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DELINEATING FUNCTIONAL TERRITORIES FROM OUTER SPACE

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ABSTRACT

The delimitation of functional spatial units or functional territories is an important topic in regional science and economic geography since the empirical verification of many causal relationships is affected by the size and shape of these areas. Most of the literature on the delimitation of these functional territories is based on developed countries, usually using contemporary and updated information of commuting flows. Conversely, in developing countries the technical contributions have been incipient. This paper proposes a complementary step in the delimitation of functional territories, combining stable satellite night lights and commuting flows, with applications for Mexico, Colombia and Chile. This method leads to a more accurate definition of functional territories, especially in cases where official data for commuting flows are unreliable and/or outdated, as is the case of several developing and underdeveloped countries. We exploit important advances associated with the use of satellite images, and specifically, the use of night lights as a source of information for the delimitation of metropolitan areas and urban settlements.

Keywords: Functional Territories, Functional Economic Areas, Local Labour Market Areas, Night Light Satellite Data, Commuting Flows.

JEL Codes: R1, R12, R23.

RESUMEN

La delimitación de unidades espaciales funcionales o territorios funcionales es un tema importante en la geografía económica y científica regional, ya que la verificación empírica de muchas relaciones causales se ve afectada por el tamaño y la forma de estas áreas. La mayoría de la literatura sobre la delimitación de estos territorios funcionales se basa en países desarrollados, usualmente utilizando información contemporánea y actualizada sobre los flujos de transporte.

Por el contrario, en los países en desarrollo las contribuciones técnicas han sido incipientes. Este documento propone un paso complementario en la delimitación de territorios funcionales, combinando luces nocturnas de satélites estables y flujos de conmutación, con aplicaciones para México, Colombia y Chile. Este método conduce a una definición más precisa de los territorios funcionales, especialmente en los casos en que los datos oficiales para los flujos de trayecto son poco confiables y / o desactualizados, como es el caso de varios países en desarrollo y subdesarrollados.

Aprovechamos importantes avances asociados con el uso de imágenes satelitales, y específicamente, el uso de luces nocturnas como fuente de información para la delimitación de áreas metropolitanas y asentamientos urbanos.

1. INTRODUCTION

Spatial agglomeration is a central part of human life and the geographic space in which most of economic and social exchanges take place (Biroch, 1988). The size and shape of this geographic space has central implications for policy design, because it affects the regular patterns of mobility and interactions of people, goods and ideas, definitely a functional reality, which is weakly captured by the usual political administrative units. These *functional territories*, as we will call them, represent a complex socio-spatial picture of overlapping markets between "areas or locational entities which have more interaction or connection with each other than with outside areas" (Brown & Holmes, 1971:57; Jones, 2016), and "with high frequency of economic and social interactions between their habitants, organizations and firms" (Berdegué, et al., 2011).[1]

The delimitation of these functional territories is crucial for several important issues in urban and regional economics. It has also key implications for the identification of appropriate places for place-based development approaches (Tomaney, Pike, & Rodríguez-Pose, 2011; Barca, McCann, & Rodríguez-Pose, 2012; Storper, 1997; Berdegué, Bebbington, & Escobal, 2015) among others. Moreover, the size and shape of these spatial units has an effect on economic geography estimations as shown in Briant, Combes and Lafourcade (2010). However, despite the importance for the appropriate identification of the economics effects and the spatial scope of public policies, the advances of these methods have not been developing at the same speed than the expansion of new sources of

[1] Hereafter we use indistinctly the term functional territory and functional area.

information or big data sources.[2]

Since the 1950s the analysis of interactions between spatial units is mainly measured using labour commuting flows (Klove, 1952). The delimitation of metropolitan and non-metropolitan areas using labour commuting flows data is a common practice in the US, UK, the Netherlands, France, Germany, Italy and other countries (Coombes & Openshaw, 1982; Tolbert & Killian, 1987; Sforzi F. , 1997; Casado-Díaz J. , 2000; Andersen, 2002; Tolbert & Sizer, 1996; Federal Register, 2000). Previous studies on the delineation of these areas have employed a variety of methodological procedures, such as: cluster analysis (Tolbert & Killian, 1987; Tolbert & Sizer, 1996), a threshold method (Coombes, Green, & Openshaw, 1986), a network-based method (Kropp & Schwengler, 2016) and recently the use of an evolutionary approach (Casado-Díaz, Martínez-Bernabéu, & Rowe, 2017).

Nonetheless, in recent years a whole new set of information from satellite images became available, in particular that revealing night lights. The use of these information has increased its popularity not only in geographical sciences but also in economics (Henderson, Storeygard, & Weil, 2012; Donaldson & Storeygard, 2016). This paper is the first to our knowledge that blends this new information with commuting data to delimit functional territories. Specifically, this paper proposes a methodology that combines the use of satellite night light data for the identification of updated boundaries of conurbated or metropolitan areas and other urban settlements, with standard clustering procedures using commuting flows, and uses both of them to delineate functional territories. Despite the large variety of methods

[2] The work of Coscia and Hausmann (2015) is an exception. Authors analyse the correspondance between human mobility patterns and phone calls in Colombia.

developed to delineate functional spatial units, and the efforts to use new sources of data, to the knowledge of authors this is the first attempt to exploit the more recent developments in remote sensing to the delimitation of these areas.

The paper is organized as follows. Section 2 reviews the literature on the delimitation of functional spatial units. Section 3 describes the data used. Section 4 describes the proposed methodology for the identification of functional territories using night light satellite images and commuting flows. Then, in Section 5 we summarize our main results for Chile, Mexico and Colombia. Finally, section 6 presents the main conclusions.

2. LITERATURE REVIEW

Regional economists and economic geographers have conceptualized the economic space as a key element to understand economic and social relationships. In one of the first comprehensive analyses, Perroux (1950:95), characterizes the economic space as a field of forces, i.e., "(…) centers (or poles or foci) from which centrifugal forces emanate and to which centripetal forces are attracted between spatial units". A natural evolution from this concept is the view of agglomerations or spatial centres of economic activity in which centripetal forces outstrip centrifugal ones and form a space in which the agglomeration concentrates, and at some point, starts to spill over, connecting other spaces in a single functionally connected area. This economic concept of space is empirically approximated in the literature as the identification of *Functional Economic Areas* (Fox & Kumar, 1965).

Many nomenclatures proliferate to refer to this type of spatial configuration depending on the nature of the data and the purpose of the analysis, such as Functional Areas (FAs), Functional Economic Regions (FERs), Functional Economic Areas (FEAs), City Regions (CR), Functional Urban Regions (FURs), Local Labour Market Areas (LLMAs), Travel-to-Work Areas (TTWAs) and Functional Territories (FTs) among others (Berry, 1968; Coombes & Openshaw, 1982; Tolbert & Killian, 1987; Tolbert & Sizer, 1996; Banai & Wakolbinger, 2011; Berdegué, Jara, Fuentealba, Tohá, Modrego, Schejtman & Bro, 2011). All the above represents a socio-spatial picture of overlapping markets between “areas or locational entities which have more interaction or connection with each other than with outside areas” (Brown and Holmes, 1971:57).

The definition of functional areas through labour market flows between spatial units has been the most widely used method for statistical and public policy purposes, mainly in the developed world. The focus on labour flows for the delimitation of these areas is explained because of the “centrality of labor relationships in social and economic life” (Casado-Díaz & Coombes, 2011). Then, commuting flows have a broad socio-economic scope and as suggest Casado-Diaz and Combes (2011) and Berdegué et al (2011), they are informative of other social, cultural or political local linkages that merge in the concept of “functional territory” as a social construction (Berdegué, Bebbington, & Escobal, 2015). This also has been influenced due that the data of commuting flows between spatial units are usually available for developed countries with a regular periodicity. Notwithstanding, despite the predominance of commuting flows as a measure delineating functional areas, other variables are also used, such as land prices, as indicators of economic integration, or information on travel times and road networks, or data on service and shopping areas (Andersen, 2002) among other measures (Bode, 2008).

In this context, it is also notable that there is no a single space that fits all development issues, which puts the problem of identification in an important position both for the debate of place-based policies, as for the investigation of the dynamics of growth, productivity and employment in urban agglomerations (Barca, McCann, & Rodríguez-Pose, 2012; Storper, 1997; Tomaney, Pike, & Rodríguez-Pose, 2011; World Bank, 2009; Berdegué, Bebbington, & Escobal, 2015).

Accordingly, the use of political administrative units for policy and research purposes "do not provide a meaningful insight of the functional reality into the territory" (Casado-Díaz , 2000), then it is an expected result that the functional territories finally delimited do not necessarily correspond with political administrative units, since in many cases they extend beyond those borders.

The lack of policies designed to account for all the interdependences of spatial units is notorious. Coordination policies and mechanisms between policy makers of those areas are necessary in order to maximize the welfare of the population that live there (Kline & Moretti, 2014; Busso, Gregory, & Kline, 2013). The policy design for those functional spatial units is strongly linked to spatial planning and urban economics. Highlighted issues are, for example, how to mitigate congestion costs and reduce commuting time (Cervero, 1995; Van Der Laan & Schalke, 2001), how to develop more efficient labour policies (Cörvers, Hensen, & Bongaerts, 2006; Ball, 1980), the reorganization and coordination of local governments (Andersen, 2002) or the proper selection of regions eligible for regional investment (Olfert, Partridge, Berdegué, Escobal, Jara, & Modrego 2014; Berdegué, Carriazo, Jara, Modrego, & Soloaga, 2015; Ramírez, Díaz, & Bedoya, 2017).

The empirical delimitation of these areas can be traced back to the end of the 1950s, when the Statistical Department of United States developed the delimitation of Standard Metropolitan Areas (SMAs), used by the academic community in an entire generation of literature on labour markets, and by governments for the calculation of local unemployment rates and regional policies.[3] This practice was

[3] For examples of articles using standard metropolitan areas see: Glaeser and Mare (2001); Moretti (2004);

followed by other developed economies, starting with Great Britain's definition of TTWAs, which were used to calculate local unemployment rates and assistance to industry through regional policies (Coombes, Green, & Openshaw, 1986); then was adopted by several countries as Italy (Sforzi, Openshaw, & Wymer, 1997), some regions in Spain (Casado-Diaz, 2000) and Denmark (Andersen, 2002), among others.

In 2002 seventeen out of twenty OECD countries performed boundary mapping of functional regions (OECD, 2002). However, those efforts have been scarce in the developing and emerging world. Even the identification of official metropolitan areas or conurbations is something difficult to empirically assess with outdated census records and the low quality of official surveys (Duranton, 2015). Attempts to incorporate the concept of functional areas into the political and research agenda are still incipient in those countries. The Latin American Center for Rural Development (Rimisp) made an outstanding attempt to delimit functional areas that are called Functional Territories in Brazil, Colombia, Chile, El Salvador, Mexico and Nicaragua (Berdegué, et al. 2011), following the methodology established by Tolbert and Killian (1987). Recently Casado-Díaz, Bernabéu and Rowe (2017), develop a methodology based on the use of grouping evolutionary algorithms, drawing attention to the importance of optimality in the delimitation of functional areas, focused on the Chilean case. However, the use of outdated data is still an important consideration at least in Latin America and the Caribbean.[4]

Glaeser and Gottlieb (2009).

[4] As an example, for Chile, the last available census asking for commuting is for 2002, and due to methodological problems in the census of 2012 and its omission in the pre-census of 2017, the question may

A variety of techniques are employed to perform a suitable delimitation of functional areas. The focus on the labour market implies ensuring that the resulting areas have the property of being self-contained, i.e., that they have a low level of interaction with other functional areas and a high level of commuting into the area generated (Coombes, Green, & Openshaw, 1986). In addition, a local labour market must fulfil two essential requirements: the first is *external perfection*, i.e., the boundaries of the delimited areas should rarely be crossed by journeys to work, and the second requirement is a *high degree of intra-market movements*, which means that the delimited area must be internally active and unified (Goodman, 1970).

In this regard, the study from Eurostat and Coombes (1992) emphasizes some principles that the delimitation of LLMAs should guarantee. The *coherence* principle states that the established limits of a LLMA must be recognizable and they must be in conformity with the political and administrative configuration. In addition, the criterion of *contiguity* is indispensable to guarantee the spatial self-containment of the generated units. In this sense, as Casado-Diaz and Coombes (2011) emphasize, commuting flows have an advantage over other variables of spatial flows, and is that the "friction of the distance", by restricting the mobility patterns of people, ensure that the relations of greater weight are found between neighbouring spatial units. This is closely related with the principle of *partition*, which indicates that a space unit must belong to one and only one functional area.

be incorporated again in the census of 2022. For other Latin American countries, the scenario is worse: for Argentina, Bolivia, Ecuador, Guatemala, Haiti, Honduras, Panama, Peru, Republica Dominicana and Venezuela, census information of commuting flows simply does not exist.

Despite the fact that commuting data are available for some developing countries, the fact is that their continuity cannot be guaranteed over time, and official statistics for studying urban phenomena, formation and growth of agglomerations are often time lagged and consequently adjust in a late manner to the rapid patterns of urban growth that these countries exhibit. Our methodological approach exploits information from stable satellite night lights, which has been used for more than a decade to identify urban agglomerations, estimate their population size and density, types of urbanization and approximate measures of electricity consumption and gas emissions (Elvidge, Baugh, Kihn, Kroeh, & Davis, 1997a; Elvidge, Baugh, Kihn, Kroeh, & Davis, 1997b; Imhoff, Lawrence, Stutzer, & Elvidge, 1997; Elvidge, Baugh, Dietz, Bland, Sutton, & Kroehl, 1999; Elvidge, Sutton, Ghosh, Tuttle, Baugh, & Bhanduri, 2009; Small, Elvidge, Balk, & Montgomery, 2011).

3. DATA

This section describes the sources and data used for the delimitation of functional territories. For each country we have used the latest available census with information of labour commuting flows at municipality level. For Chile we use the 2002 National Census of Population and Housing of the National Statistical Office (INE); for Colombia the 2005 National Census of Population and Housing of the National Administrative Department of Statistics (DANE); for Mexico the 2010 National Census of Population and Housing of the National Institute of Statistics and Geography (INEGI). On the other hand, our methodology incorporates the satellite images of night lights obtained from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) of the Department of Defense of the Air Force Space and Missile Systems Center (SMC).

3.1 Commuting flows

We build the commuting flows matrix using information at the municipality level as a unit of analysis. This considers: 2,446 municipalities in Mexico; 1,124 in Colombia, and 346 in Chile. The commuting flows vary substantially among countries, as Table 1 shows; the average number of commuters in the municipality of origin and destination is greater for Chile (origin: 5,285; destination: 5,347) than Mexico (origin: 3,270; destination: 2,840) and Colombia (origin: 1,001; destination: 952). Although, also there is more dispersion in the number of commuters in Chile (origin: 13,963; destination: 23,190) and Mexico (origin: 14,092, destination: 15,623) than in Colombia (origin: 5,300; destination: 7,143). On the other hand, the percentage of commuters as a proportion of the work force in the municipality of origin shows that in Mexico, on average, 16.1% of the municipal workforce is composed of workers who commute to other municipalities, 6.7% in Chile and 5.3% in the case of Colombia. These values show an important dispersion especially in the case of Mexico. At the same time, commuting can be as large as77.3% of a municipality's workforce in Mexico, followed by Chile with 63.8% and 52.2% in Colombia.

In relation to the destinations of commuters, on average, 9.5% of the workforce of a municipality in Mexico come from workers who commute from other municipalities, a percentage that reaches 7% in both Colombia and Chile. The high dispersion in Chile and Colombia is notorious, with municipalities whose share of commuters exceeds 100%. This might occur in the case of high commuting flows between small and large municipalities, when adding the bidirectional flows of commuting as a proportion of the small municipalities' workforce.

Table 1 – Descriptive statistics of commuting flows by country

		Number of commuters in the municipality of origin	Number of commuters in the municipality of destination	Commuters as a % of the population in the municipality of origin	Commuters as a % of the population in the municipality of destination
Mexico	Average	3,270	2,840	16.1	9.5
	Maximum	287,836	323,902	77.3	99.3
	Minimum	1	1	0.1	0.2
	Median	424	254	10.1	6.4
	Std. Error	14,092	15,623	15.3	10.7
Colombia	Average	1,001	952	5.3	7.1
	Maximum	78,715	141,949	52.2	733.8
	Minimum	1	1	0.02	0.04
	Median	87	122	2.6	3.5
	Std. Error	5,300	7,143	7.7	26.0
Chile	Average	5,285	5,346	6.7	7.2
	Maximum	119,107	349,033	63.8	173.8
	Minimum	2	8	0.4	0.5
	Median	622	645.5	3.7	3.5
	Std. Error	13,963	23,190	7.5	13.8

The geography or the spatial configuration of the functional territories may vary greatly among countries. They could be affected by historical patterns of urbanization, the level of development, geographic characteristics of the territory and the existence and quality of infrastructure, among other variables. Notwithstanding, the extension or sprawl of cities and the spatial concentration of their urban populations is probably the main factor influencing the results. Thus a higher population living in cities, or a high number of cities, usually means a high number of conurbated municipalities that are added in our method through lit areas. At this respect, we argue that most of the lit areas capture quiet well the urban boundaries, supported by a long tradition of literature in studies of remote sensing.

3.2 Night light data

Light intensity measured by satellites at night has been broadly used as a proxy for local economic activity or a high number of other welfare variables (Michalopoulos & Papaioannou, 2013; Pinkovskiy, 2013; Hodler & Raschky, 2014; Henderson, Storeygard, & Weil, 2012; Keola, Andersson, & Hall, 2015; Donaldson & Storeygard, 2016). Through night-time light images, satellite remote sensing has also been a useful alternative for calculating urban population growth (Sutton, Elvidge , & Obremski, 2003; Amaral, Montero, Camara, & Quintanilha, 2006), redefining urban boundaries (Cheng, et al., 2016) and monitoring the expansion of urban land uses (Henderson, Yeh, Gong, Elvidge, & Baugh, 2003). Furthermore, it has also been proven that the intensity of the lights is a good proxy to estimate the Gross Domestic Product (GDP) and its growth, especially in developing countries, where information at local level is often scarce and of poor quality (Chaturvedi , Ghosh , & Bhandari, 2011; Hodler & Raschky, 2014).

We use the average visible, stable lights and cloud free coverage composite. This information comes from a satellite that follows a Sun-synchronous orbit at an altitude of approximately 830 km and covers any point on the earth once or twice daily depending on the latitude.[5] This data have been available since 1992, and we

[5] Despite the fact that there are other recent sources of satellite information capturing night lights with higher resolution (e.g., the Moderate Resolution Imaging Spectroratiometer-MODIS-). We

used the latest available year at the time of the exercise, namely 2012. The stable satellite night light images are based on 1 km^2 sized pixels, each one with a light intensity value that varies in the range from 0 (basically unlit) to 63 (pixel is saturated by light intensity). This night light data may overestimate urban boundaries and also be affected by the different stages of economic development, climate and geological differences when cross country comparisons are made (Henderson, Yeh, Gong, Elvidge, & Baugh, 2003).

Therefore, the method also is affected by the election of the lit area threshold, which is informative of the sprawl pattern of the urbanization process in each country. Table 2 shows the descriptive statistics of the urban light areas captured in each country in 2012. The high number of people living in cities in Mexico is also captured by the lit areas. The average lit area in Mexico is 366.852 $km^{2,}$ while the averages in Colombia and Chile are 21.192 and 21.697 km^2 respectively. This means that Mexican cities are more sprawling than cities in Colombia and Chile. This indicator is highly influenced by the extension of the Mexico D.F. since a city area is defined using night lights as a contiguous lit area.[6] Thus, despite the fact that the City of Mexico has a similar population to those of the cities of Bogota and Santiago, the metropolitan area of Mexico D.F., which is captured by the night lights, is larger than the metropolitan areas of Bogota and Chile together. Notwithstanding, the median of lit areas in Mexico (7.456) is similar to that in Colombia (7.185), and lower than that in Chile (11.182), revealing the high number

choose to use DMSP OLS data in order to show the exercise with the most popular night light data source and with more years of coverage.

[6] For similar definitions of city areas using night light data see Henderson, Storeygard and Deichman (2017).

of small and medium-sized cities in Mexico and Colombia, and the low number of cities in Chile but also its high spatial concentration of the urban population.

Table 2 – Descriptive statistics of urban lights areas by country

	Mexico		**Colombia**		**Chile**	
	Lit areas (km^2)	Lit areas (as % of total municipal land area)	Lita reas (km^2)	Lit areas (as % of total municipal land area)	Lit areas (km^2)	Lit areas (as % of total municipal land area)
Average	366.852	0.1	21.192	9.3	21.697	16.5
Maximum	0.395	100	534.468	100	189.103	100
Median	7.456	1.8	7.185	1.9	11.182	1.19

Finally, we did not use any other information regarding infrastructure such as roads or travel times in order to avoid potential endogeneity problems for subsequent econometric analysis using these areas, as is the purpose in many applications and uses (Autor & Dorn, 2013; Amior & Manning, 2015; Berdegué, Carriazo, Jara, Modrego, & Soloaga, 2015). For the same reason, we did not use the night light information itself to characterize those functional areas.

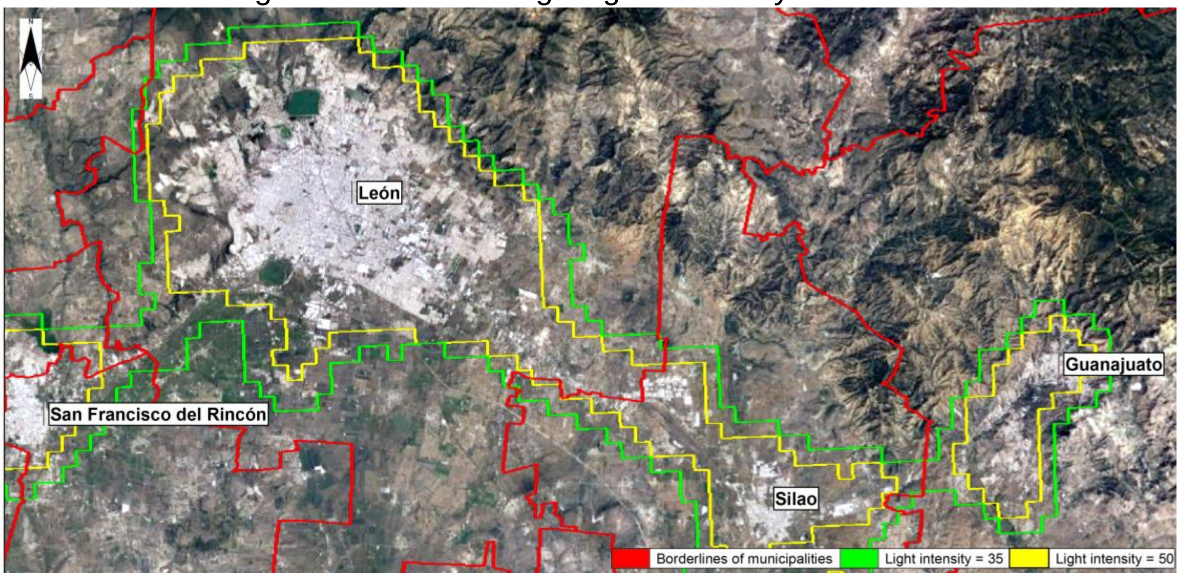
4. METHODOLOGY

Our methodology for the delimitation of functional territories relies on two main steps. First, we used stable satellite night light images to define metropolitan areas or conurbations as groups of municipalities that form an area that in many cases spreads beyond the political administrative borderlines. We unify these polygons of municipalities, on the basis that night lights are informative of the extension of urban agglomerations, as explained before. This first step allows us to update, in some way, the functional area generated by the urban expansion to the most recent year with information available from the satellite. Second, using these new spatial units generated in the first step, we apply a hierarchical clustering procedure based on Tolbert and Sizer (1996) in order to account for the interaction of both those municipalities that were not captured by night lights, as well as the conurbated municipalities. In addition, we present a sensitivity analysis of our results in order to prove the robustness of the method.

4.1 Identifying functional territories using night light data

In the first step we identified the location and boundaries of urban settlements using the stable satellite night light images described in the previous section. Thus, for all countries, the light threshold was selected through the observation of the correspondence between night light satellite images and the urban areas observed through Google Earth. This exercise was undertaken for all countries. This first part of the method is described in Figure 1, with an example for Mexico, showing two different cutoff thresholds of light intensity in the yellow and green lines, and the urban area that is covered by that lit area in each case.

Figure 1 – Different night lights intensity thresholds



Note: Green: light intensity=35. Yellow: light intensity=50. Red: administrative boundaries of Mexican municipalities. The figure describes how the urban area is captured by the lit area of night lights, but also how different light intensity thresholds of these lit areas change the estimate of the urban area. For example, the municipalities of Leon and San Francisco del Rincón are merged in the first step of the method with the lower light intensity threshold of 35, but not with the light intensity threshold of 50.

Figure 1 also describes how municipalities are merged in the first step. For this purpose, we overlap a map of political-administrative boundaries at the level of municipalities (red lines), and test different thresholds to detect, in each case, the remaining lit areas (grouped pixels) that extent beyond these boundaries. We then merge the municipalities that contain the same lit area into a single functional area, which are areas that correspond to the same spatial unit because they are geographically integrated as seen from outer space. In Figure 1, we present the example of Mexico. Contiguous lit areas are shown for 35 (green lines) and 50 (yellow lines) light intensities.[7] The figure shows that if s light threshold of 35 is

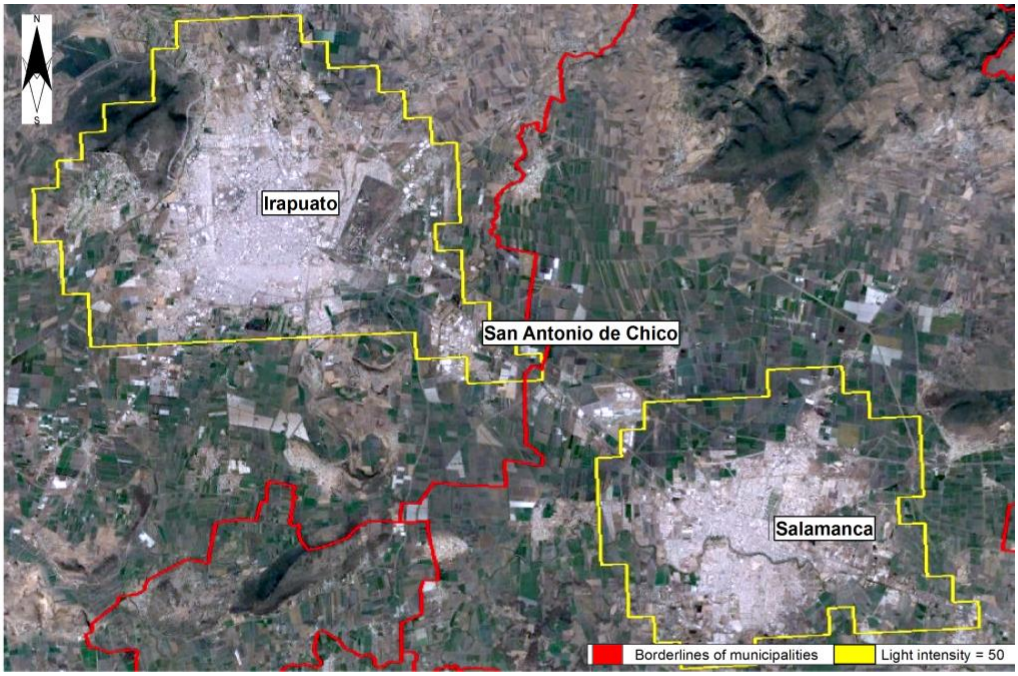
[7] The indicated values represent the threshold of light from night lights and areas that are greater than or equal to such a threshold are selected, so that the higher the threshold of light, the smaller the selected geographical area, since the values are located in the most saturated area of light, i.e.,

chosen, the urban area may spread to include those merged polygons of four municipalities: Leon, Silao, Guanajuato and San Francisco del Rincón. Following a light intensity of 50, only Leon and Silao´s urban areas are joined in a single functional area, whereas Guanajuato and San Francisco del Rincón stand alone. Once all those metropolitan areas and conurbations are identified for the whole country, greater areas of merged municipalities are constructed by collapsing all municipalities with a common lit area into a single spatial unit.

In some cases, where municipalities are somewhat isolated, the choice of light intensity makes no difference since in those cases the light intensity thresholds chosen simply spread slightly the area delimited by the night lights, as is shown in Figure 2, with the cases of Salamanca and Irapuato in México. Notwithstanding, eventually, a single municipality could contain small proportions of two or more lit areas. To deal with this issue, we establish a decision-making criterion based on computing the share of each lit area as a percentage of the total municipality polygon, and use the one with the larger share to make the allocation. Figure 2 describes this with an example for Irapuato, a Mexican municipality with two lit areas. The largest comprises 15.8% of the total municipal area, whereas the other lit area represents only 1.2%. The same figure shows also a case where the largest lit area of a given municipality (in this example Irapuato) crosses the boundary of one of its neighbours (in this case Salamanca) but the overlap is not important when compared to that of the other lit area in the neighbour (0.03% versus 12.2%). For cases like these, municipalities were not paired up.

the area is effectively agglomerated.

Figure 2: Nighttime lights and municipal boundaries



Note: Yellow: light intensity=50. Red: administrative boundaries of mexican municipalities. The figure describes two examples of Mexican municipalities that are not merged in the first step of the method due that the lit area is cointained almost enterily in the boundaries of the municipalities.

4.2 Identifying functional territories using census data

After identifying the areas of analysis as single municipalities or groups of municipalities representing a single spatial unit using night light data, we follow Tolbert and Sizer (1996) to aggregate to those spatial units previously defined, the municipalities that have a high level of commuting flows but whose interactions with other spatial units are not fully captured by night light data. This could be the case because they are predominantly dispersed locations, or because the urban area is perfectly contained in the polygon of the administrative boundaries of the municipality. Therefore, first we compute a symmetrical dissimilarity matrix *D*, where each cell of the matrix is defined as $D_{ij} = 1 - P_{ij}$, with

$$P_{ij} = \frac{f_{ij} + f_{ji}}{\min(f_i, f_j)}$$

where P_{ij} is the ratio of the sum of f_{ij}, namely, the commuters between an area i and an area j, and the minimum between f_i and f_j, which represents the resident labour force of the origin and destination area, respectively. The previous procedure that aggregated municipalities that share an area of lights reduces the matrix dimensions from its original municipality-to-municipality form by collapsing the matrix for those municipalities that are part of the same spatial unit. Hence, if municipality *A* and municipality *B* form a new area *AB*, the commuting flow from *AB* to municipality *C,* is simply the sum of the commuters from municipality *A* to *C*, and the commuters from *B* to *C*. On the other hand, *AB's* resident labour force stands as the sum of resident labour force in *A* and resident labour force in *B.*

In general terms, the literature has called P_{ij} each element of a matrix of proportional flows (Tolbert & Killian, 1987); this measure allows us to represent in the numerator the degree of interconnection between two municipalities (or bidirectional commuting flows), instead of the directionality of the relation between them. This is reached through the symmetry of the matrix. On the other hand, the denominator describes the minimum of the labour force between those municipalities *i* and *j*, and therefore the analysis is not dominated by those of greater size, and confers greater relative importance to interrelationships with small municipalities, which are often hidden by the use of the larger work force or the sum of the workforce of the two places.

After computing the dissimilarity matrix, we apply a hierarchical cluster procedure to agglomerate all spatial units that are part of the same functional area because they share a high level of commuting. While doing so, a challenge arises: according to Kropp and Schwengler (2016), even though "…bidirectional commuting flows are the most suitable basis for the delineation of Labour Market Areas", there is a lack of theoretical arguments to support the - otherwise arbitrary - choice of a threshold value to determine which spatial units merge or do not merge into functional areas. To address this problem, we use a wide range of threshold values to analyse marginal changes in the composition of the functional areas, but most importantly, we focus on the data distribution to use a threshold α defined by: $\alpha = \mu + 1.5\sigma$, where μ and σ represent the average and the standard deviation of the dissimilarity coefficients disregarding outlying values (scores), respectively.

Although the methodology of clustering of municipalities based on commuting flows by Tolbert and Sizer has found some critics (Casado-Díaz, Martínez-Bernabéu, & Rowe, 2017), it is also widely used in applied economics research (Autor & Dorn, 2013; Autor, Dorn, & Hanson, 2013; Raj, Hendren, Kline, & Saez, 2014; Amior & Manning, 2015; Berdegué, y otros, 2011). Moreover, we think that by using satellite information, other methods that define functional areas could be improved, such as for example the recent developments of Goetz, Han, Findeis and Brasier (2010); Kropp and Schwengler (2016); and Casado-Díaz, Martínez-Bernabéu and Rowe (2017) even more so when there are a lack of census data. In this sense, our methodology should be seen as a complementary tool to recent developments in the computation of functional areas.

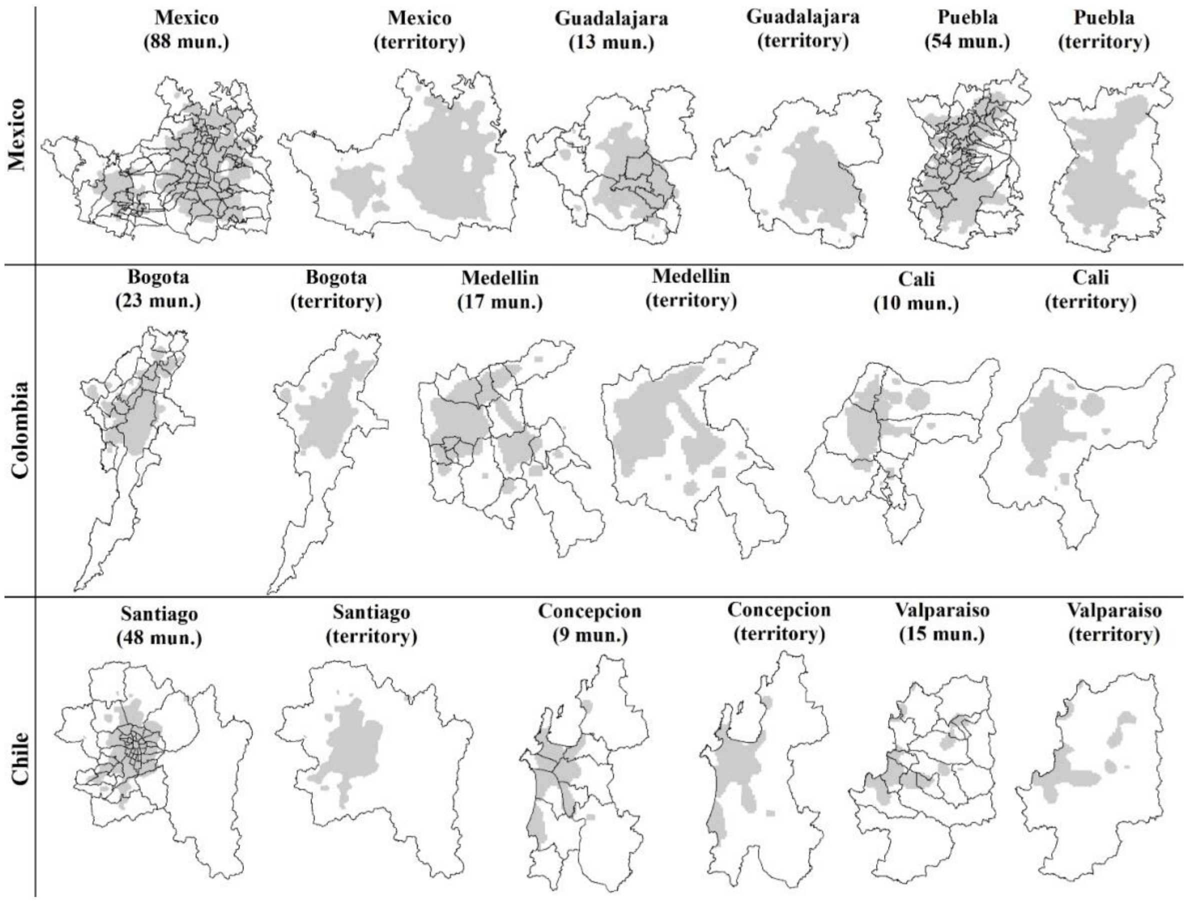
5. RESULTS

a) Applications

This section describes the most representative cases for each country. A complete map of functional territories for each country can be found in the Supplementary Material (S1). Figure 3 describes the functional territories created in the three most densely populated areas of each country. The first row represents Mexico, the second row Colombia and the third row Chile. For each area in the figure, the black borderlines on the left-hand side delineate the administrative municipalities' boundaries, while on the right-hand side the black borderline delineates the shape of the functional territory. The grey shaded area describes the urban area captured with satellite night lights using an intensity threshold of 35 for Colombia and Chile and 50 for Mexico.

The figure shows that all urban areas detected with night lights are perfectly contained in the polygons of the functional territories constructed by the method. In the case of Mexico, the largest territory is the area that contains Mexico City, which groups 88 municipalities. Despite the fact that the second more populated area is Guadalajara grouping 13 municipalities, the area of Puebla groups a higher number of municipalities (54). In the case of Colombia, the area of Bogota groups 23 municipalities, Medellin 17 and Cali 10. Finally, the functional territory that contains Santiago concentrates 48 municipalities, and the coastal areas of Concepción and Valparaiso group 9 and 15 municipalities respectively. The area of Valparaiso is north-west of Santiago and the urban centre is located approximately one and a half hours by car from the centre of Santiago.

Figure 3: Functional territories and the main urban centers by country.



Note: the shadows are lit areas. The figure describes the results of the method for the most densely populated areas of each country. As more fragmented are the municipality boundaries, and the more expanded is the city, more municipalities are going to be grouped by the method. The results are non-fragmented areas of high economic and social interaction.

b) Results and robustness check

In this section we show, for each country, the sensitivity of the proposed method with respect to alternative cutoffs for the light intensity as well as for commuting rates. Table 3 describes the sensitivity analysis of the identification of functional territories to different thresholds of night light intensity and commuting rates for Mexico, Colombia and Chile. The table describes the results of the sensitivity analysis in terms of: (a) the changes in the number of functional territories; (b) the percentage of municipalities grouped in functional territories; and (c) the percentage of the population grouped in these functional territories. The night light intensity takes a minimum value of 0, when no light is identified over a year by the satellite, and a maximum of 63 that usually occurs in dense and rich areas (Henderson et al, 2012).

Table 3 – Sensitivity analysis of functional territories by country

Panel a): Mexico

Light intensity	Number of functional territories				% of municipalities grouped in functional territories				% of the population grouped in functional territories			
	1%	2%	μ+1.5σ	10%	1%	2%	μ+1.5σ	10%	1%	2%	μ+1.5σ	10%
12	603	878	1,284	1,507	0.90	0.80	0.60	0.48	0.97	0.94	0.85	0.79
22	662	964	1,407	1,683	0.90	0.79	0.56	0.41	0.97	0.93	0.83	0.75
35	687	1,001	1,475	1,767	0.89	0.78	0.54	0.38	0.97	0.93	0.82	0.73
50	700	1,036	1,533	1,851	0.89	0.77	0.52	0.34	0.97	0.92	0.81	0.71
NO*	738	1,090	1,660	2,042	0.89	0.76	0.49	0.28	0.97	0.92	0.77	0.64

Panel b): Colombia

Light intensity	Number of functional territories				% of municipalities grouped in functional territories				% of the population grouped in functional territories			
	1%	2%	μ+1.5σ	10%	1%	2%	μ+1.5σ	10%	1%	2%	μ+1.5σ	10%
12	545	651	720	788	0.65	0.54	0.46	0.38	0.86	0.81	0.78	0.73
22	602	729	813	910	0.61	0.47	0.37	0.25	0.85	0.79	0.75	0.67
35	626	760	848	955	0.59	0.44	0.33	0.20	0.84	0.78	0.73	0.63
50	645	781	872	987	0.57	0.42	0.30	0.16	0.83	0.77	0.71	0.60
NO*	669	805	910	1,041	0.56	0.41	0.28	0.11	0.83	0.76	0.70	0.56

Panel c): Chile

Light intensity	Number of functional territories				% of municipalities grouped in functional territories				% of the population grouped in functional territories			
	1%	2%	μ+1.5σ	10%	1%	2%	μ+1.5σ	10%	1%	2%	μ+1.5σ	10%
12	55	93	117	195	0.95	0.98	0.95	0.84	0.99	0.98	0.95	0.91
22	58	97	123	203	0.95	0.98	0.95	0.83	0.99	0.98	0.95	0.90
35	61	101	132	216	0.95	0.97	0.95	0.81	0.99	0.97	0.95	0.89
50	64	103	135	222	0.95	0.97	0.95	0.81	0.99	0.97	0.95	0.89
NO*	73	114	153	273	0.96	0.97	0.95	0.64	0.99	0.97	0.95	0.83

Columns show commuting rates. The measure μ+1.5σ is 5,52%, 3,33%, and 3,0% for México, Colombia and Chile, respectively.

The most representative values of 12, 22, 35 and 50 were chosen to be presented.[8] The last row of each panel of Table 3 shows the resulting functional territories without taking into account the night lights, i.e., when functional territories are identified only with commuting rates. On the other hand, the different commuting rate thresholds are presented in the columns. Due to the fact that geographic differences between countries lead to differences in the average commuting rates in each country, the commuting rate threshold chosen for each country is a similarity score of $\mu+1.5\sigma$. However, we also present the results with 1%, 2% and 10% commuting rate thresholds.

The results of the sensitivity analysis are similar for the three countries, and they show that the lower the similarity score (i.e., the higher the commuting rate), the lower the influence of the light intensity threshold to the municipalities grouped in functional territories and the percentage of the population contained in these areas.

Since the first step of the method is the union of municipalities sharing a lit area, the commuting rate affects the results after the light intensity threshold choice. Thus, when the light intensity threshold is high (low), a low (high) number of municipalities are grouped in the first step. For that reason, the more municipalities are grouped in the first step, the fewer municipalities are grouped in the second step, independently of the commuting rate threshold. And the higher the commuting rate threshold, the fewer municipalities are grouped in the second step, and therefore, we will see more spatial fragmentation (more functional territories of

[8] This means that the polygon formed by the light area considers digital numbers of light intensity greater than or equal to the threshold value. Then the larger the threshold, the lower is the area of the resulting polygon.

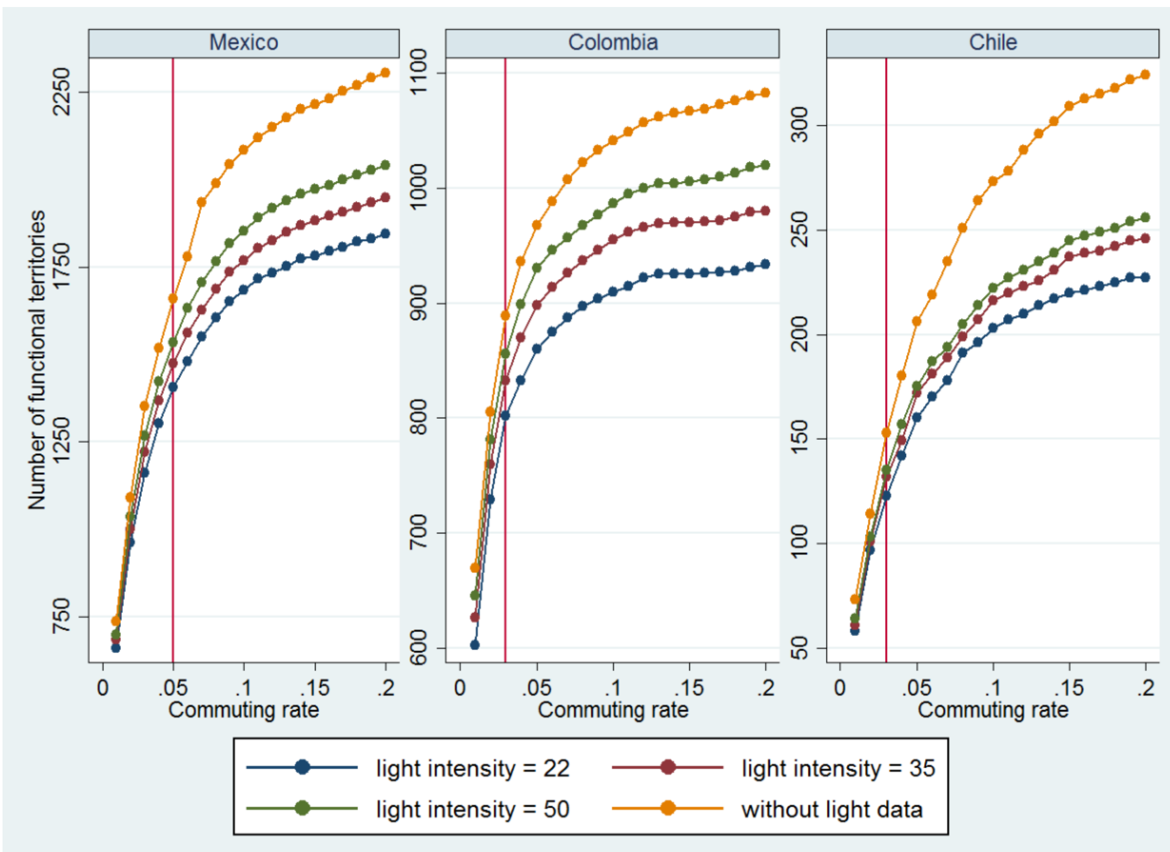
only one municipality).

We will illustrate these results for the case of Mexico (Table 3, Panel a). The number of functional territories increases considerably when a higher commuting rate is set. With a low light intensity threshold of 12, the number of functional territories goes from 603 to 1,507 when the commuting rate threshold varies from 1%, to 10%. When no lights are used, the number of functional territories increases almost 2.8 times, from 738 with a commuting rate of 1% to 2,042 with a commuting rate of 10%. This increase in the number of functional territories means that there is less grouping of municipalities with a commuting rate threshold of 10% (28% percent of municipalities are grouped into functional territories) than with a commuting rate of 1% (89% of municipalities are grouped into functional territories). Incorporating night light information into the procedure increases the proportion of municipalities that are grouped into functional territories: with a 10% commuting rate the proportion of municipalities goes from 28% with no lights to 34% with a light intensity of 50, and to 48% with a light intensity of 12. However, the sensitivity of these results decreases when using a lower commuting rate.

The same pattern is observed with respect to the population grouped into functional territories. With no lights and a commuting rate of 10%, 64% of the population is grouped into functional territories. That proportion increases to 71% with a light intensity of 50% and to 79% with a light intensity of 12. Note that the proportion of the population grouped into functional territories is, in all cases, larger than the proportion of municipalities. This result indicates, of course, the spatial concentration of population in some municipalities.

It is interesting to note that the percentage of municipalities and population grouped at the different combination of commuting rates and night lights intensity thresholds is much lower in Colombia than in the other countries. This reflects a lower level of interactions between municipalities, captured by lights and/or commuting, than in Chile or Mexico. This is probably related with the existence of a very intricate geography together with a weak transportation infrastructure in that country. Thus, it has more isolated territories.

Figure 4: Sensitivity analysis of the number of functional areas to different dissimilarity thresholds and night light intensity.



Note: The figure shows the sensibility of the number of functional territories identified to different commuting rates and light night intensity thresholds. The lower the light night intensity threshold chosen, the lower the number of functional territories created, i.e., a larger number of municipalities are grouped.. This is because more municipalities are grouped in the first step of the method. Notwithstanding, the election of the night light intensity threshold does not influence significantly the results when the dissimilarity rate is high, or equivalently the commuting rate threshold is low. The vertical red line in each graph shows the commuting rate threshold chosen in each country for the identification of functional territories.

Figure 4 describes the sensitivity analysis of the number of functional areas to different commuting rates and night light intensity thresholds. As stated before, it is clear for the three countries that when the commuting rate threshold decreases, the number of functional territories also decreases. In addition, the lower the light intensity threshold (i.e., the greater the lit area), the larger the number of functional territories. Notwithstanding, these differences are reduced significantly when a low commuting rate threshold is selected.

The vertical red line in each graph shows the commuting rate chosen in each country for the exercise.[9] At these values, the light intensity thresholds makes a difference in the number of conurbated areas identified in the first step, in particular the size of big agglomerations within countries remains stable, avoiding that they adhere distant municipalities to the functional area, that in practice share low commuting movements and affect the internal perfection of the conurbations and later of the functional territories.

To illustrate this point, Table 4 describes the statistics of commuting rate of conurbated areas to light intensity thresholds by country. The mean, standard error, minimum and maximum are presented for conurbated and not conurbated areas for light intensity thresholds of 12, 22, 35 and 50. The term “conurbated” describes those municipalities that were grouped in a functional territory with each one of the light intensity thresholds presented in the table. On the other hand, the

[9] It corresponds to a similarity score of $\mu+1.5\sigma$ for each country.

term “not conurbated” is used to describe those municipalities that do not group with any other at that stage of the method. There is an important difference in the commuting rate between the conurbated and not conurbated areas for all the different commuting rate thresholds. This difference is greater for the case of Chile, that has a higher commuting rate in conurbated areas (2.59%) in the case of light intensity of 12, in comparison to Colombia (2.01%) and Mexico (0.57%). Notwithstanding, Colombia has a higher commuting rate for conurbated areas with a light intensity threshold equal or greater than 22 (4.09% in comparison to 3.85% for Chile and 1.29% for Mexico). With the higher light intensity threshold (50), this difference in the commuting rate of conurbated areas increases. Colombia has a 9.06% average “intra-urban commuting rate” in comparison to 4.41% for Chile and 2.11% for Mexico. Despite the fact that Mexico reaches a maximum in the commuting rate inside the territory of 63.3%, which is greater than Colombia and Chile, the average is lower than in the other two countries. In addition, the dispersion or variability in the commuting rate in relation to the mean inside the conurbated area is also greater in Mexico and lower in Colombia.

Table 4 – Descriptive statistics of commuting rate of conurbated areas to light intensity thresholds by country

		Light intensity threshold							
		12		22		35		50	
		Not conurbated	Conurbated	Not conurbated	Conurbated	Not conurbated	Conurbated	Not conurbated	Conurbated
Mexico	Mean	0,004%	0,568%	0,005%	1,288%	0,005%	1,850%	0,006%	2,111%
	Std. Error	0,000%	1,365%	0,000%	2,293%	0,000%	2,958%	0,000%	3,443%
	Minimum	0,004%	0,145%	0,005%	0,141%	0,005%	0,404%	0,006%	0,427%
	Maximum	0,004%	63,32%	0,005%	63,327%	0,005%	63,327%	0,006%	63,327%
Colombia	Mean	0,017%	2,013%	0,019%	4,087%	0,018%	6,769%	0,021%	9,056%
	Std. Error	0,000%	1,498%	0,000%	2,992%	0,000%	3,817%	0,000%	3,952%
	Minimum	0,017%	0,000%	0,019%	0,000%	0,018%	0,000%	0,021%	0,581%
	Maximum	0,017%	12,216%	0,019%	29,020%	0,018%	37,170%	0,021%	28,173%
Chile	Mean	0,080%	2,590%	0,082%	3,850%	0,087%	4,204%	0,087%	4,410%
	Std. Error	0,000%	2,624%	0,000%	3,512%	0,000%	4,077%	0,000%	4,400%
	Minimum	0,080%	0,000%	0,082%	0,000%	0,087%	0,000%	0,087%	0,000%
	Maximum	0,080%	49,559%	0,082%	49,559%	0,087%	48,885%	0,087%	48,885%

Although our choice of an appropriate light threshold for the delimitation of conurbations seems to be an arbitrary decision, there are some alternative measures that can inform this process. To the statistics discussed above, we add the modularity measure following Kropp and Schwengler (2016), to show how the different thresholds of light lead or not to clusters whose links offer a better description of the functional relationships of the municipalities, in contrast to a random clustering. This measure varies between 0 and 1, where Q = 0 indicates that clustering is no better than random division, while Q = 1 indicates that the clustering is better than a situation in which all are grouped into one single municipal region. Nevertheless, this measure in our case is only referential, since the commuting flows in all the countries are quite outdated, in contrast to the night lights captured in 2012. Then, modularity provides complementary evidence that the conurbations are being approximated correctly. For example, in the case of Chile, the political-administrative grouping has a structure with Q = 0.59, but the grouping of those municipalities in conurbations increases the modularity to Q = 0.7. In the case of Colombia the modular structure of administrative units seems to be better option and for Mexico the modularity rises with the different light thresholds, in contrast to the political-administrative grouping (Q = 0,807), reaching the highest value with intensity 12, which however have to oversize the big agglomerations, in this case intensity 50 offers a more stable approximation for the size of large agglomerations.[10]

Table 5 –Modularity of first step of the method, by country

Light intensity	Modularity		
	Mexico	Colombia	Chile
12	0,871	0,870	0,686
22	0,875	0,854	0,708
35	0,867	0,839	0,700
50	0,858	0,850	0,692
NO*	0,807	0,863	0,591

[10] The modularity index was computed following Kropp and Schwengler (2016), as $Q = \sum_i (e_{ii} - a_i^2)$ where $a_i = \sum_j e_{ij}$, with e_{ij} representing the commuting between the municipality i and municipality j as a proportion of the sum of all commuting flows of the matrix.

One of the validation criteria of a functional delimitation is reached in the first stage of the method. The internal perfection is achieved since night light data capture the extension of great metropolitan areas with a high flow of commuting. The contribution of the second step is oriented to account for interaction with low density municipalities that are not captured in the first step, because they do not project a quantity of light intense enough to consider them as conurbated areas, but as urban agglomerations with a more local reach.

6. CONCLUSIONS

In this paper we propose a novel approach for the delimitation of functional spatial units or functional territories using satellite imagery. We argue that our methodology can be considered as a complementary previous step to other approaches using commuting data such as cluster analysis or network approaches. The objective of our methodology is to use night light data to identify urban agglomerations that form conurbations of municipalities (that we call functional territories) in order to characterize them in a better and updated way instead of using only commuting data. Empirically, this is an important step, since in many countries there is no updated census information with commuting data or accurate travel time estimates. For this purpose we describe our methodology using as empirical examples the cases of three developing countries, namely Mexico, Colombia and Chile. Despite the important recent advances in the study and use of functional areas, this is the first paper that brings a new class of information for the delimitation of these areas. We show that the conurbated areas constructed through our approach in its first step present a high degree of auto-contention of commuting flows, and reach high modularity and low fragmentation.

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