FMF for each time period, and the intercepts coefficients and standard error for each model. The other mentioned regression coefficients and standard errors were calculated as part of the models but are not shown.

Figure 6. Effect of one lag FMF over the ApES from 1992 to 1999.

Table 5. GWR: One lag model over ApSE from 1992 to 1999 (T1)

We also found that AsPE in the 1990's for both the Pacific and Caribbean coasts of Colombia were less related to FMF than what inland territories were and thus, there seems to be a periphery-center behavior with respect to violence and urban expansion. In the Nariño and Amazon regions it isshown that the effect of the FMF over the ApSE was significantly higher than the rest of the country (*p-value* < 0.01) (Table 5).

Figure 7 shows the relationship between FMF from the 1980s and the ApSE since the 1990s.e also found several key differences in the relationship between forced migration in the 1990s and the ApSE from 2000 to2008. In particular, the loss in the significance of FMF in five of the 10 regions was notable. This, however, does not suggest that there was no expansion of the anthropogenic print in these regions or forced migration; in fact, the Antioquia region experienced the largest proportional expansion. But rather, there seems to be no significant relationship between these two variables for half of the regions within this period of time. We also observed a loss in significance of FMF effect over the anthropogenic print for both Antioquia and the central regions of Colombia.

Figure 7. Effect of one lag FMF over the ApES from 2000 to 2008.

Figure 8. Effect of one lag FMF over the ApES from 2007 to 2014.

Table 6. GWR: One lag model over ApSE from 2000 to 2007 (T2)

Our results indicate the relationship between FMF and ApSE over the last time period as an instance where FMF recovers predictive ability towards anthropogenic change compared with T2 (Table 6).

Table 7. GWR: One lag model over ApSE from 2008 to 2014 (T3)

Finally, we also estimated the effect of one lag of FMF on the ApSE of the seven biggest metropolitan areas (MA) in the country: Bogota, Aburra Valley, Cali, Barranquilla, Cartagena, Bucaramanga and Cucuta. Our results show that more than 20.2 million people live in these areas, accounting for 45% of Colombia's censed population (CENSO 2019, preliminary data) (Table 7). Results are shown in Figure 9 and suggest there is little effect of FMF on ApSE in MAs, or not adequately captured by our model, particularly during T2. T1 is significant and shows a positive effect with coefficients above 0.5 for most MAs (larger for those close to Venezuela), except in the Aburra Valley (Medellin) MA, Thus confirming the observed regional effect in previous models.

Figure 9. Effect of one lag FMF over ApES of metropolitan areas above one million inhabitants.

Discussion

This study explored the complex spatial and temporal relationships and dynamics related to armed conflict, forced displacement, and anthropogenic and demographic changes in Colombia. Our integrated approach using remote sensing and Google Earth

Engine to measure national-level anthropogenic change over a period of 20 years marked by armed conflict indicated that effect of the lagged migration on urban expansion was stronger in the period when the armed conflict reached its pick in terms of displacement (T1=1992-1999) and had the inertia of a period with strong violence triggered by guerrillas and drug traffic (Lag T1=1984-1992). Furthermore, our results suggest a strong spatial interaction among neighboring municipalities in the process of urban expansion. As the urban expansion of neighboring municipalities increases, so does the urban expansion of an observed municipality. Conversely, urban expansion in a determined municipality influences positively the urban expansion of the neighboring municipalities. In the case of the AsPE, it was less related to FMF in the coasts during the 1990´s, and and this is possibly due to as the fact that violence was stronger in these regions, so they could be categorized as sources of migration, while other regions were receiving (sinks).

Our findings are consistent with other studies (Williamson, 1986, 1988; Zhang and Shunfeng, 2003; Green, L., 2018). First, we find that both migration and demographic change play an important role in urban growth, and most interestingly, we find that these roles can change in importance in terms of explaining potential spatial patterns such as urban sprawl. We found that internal migration over the period 2000-2007 was more influential in explaining urbanization, than in previous periods. However, we did find evidence that population structure is strongly associated with urban growth over periods of less intense forced migration. This increase in rural - urban migration observed during 2000-2007 rendered structural characteristics of the population less important in terms of urbanization. This finding has strong implications in terms of the importance between migration and vital rates in the demographic transition. However, we have observed that their importance can vary across specific decades, which is a short time in terms of demographic transitions.

Our analysis of the spatial dynamics between anthropogenic change and forced displacement were found to be driven by conflict and other demographic factors (Table 2 and Figures 5, 6 and 7). For example, the loss of significance of the FMF over anthropogenic print in Antioquia does not mean that they did not experience spatial expansion of the anthropogenic print, in fact they were also among the regions with the largest spatial change in the country over that period (Table 4). We hypothesize, though further research is needed, that rural to urban migrations was not related to violence, but to rural poverty and conditions of living, and it rendered the effect of FMF insignificant. Another factor that could affect this estimate is the anthropogenic print expansion's morphology: Porous or spongy urban areas and peripheries, could lead to densification process that are hard to identify by means of the type of information which was used. Nevertheless, these results provide new insights into the identification of other key drivers of the expansion of the city and the human activity in Colombia's landscape.

The fact that FMF recovers predictive power in the last time period suggests that the expansion of the anthropogenic print between 2000 and 2007 follows a different trend with respect to the ApSE between 1992 and 1999, and the ApSE between 2007 and 2014. The political history associated with each of these time periods provides the context to understand such changes, since T2 is both the peak of FMF and coincides with one of the most controversial political events during this analysis period; a public policy by a right-wing government whose aim was to recover security. T1, on the contrary, is associated with a context of violence due to drug-trafficking. Another example is the relationship between areas receiving IDP and their rates of deforestation (He *et al.*, 2016). Carrillo (2009) suggests that the precarious conditions in which some IDPs arrive not only in peri-urban but also in rural areas force them to participate in activities such as logging, illegal crops or cattle ranching, which leads to land use-land cover changes and deforestation, similar to what is reported by several authors (Alix-Garcia *et al.*, 2013; García, 2014). In particular, certain illegal activities such as illegal drug cultivation and mining are key activities in which IDPs participate (Angrist and Kugler, 2008). As such, the migration paths taken by IDPs are not strictly rural-urban but also rural-rural migration.

This takes place both in the receiving and expelling areas but is more significant in the former given the population density. Overall, studies on forced migration document how IDPs experience a substantial decrease in overall well-being. Such internally displaced households also experience considerable drops in aggregate consumption per adult equivalent (Ibáñez, Ana María *et al.*, 2006), and only access to state services and infrastructure and a strong institutional presence contribute to mitigating the incidence of IDP (Ibáñez, Ana María, 2004).

We do not overlook the fact that our study does have some limitations. First, we are inferring the anthropogenic print from nighttime satellite imagery, which is only one of many methods used to study urban growth. Further studies with other image collections will probably increase our understanding of the relationship between these variables (migration and urban growth), with greater heterogeneity and resolution. Our migration dataset was also composed of aggregated values. As better information becomes available over the routes of individuals over space and time, these processes will also be better understood. As mobile phone data, for example, becomes available to describe mobility patterns of migrant populations, we will also be able to associate specific migrant profiles to spatial patterns. Our study, however, lays forward a set of questions that can be better framed after this exploratory study.

Conclusion

Internal migrations due to armed conflicts have been documented to affect the social fabric of many societies. We found that the migration of IDP has not directly impacted the larger urban centers rather, this rural-urban migration has substantially impacted peri-urban, and this has important implications given their lower response capacity, lack of infrastructure and resilience. However, migration due to violence does not have a static logic. That is, the flows vary according to different contexts such as violence and the demographic transition of the local population, which makes formulation of public policies aimed at dealing with the effects of IDP migrating to cities very complex.

The problems associated with displaced persons and their migration are not exclusive to the peri-urban and urban areas that are receiving them, although these are the areas and sorts of IDP that require the most assistance (Landau, 2018). Similarly, it was found that sources of IDP also undergo particular detrimental dynamics such as reduced economic activity and increased deforestation due to urban and rural land abandonment (Ibáñez, Ana María *et al.*, 2006). Hence, it is important to address the problems of IDP in both expelling and receiving areas.

Our study illustrates growth of anthropogenic interventions as an effect of migration processes in a Latin American country. Little is known of how that migration has impacted human occupation of the environment, among many other questions in which this type of analysis can be used as a proxy for population flows. The use of satellite imagery is likely only one of the arising technology driven datasets to explore human flows. Further studies of this phenomenon can include data science contributions such as machine learning in classification of images and also the application of heterogeneous methodologies to analyze these types of human flow datasets.

Understanding human flows and being able to estimate them from readily available and charge-free information can be crucial for public policy formulation and impact evaluation. Estimating flows of vulnerable populations, often undocumented, within a country is fundamental to many government responsibilities, including resource allocation, disease risk, epidemics and other public health activities and maps in the context of natural hazards and climate change, among others. Our study shows, with several limitations, that it is possible to measure human flows from satellite imagery and to link them with social phenomena such as violence to inform public policy.

References

Abu-Lughod, J. and Hay, R. J. (2013) *Third world urbanization*. Routledge.

Aguilera Peña, M. (2016) *Las FARC: la guerrilla campesina, 1949-2010?` Ideas circulares en un mundo cambiante?* Organización Internacional para las Migraciones (OIM-Misión Colombia).

Alix-Garcia, J., Bartlett, A. and Saah, D. (2013) The landscape of conflict: IDPs, aid and land-use change in Darfur. *Journal of Economic Geography* 13.4, 589–617.

Angrist, J. D. and Kugler, A. D. (2008) Rural windfall or a new resource curse? Coca, income, and civil conflict in Colombia. *The Review of Economics and Statistics* 90.2, 191–215.

Aronson Myla F. J., La Sorte Frank A., Nilon Charles H., Katti Madhusudan, Goddard Mark A., Lepczyk Christopher A., Warren Paige S., Williams Nicholas S. G., Cilliers Sarel, Clarkson Bruce, Dobbs Cynnamon, Dolan Rebecca, Hedblom Marcus, Klotz Stefan, Kooijmans Jip Louwe, Kühn Ingolf, MacGregor-Fors Ian, McDonnell Mark, Mörtberg Ulla, Pyšek Petr, Siebert Stefan, Sushinsky Jessica, Werner Peter and Winter Marten (2014) A global analysis of the impacts of urbanization on bird and plant diversity reveals key anthropogenic drivers. *Proceedings of the Royal Society B: Biological Sciences* 281.1780, 20133330.

Bakewell, O. (2011) Conceptualising Displacement and migration: Processes, conditions, and categories. *The migration-displacement nexus: Patterns, processes, and policies. Oxford: Berghahn Books* 14–28.

Balcells, L. and Steele, A. (2016) Warfare, political identities, and displacement in Spain and Colombia. *Political Geography* 51, 15–29.

Bennett, J. (1998) Forced migration within national borders: the IDP agenda. *Forced Migration Review* 1998.1, 4–6.

Bertinelli, L. and Black, D. (2004) Urbanization and growth. *Journal of Urban Economics* 56.1, 80–96.

Carrillo, A. C. (2009) Internal displacement in Colombia: humanitarian, economic and social consequences in urban settings and current challenges. *International Review of the Red Cross* 91.875, 527–546.

Castles, S. (2003) Towards a sociology of forced migration and social transformation. *Sociology* 37.1, 13–34.

Chauvin, J. P., Glaeser, E., Ma, Y. and Tobio, K. (2017) What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States. *Journal of Urban Economics* 98, 17–49.

Cinep (/2010) The Legacy of Uribe Policies: challenges for the Santos administration. *Issuu*. [WWW document]. URL https://issuu.com/cinepppp/docs/the_legacy_of_uribe_policies_specialr_august2010 (accessed 17th December 2019).

Corte Constitucional de Colombia (/2014) T-689-14 Corte Constitucional de Colombia. [WWW document]. URL https://www.corteconstitucional.gov.co/relatoria/2014/T-689-14.htm (accessed 12th March 2020).

Creutzig, F., Baiocchi, G., Bierkandt, R., Pichler, P.-P. and Seto, K. C. (2015) Global typology of urban energy use and potentials for an urbanization mitigation wedge. *Proceedings of the National Academy of Sciences* 112.20, 6283–88.

Departamento Administrativo Nacional Estadística (DANE) (/2018) Censo Nacional de Población y Vivienda 2018. [WWW document]. URL https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/censo-nacional-de-poblacion-y-vivenda-2018 (accessed 12th March 2020).

Escobar, A. (2004) Desplazamientos, desarrollo y modernidad en el Pacífico colombiano. *Conflicto e (in) visibilidad. Retos en los estudios de la gente negra en Colombia* 53–72.

García, H. (2014) Deforestación en Colombia: Retos y perspectivas.

Gollin, D., Jedwab, R. and Vollrath, D. (2016) Urbanization with and without industrialization. *Journal of Economic Growth* 21.1, 35–70.

Green, L. (2018) Migration, urbanization, and national development in Nigeria. In *Modern Migrations in Western Africa*. Routledge.

Green, N. E. (1957) *Aerial photographic interpretation and the social structure of the city*. American Society of Photogrammetry.

Griffiths, P., Hostert, P., Gruebner, O. and van der Linden, S. (2010) Mapping megacity growth with multi-sensor data. *Remote Sensing of Environment* 114.2, 426–439.

Hamdani, K. (2014) Trans-border Vulnerabilities. *Human Development Research Paper. United Nations Development Programme, Human Development Report Office, New York.*

Hathaway, J. C. (2007) Forced Migration Studies: Could We Agree Just to 'Date'? *Journal of Refugee Studies* 20.3, 349–369.

He, C., Chen, T., Mao, X. and Zhou, Y. (2016) Economic transition, urbanization and population redistribution in China. *Habitat International* 51, 39–47.

Ibáñez, Ana María, Moya, A. and others (2006) *Cómo el desplazamiento forzado deteriora el bienestar de los hogares desplazados?: análisis y determinantes del bienestar en los municipios de recepción*. CEDE.

Ibáñez, Ana María and Velásquez, A. (2008) *El impacto del desplazamiento forzoso en Colombia: condiciones socioeconómicas de la población desplazada, vinculación a los mercados laborales y políticas públicas*. CEPAL.

Ibáñez, Ana María (2004) Génesis del desplazamiento forzoso en Colombia: sus orígenes, sus consecuencias y el problema del retorno.

Ibáñez, Ana María (2008) *El desplazamiento forzoso en Colombia: un camino sin retorno hacia la pobreza*. Ediciones Uniandes-Universidad de los Andes.

Internal Displacement Monitoring Center (/2015) Internal Displacement Monitoring Center. *IDMC.* [WWW document]. URL https://www.internal-displacement.org/home (accessed 12th March 2020).

Kalnay, E. and Cai, M. (2003) Impact of urbanization and land-use change on climate. *Nature* 423.6939, 528–31.

Kalyvas, S. N. (2010) *La lógica de la violencia en la guerra civil*. Vol. 299. Ediciones Akal.

Kasman, A. and Duman, Y. S. (2015) CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: A panel data analysis. *Economic Modelling* 44, 97–103.

Landau, L. B. (2018) Displacement and the pursuit of urban protection: Forced migration, fluidity and global cities. In *Forced Migration*. Routledge.

Leighton, M. (2016) Desertification and migration. In *Governing Global Desertification*. Routledge.

Lo, C. P. and Faber, B. J. (1997) Integration of Landsat Thematic Mapper and census data for quality of life assessment. *Remote sensing of environment* 62.2, 143–157.

Lu, D. and Weng, Q. (2004) Spectral mixture analysis of the urban landscape in Indianapolis with Landsat ETM+ imagery. *Photogrammetric Engineering & Remote Sensing* 70.9, 1053–1062.

Ma, T., Zhou, Y., Zhou, C., Haynie, S., Pei, T. and Xu, T. (2015) Night-time light derived estimation of spatio-temporal characteristics of urbanization dynamics using DMSP/OLS satellite data. *Remote Sensing of Environment* 158, 453–464.

McKinney, M. L. (2002) Urbanization, Biodiversity, and ConservationThe impacts of urbanization on native species are poorly studied, but educating a highly urbanized human population about these impacts can greatly improve species conservation in all ecosystems. *BioScience* 52.10, 883–90.

Mellander, C., Lobo, J., Stolarick, K. and Matheson, Z. (2015) Night-time light data: A good proxy measure for economic activity? *PloS one* 10.10, e0139779.

Metivier, E. and McCoy, R. (1971) Mapping urban poverty housing from aerial photographs. In *Proceedings of the Seventh International Symposium on Remote Sensing of Environment, Ann Arbor: University of Michigan Press* Vol. 15631569.

Miller, P. R. and Winer, A. M. (1984) Composition and dominance in Los Angeles Basin urban vegetation. *Urban Ecology* 8.1–2, 29–54.

Monier, R. B. and Green, N. E. (1957) Aerial photographic interpretation and the human geography of the city. *The Professional Geographer* 9.5, 2–5.

Mullens Jr, R. H. and Senger, L. W. (1969) Analysis of urban residential environments using color infrared aerial photography: An examination of socioeconomic variables and physical characteristics of selected areas in the Los Angeles basin, with addendum: An application of the concepts of the Los Angeles residential environment study to the Ontario-Upland region of California.

Mumbower, L. E. and Donoghue, J. (1967) Urban poverty study. *Photogrammetric Engineering* 33.6, 610–618.

Ocampo, J. (2015) El Campo Colombiano: un camino hacia el bienestar y la paz. *Departaménto de Planeación Nacionlal (DNP): Misión para la transformación del campo*.

Ogden, L. A. (2018) The Beaver DiasporaA Thought Experiment. *Environmental Humanities* 10.1, 63–85.

Patino, J. E. and Duque, J. C. (2013) A review of regional science applications of satellite remote sensing in urban settings. *Computers, Environment and Urban Systems* 37, 1–17.

Phinn, S., Stanford, M., Scarth, P., Murray, A. and Shyy, P. (2002) Monitoring the composition of urban environments based on the vegetation-impervious surface-soil (VIS) model by subpixel analysis techniques. *International Journal of Remote Sensing* 23.20, 4131–4153.

Raleigh, C. (2011) The search for safety: The effects of conflict, poverty and ecological influences on migration in the developing world. *Global Environmental Change* 21, S82–93.

Rashed, T., Weeks, J. R., Gadalla, M. S. and Hill, A. G. (2001) Revealing the anatomy of cities through spectral mixture analysis of multispectral satellite imagery: a case study of the Greater Cairo region, Egypt. *Geocarto International* 16.4, 7–18.

Sierra, J. R. (2019) *Breve historia del conflicto armado en Colombia*. Los Libros de la Catarata.

Soja, E. W. (19/02/2016) Regional urbanization and the end of the metropolis era. *Cities in the 21st Century*. doi:10.4324/9781315652221-13.

Sutton, P. (1997) Modeling population density with night-time satellite imagery and GIS. *Computers, Environment and Urban Systems* 21.3–4, 227–244.

Tao, R. and Xu, Z. (2007) Urbanization, rural land system and social security for migrants in China. *The Journal of Development Studies* 43.7, 1301–1320.

Taubenböck, H., Wegmann, M., Roth, A., Mehl, H. and Dech, S. (2009) Urbanization in India–Spatiotemporal analysis using remote sensing data. *Computers, environment and urban systems* 33.3, 179–188.

Weber, C. and Hirsch, J. (1992) Some urban measurements from SPOT data: urban life quality indices. *International Journal of Remote Sensing* 13.17, 3251–3261.

Weiss, T. G. and Korn, D. A. (2006) *Internal displacement: conceptualization and its consequences*. Routledge.

Williamson, J. G. (1986) Migration and urbanization in the Third World.

Williamson, J. G. (1988) Migration and urbanization. *Handbook of development economics* 1, 425–465.

Witmer, F. D. (2015) Remote sensing of violent conflict: Eyes from above. *International Journal of Remote Sensing* 36.9, 2326–2352.

Xiao, H., Ma, Z., Mi, Z., Kelsey, J., Zheng, J., Yin, W. and Yan, M. (2018) Spatio-temporal simulation of energy consumption in China's provinces based on satellite night-time light data. *Applied Energy* 231, 1070–1078.

Xie, Y. and Weng, Q. (2016) Detecting urban-scale dynamics of electricity consumption at Chinese cities using time-series DMSP-OLS (Defense Meteorological Satellite Program-Operational Linescan System) nighttime light imageries. *Energy* 100, 177–189.

Yin, Z.-Y., Stewart, D. J., Bullard, S. and MacLachlan, J. T. (2005) Changes in urban built-up surface and population distribution patterns during 1986–1999: A case study of Cairo, Egypt. *Computers, Environment and Urban Systems* 29.5, 595–616.

Zetter, R. (2007) More labels, fewer refugees: Remaking the refugee label in an era of globalization. *Journal of refugee studies* 20.2, 172–192.

Zhang, K. H. and Shunfeng, S. (2003) Rural–urban migration and urbanization in China: Evidence from time-series and cross-section analyses. *China Economic Review* 14.4, 386–400.

Figure 1

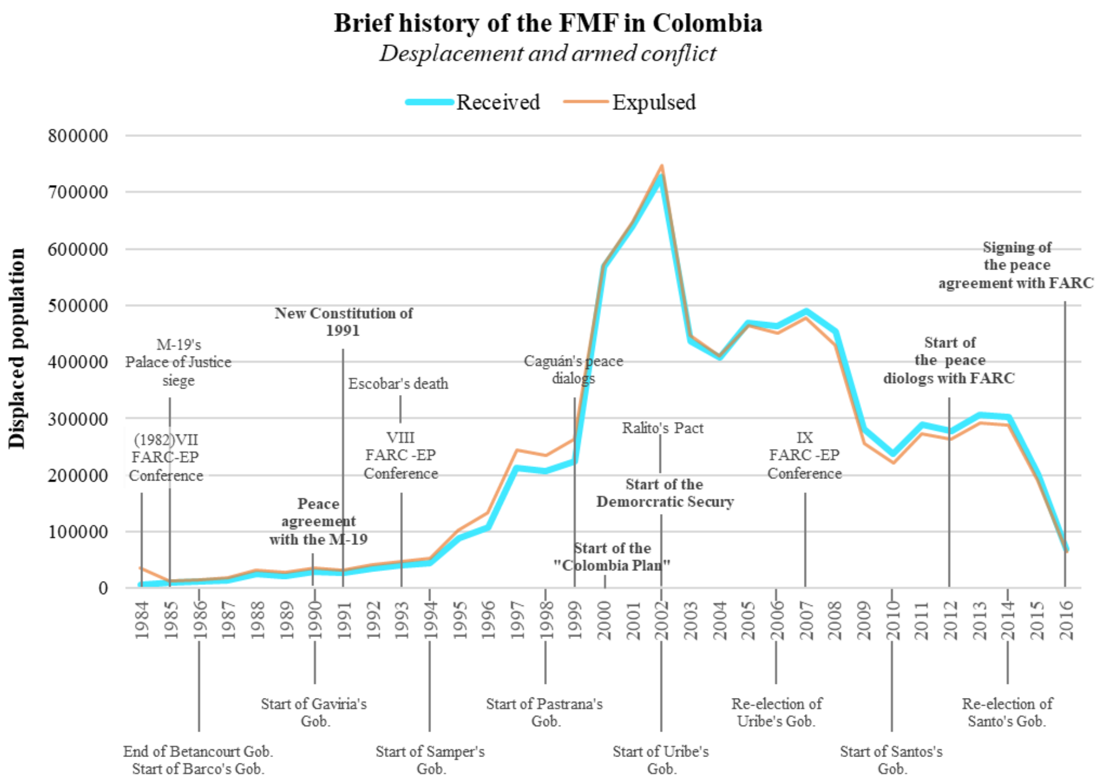


Figure 2

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 March 2020

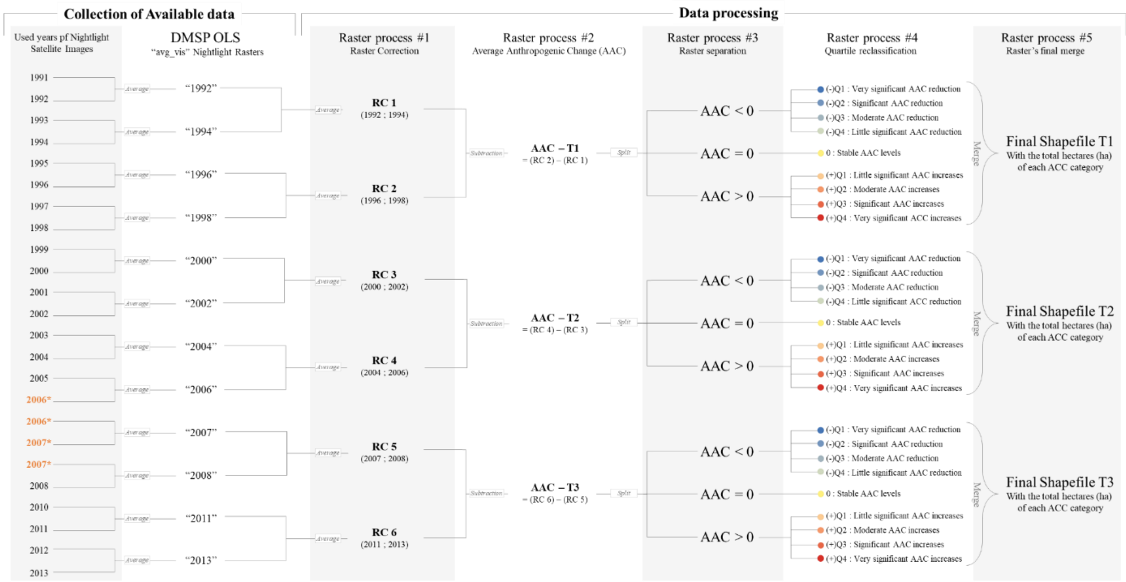


Figure 3

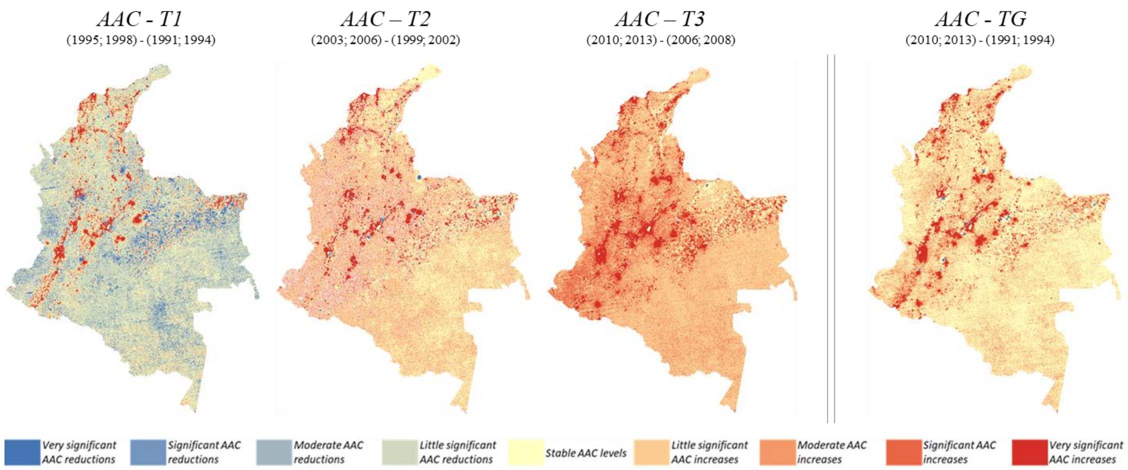


Figure 4. Study´s time lags representation

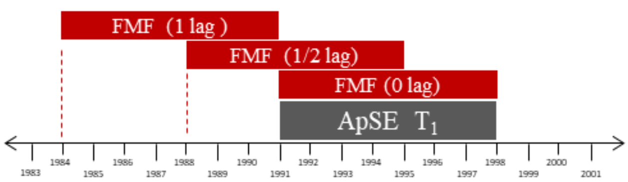


Table 1

Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Description
AAC T_1	1120	0.38	1.27	-5.59	11.56	Average change in nightlight level
AAC T_2	1120	-0.98	0.85	-9.12	5.61	
AAC T_3	1120	2.12	1.42	0.35	11.76	
AAC $T_{General}$	1120	1.88	2.30	-5.88	23.66	
ApSE T_1	1120	16.9%	21.1%	0.0%	100.0%	Average growth of municipality's urban footprint
ApSE T_2	1120	42.8%	22.1%	0.0%	100.0%	
ApSE T_3	1120	39.0%	26.8%	0.2%	100.0%	
ApSE $T_{General}$	1120	23.4%	26.7%	0.0%	100.0%	
ApSC T_1	1120	9.9%	9.4%	0.0%	74.1%	Average contraction of municipality's urban footprint
ApSC T_2	1120	1.0%	5.2%	0.0%	97.3%	
ApSC T_3	1120	0.2%	0.9%	0.0%	12.2%	
ApSC $T_{General}$	1120	0.3%	1.4%	0.0%	12.7%	
Forced Migration Flow (FMF): 1992-1999	1103	-2.4%	8.2%	-160.6%	15.8%	Percentage contraction of municipality's urban footprint
Forced Migration Flow (FMF): 2000-2007	1117	-9.7%	23.8%	-241.1%	45.0%	
Forced Migration Flow (FMF): 2007-2014	1120	-3.5%	8.8%	-62.6%	24.1%	
Forced Migration Flow (FMF): 1992-2014	1120	-14.7%	32.9%	-326.4%	58.8%	
Demographic Bonus (DB)	1111	0.72	0.12	0.33	1.46	Ratio between active and dependent population
% of urban population in 1992	1047	0.36	0.23	0.00	1.00	Percentage of municipal population who live in the urban area
% of urban population in 1999	1103	0.39	0.24	0.00	1.00	
% of urban population in 2000	1112	0.39	0.24	0.00	1.00	
% of urban population in 2007	1117	0.42	0.24	0.00	1.00	
% of urban population in 2017	1120	0.44	0.25	0.00	1.00	

Distance to a Capital City	1117	61.34	43.95	1.00	414.56	Distance in kilometers to departmental capital
% of municipal area with forest loss: 2000 – 2017	1120	0.03	0.04	0.00	0.26	Percentage of deforested municipal area

Figure 5

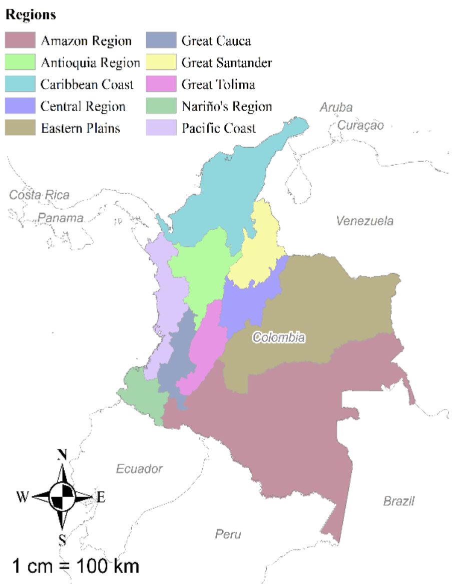


Table 2

Table 2. Anthropogenic Print Spatial Expansion (ApSE) regression analysis with one lag over FMF

Independent Variables	One lag over FMF								
	OLS Robust Regression Model			**Spatial Lag Regression**			**Spatial Error Regression**		
	T1	**T2**	**T3**	**T1**	**T2**	**T3**	**T1**	**T2**	**T3**
	1992-1999	2000-2007	2007-2014	1992-1999	2000-2007	2007-2014	1992-1999	2000-2007	2007-2014
Forced Migration Flow (FMF)	1.540***	0.278***	0.160***	0.650**	0.119**	0.086***	0.544	0.109	0.085***
	(0.362)	(0.093)	(0.034)	(0.281)	(0.058)	(0.018)	(0.34)	(0.067)	(0.022)
Demograpchic Bonus	-1.708***	0.549	-1.110**	-1.192***	-0.026	-0.596**	-1.527***	-0.35	-0.737**
	(0.38)	(0.357)	(0.472)	(0.237)	(0.261)	(0.243)	(0.316)	(0.348)	(0.327)
Demograpchic Bonus Squered	0.826***	-0.363*	0.427	0.640***	0.006	0.315**	0.818***	0.18	0.428**
	(0.219)	(0.213)	(0.276)	(0.15)	(0.166)	(0.154)	(0.196)	(0.216)	(0.203)
% of urban population	0.250***	0.155***	0.132***	0.181***	0.089***	0.107***	0.172***	0.071***	0.110***
	(0.032)	(0.031)	(0.034)	(0.02)	(0.022)	(0.02)	(0.025)	(0.027)	(0.024)
Distance to a Capital City (km)	-0.034***	-0.060***	-0.069***	-0.012**	-0.018***	-0.012**	-0.006	-0.006	0.005
	(0.01)	(0.011)	(0.013)	(0.005)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)
% of municipal area with forest loss	0.015	-0.088	-0.038	-0.028	0.062	0.118	0.171	0.155	0.428**
	(0.157)	(0.194)	(0.187)	(0.13)	(0.141)	(0.132)	(0.177)	(0.195)	(0.186)
RHO				0.695***	0.767***	0.846***			
				(0.025)	(0.023)	(0.017)			
Lamda							0.753***	0.790***	0.886***
							(0.026)	(0.023)	(0.016)
Constant	1.004***	0.405***	1.190***	0.558***	0.153	0.331***	0.812***	0.601***	0.693***
	-0.158	-0.148	-0.193	-0.094	-0.102	-0.097	-0.127	-0.14	-0.136
Observations	1,041	1,096	1,109	1,041	1,041	1,041	1,041	1,041	1,041
R-squared	0.343	0.147	0.259	0.633	0.595	0.757	0.324	0.102	0.137
AIC	-704.6	-374.8	-99.3	-1171	-927.1	-1020	-1103	-895.2	-961.7
BIC	-670	-339.8	-64.2	-1127	-882.5	-975.1	-1058	-850.7	-917.2
Log-likelihood	359.3	194.4	56.63	594.7	472.5	518.8	560.3	456.6	489.9

*** p- value < 0.01, ** p-value < 0.05, *p-value < 0.10. Standard error in parenthesis.

Table 3

Table 3. Anthropogenic Print Spatial Expansion (ApSE) Spatial lag regression output

	One lag over **FMF**			Half lag over **FMF**			Cero lag over **FMF**		
Independent Variables	T1 1992-1999	T2 2000-2007	T3 2007-2014	T1 1992-1999	T2 2000-2007	T3 2007-2014	T1 1992-1999	T2 2000-2007	T3 2007-2014
Forced Migration Flow (FMF)	0.650**	0.119**	0.086***	0.293*	0.032	0.199***	0.076	0.036*	0.260***
	((0.281)	((0.058)	(0.018)	(0.163)	(0.021)	(0.035)	(0.052)	(0.02)	(0.056)
Demographic Bonus	-1.192***	-0.026	-0.596**	-1.195***	-0.035	-0.631***	-1.213***	-0.037	-0.711***
	(0.237)	(0.261)	(0.243)	(0.238)	(0.261)	(0.242)	(0.237)	(0.261)	(0.243)
Demographic Bonus Squared	0.640***	0.006	0.315**	0.641***	0.013	0.345**	0.653***	0.016	0.398**
	(0.15)	(0.166)	(0.154)	(0.15)	(0.166)	(0.154)	(0.15)	(0.166)	(0.155)
% of urban population	0.181***	0.089***	0.107***	0.183***	0.089***	0.097***	0.185***	0.087***	0.097***
	(0.02)	(0.022)	(0.02)	(0.02)	(0.022)	(0.02)	(0.02)	(0.022)	(0.02)
Distance to a Capital City (km)	-0.012**	-0.018***	-0.012**	-0.012**	-0.018***	-0.010*	-0.012**	-0.018***	-0.010*
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
% of municipal area with forest loss	-0.028	0.062	0.118	-0.06	0.048	0.16	-0.072	0.058	0.114
	(0.13)	(0.141)	(0.132)	(0.128)	(0.141)	(0.132)	(0.128)	(0.142)	(0.132)
RHO	0.695***	0.767***	0.846***	0.698***	0.769***	0.843***	0.699***	0.768***	0.846***
	(0.025)	(0.023)	(0.017)	(0.025)	(0.023)	(0.018)	(0.025)	(0.023)	(0.017)
Constant	0.558***	0.153	0.331***	0.558***	0.157	0.341***	0.564***	0.156	0.368***
	(0.094)	(0.102)	(0.097)	(0.094)	(0.102)	(0.096)	(0.094)	(0.102)	(0.097)
Observations	1,041	1,041	1,041	1,041	1,041	1,041	1,041	1,041	1,041
R-squared	0.633	0.595	0.757	0.633	0.595	0.759	0.633	0.596	0.757
AIC	-1171	-927.1	-1020	-1169	-925.1	-1029	-1168	-926	-1020
BIC	-1127	-882.5	-975.1	-1125	-880.5	-984.7	-1124	-881.4	-975.1
Log-likelihood	594.7	472.5	518.8	593.6	471.5	523.6	593	472	518.8

*** p- value < 0.01, ** p-value < 0.05, *p-value < 0.10. Standard error in parenthesis.

Table 4

Region	AAC T1	AAC T2	AAC T2	ApSE T1	ApSE T2	ApSE T3
Amazon Region						
Antioquia Region	-0,21	-0,58	1,43	3,1%	21,2%	17,0%
Caribbean Coast	0,33	-1,08	2,08	15,8%	49,8%	38,5%
Central Region	0,61	-1,23	2,42	19,2%	47,9%	38,4%
Eastern Plains	0,24	-0,88	2,11	14,6%	43,8%	42,4%
Great Cauca	0,13	-0,76	1,74	11,0%	34,9%	28,5%
Great Santander	0,55	-0,93	2,10	19,9%	36,7%	37,7%
Great Tolima	0,53	-1,08	2,33	22,4%	44,7%	47,3%
Nariño's Region	0,57	-0,87	2,00	20,2%	43,0%	40,4%
Pacific Coast	0,66	-1,14	2,52	24,6%	46,2%	51,5%
COLOMBIA	0,15	-0,76	1,79	13,0%	37,6%	40,0%

Figure 6

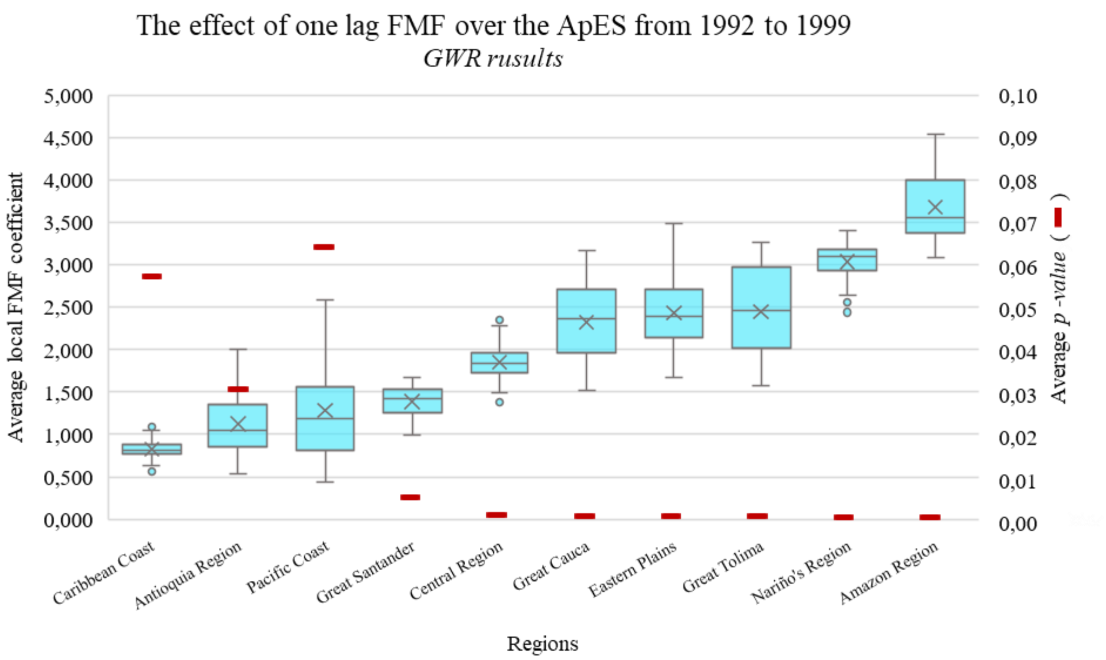


Table 5

Table 5. GWR: One lag model over ApSE from 1992 to 1999 (T1)

Regions	Avg Local R2	Intercept	Intercept's Std Error	FMF's Coefficient	FMF's *p-value*
Amazon Region	0,308	0,484	0,065	3,678	0,000
Nariño's Region	0,350	0,652	0,063	3,033	0,000
Great Tolima	0,353	0,707	0,063	2,450	0,000
Eastern Plains	0,312	0,605	0,070	2,436	0,000
Great Cauca	0,362	0,695	0,061	2,323	0,000
Central Region	0,338	0,687	0,069	1,851	0,001
Great Santander	0,323	0,593	0,068	1,385	0,005
Pacific Coast	0,394	0,699	0,069	1,283	0,065
Antioquia Region	0,380	0,703	0,068	1,121	0,031
Caribbean Coast	0,392	0,555	0,065	0,824	0,058

Figure 7

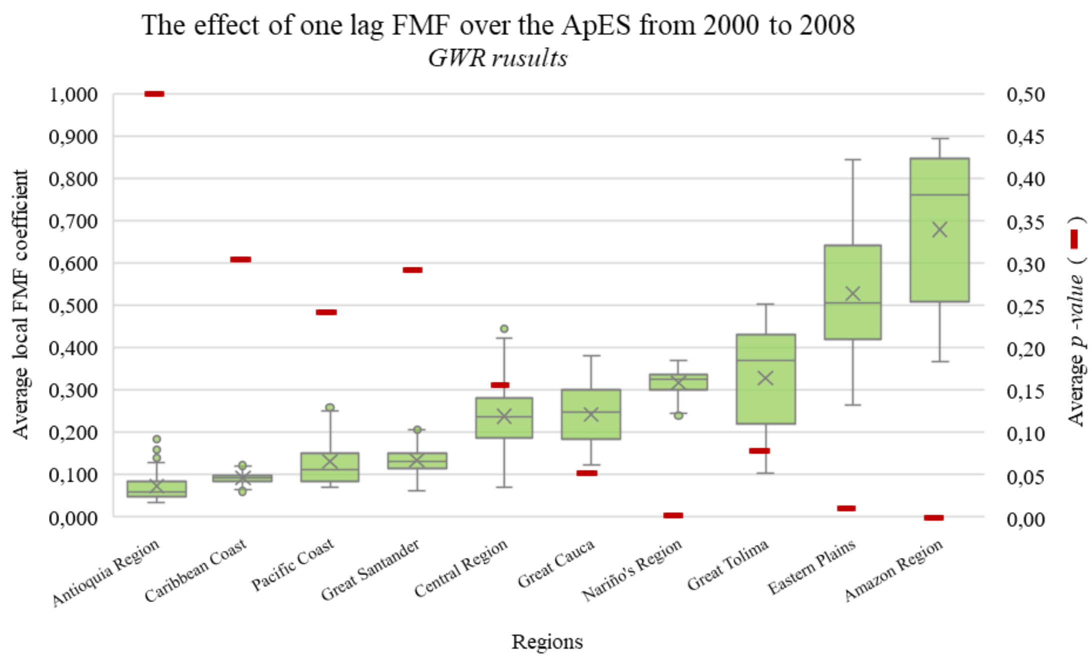


Table 6

Table 6. GWR: One lag model over ApSE from 2000 to 2007 (T2)

Regions	Avg Local R2	Intercept	Intercept's Std Error	FMF's Coefficient	FMF's *p-value*
Amazon Region	0,125	0,427	0,075	0,678	0,002
Antioquia Region	0,162	0,899	0,078	0,072	0,496
Caribbean Coast	0,227	0,902	0,075	0,092	0,303
Central Region	0,132	0,802	0,079	0,238	0,157
Eastern Plains	0,118	0,661	0,080	0,528	0,013
Great Cauca	0,101	0,562	0,071	0,242	0,054
Great Santander	0,168	0,853	0,078	0,134	0,291
Great Tolima	0,104	0,626	0,072	0,329	0,079
Nariño's Region	0,104	0,434	0,073	0,316	0,005
Pacific Coast	0,143	0,768	0,079	0,131	0,241

Figure 8

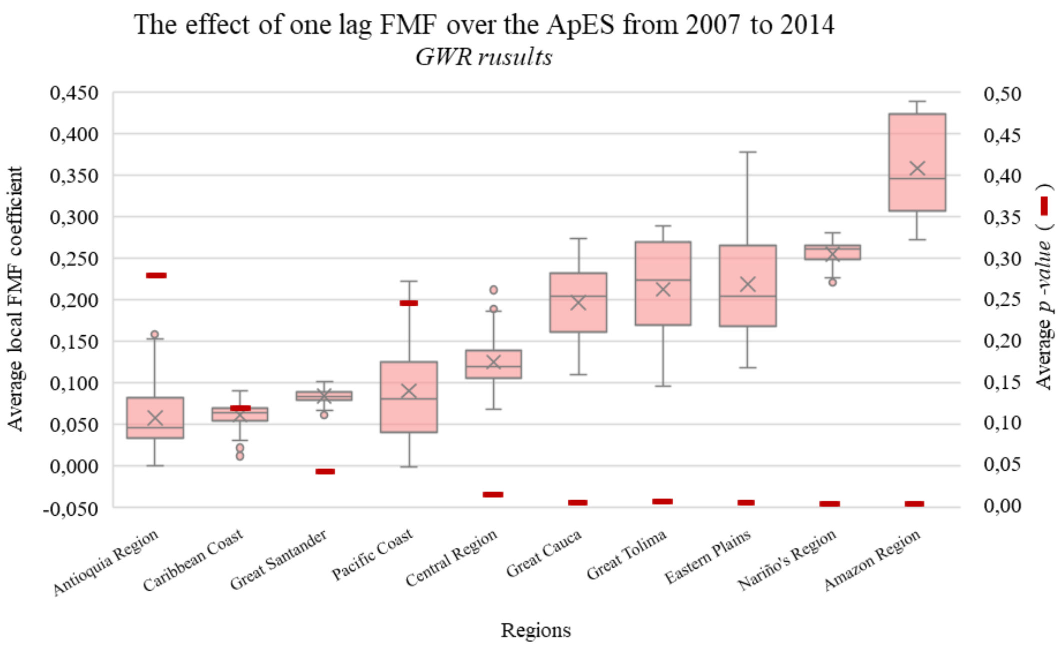
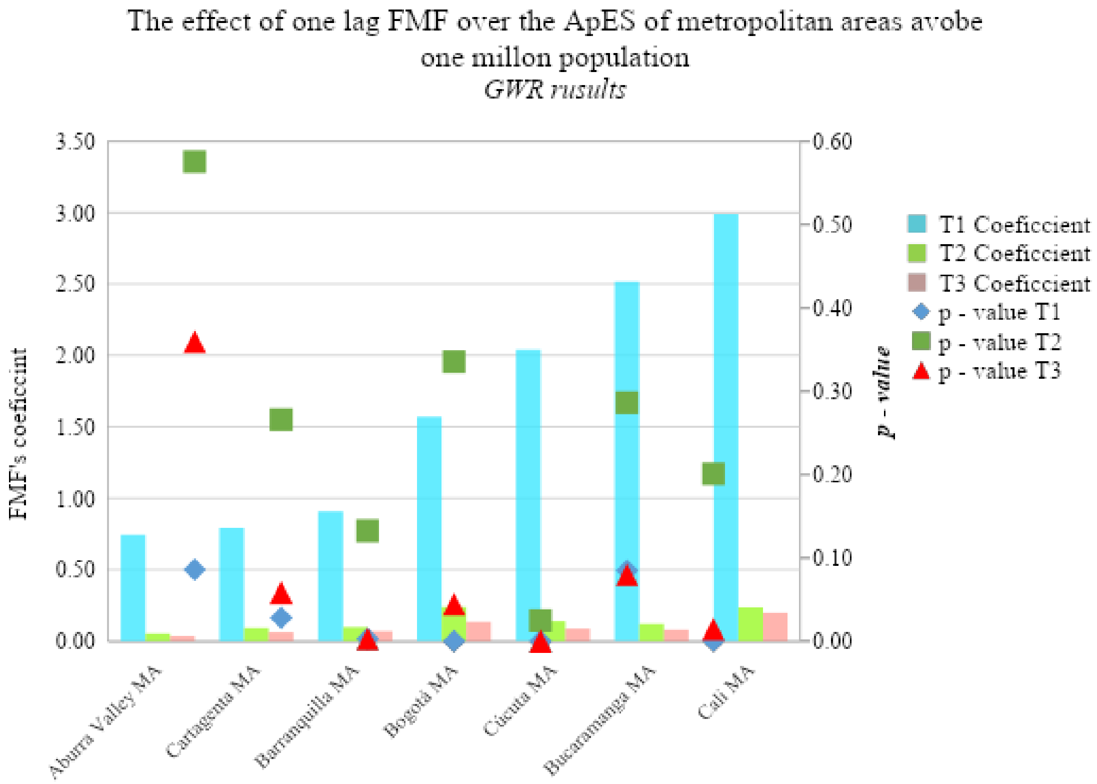


Table 7

Table 7. GWR: One lag model over ApSE from 2008 to 2014 (T3)

Regions	Avg Local R2	Intercept	Intercept's Std Error	FMF's Coefficient	FMF's *p-value*
Amazon Region	0,235	0,665	0,085	0,358	0,000
Antioquia Region	0,322	1,303	0,087	0,058	0,274
Caribbean Coast	0,369	1,161	0,085	0,061	0,114
Central Region	0,271	1,181	0,088	0,125	0,010
Eastern Plains	0,239	1,004	0,089	0,219	0,001
Great Cauca	0,248	0,969	0,079	0,197	0,000
Great Santander	0,313	1,223	0,087	0,084	0,038
Great Tolima	0,245	1,000	0,081	0,213	0,002
Nariño's Region	0,244	0,830	0,082	0,255	0,000
Pacific Coast	0,308	1,198	0,088	0,091	0,240

Figure 9


The effect of one lag FMF over the ApES of metropolitan areas avobe
one millon population
GWR rusults
FMF's coeficcint
p - value
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Aburra Valley MA
Cartagenta MA
Barranquilla MA
Bogotá MA
Cúcuta MA
Bucaramanga MA
Cali MA
T1 Coeficcient
T2 Coeficcient
T3 Coeficcient
p - value T1
p - value T2
p - value T3