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A first attempt of geographically-distributed Multi-scale integrated analysis of societal and ecosystem metabolism (MuSIASEM): Mapping Human Time and Energy Throughput in metropolitan Barcelona

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ABSTRACT

This study presents a first attempt to extend the “Multi-scale integrated analysis of societal and ecosystem metabolism (MuSIASEM)” approach to a spatial dimension using GIS techniques in the Metropolitan area of Barcelona. We use a combination of census and commercial databases along with a detailed land cover map to create a layer of Common Geographic Units that we populate with the local values of human time spent in different activities according to MuSIASEM hierarchical typology. In this way, we mapped the hours of available human time, in regards to the working hours spent in different locations, putting in evidence the gradients in spatial density between the residential location of workers (generating the work supply) and the places where the working hours are actually taking place. We found a strong three-modal pattern of clumps of areas with different combinations of values of time spent on household activities and on paid work. We also measured and mapped spatial segregation between these two activities and put forward the conjecture that this segregation increases with higher energy throughput, as the size of the functional units must be able to cope with the flow of exosomatic energy. Finally, we discuss the effectiveness of the approach by comparing our geographic representation of exosomatic throughput to the one issued from conventional methods.

Keywords: Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM), GIS Techniques, Metropolitan Area of Barcelona, spatial analysis, metabolic pattern, geographically-distributed bioeconomics

1. Introduction

Multi-scale integrated analysis of societal and ecosystem metabolism (MuSIASEM, Giampietro et al. 2008 and 2009) approaches socio-ecologic systems by simultaneously considering variables of different natures (flows and funds) and their mutual restrictions through a hierarchically organized set of categories. Defining the structured tree of human activities is of critical importance in the analysis because human time is the primary fund and different human activities channel the flow of exosomatic energy. The main goal of MuSIASEM is to provide benchmarks of societal metabolism (Giampietro, 2003) in terms of flows per unit of fund at equivalent levels, thus providing meaningful comparisons across different systems. For example, the gross domestic product of a set of countries can be compared in terms of the time spent on working rather than the usual per capita ratio, which implies that not only total populations but demographic structures are taken into account. Also, MuSIASEM considers the different flows of economic subsectors, since the same per capita GDP can be produced by totally different arrays of economic sub-sectors, thus hiding fundamental differences and precluding forecasting. Ramos-Martín et al. (2009) and Giampietro and Sorman (2009) provide useful examples.

Up to now, MuSIASEM has been used to characterize different human systems in terms of societal metabolism by their mean field behaviour. Nevertheless, human activities and its associated energy flows do not take place in virtual space but are constrained to a finite piece of land. As land is finite, land is also a fund that can be included in MuSIASEM to create a dual representation of the societal metabolism (Giampietro, 2003). Space imposes severe constraints because the organization of human (and ecosystem) activity cannot take place in a random field: different human activities imply different spatial patterns, and problems of transport of energy and goods (including the most important one: human time) arise. The geographic structure of human activity and its associated flows of energy interact with the physical environmental matrix creating landscapes.

In addition to the obvious practical interest for policy makers, this geographically-distributed MuSIASEM will let us investigate the internal organization of the system. This is important because constraints on the actual location of human activities slow down the dynamics of the system: goods (including human time) have to be transported from one place to another. In this regard, assessing the degree of spatial segregation among different human activities and investigating the relationship between the spatial pattern and the flow of exosomatic energy is of critical importance to understand the dynamics of the socio-economic system.

Our aim in this article is to represent the geographic distribution of human time invested in different activities according to the hierarchical scheme of MuSIASEM for the case study of metropolitan Barcelona, and to provide a first approach to the geographic distribution of exosomatic energy throughput, comparing to a conventional, aggregated estimate. We characterize the geographic structure of metropolitan Barcelona in terms of units arisen from the non-uniform distribution of the mapped variables, and in terms of the spatial segregation of human activities. Our hypothesis is that such a spatial structure, defined in terms of functional units, depends on the size and pace of the total energy throughput, an hypothesis that we plan to test in the future by comparing the spatial structure of different urban areas. The root of our hypothesis is that human societies are instruments for the control of exosomatic energy (Lotka, 1956; Georgescu-Roegen, 1971).

2. Area of Study

The area of study (Table 1 and Fig.1) includes what is usually known as the Area Metropolitana de Barcelona, an area that currently has no administrative identity and that is made up of the union of municipalities included in any of the two main metropolitan agencies for basic services (EMT for transportation and EMSHTR for waste processing and disposal) and/or the MMAMB (a commonwealth of municipalities sharing basic infrastructures). The area of study occupies 635.84 km^2, 2% of the total 31,896 km^2 of Catalonia, and has 3,150,380 inhabitants, 44% of the total 7,134,697 inhabitants of Catalonia in 2006.

Figure 1. Area of study

Table 1. Municipalities included of in the Area of Study

NAME	ACRONYME	AGENCY		
		MMAMB	EMSHTR	EMT
Barberá del Vallés	BBV	N	Y	N
Castellbisbal	CAS	N	Y	N
Montcada i Reixac	MIR	Y	Y	Y
Sant Cugat del Vallés	SCV	N	Y	N
Badia del Vallés	BDV	Y	Y	N
Cerdanyola del Vallés	CDV	Y	Y	N
Ripollet	RPT	Y	Y	N
Tiana	TNA	Y	Y	Y
Badalona	BDA	Y	Y	Y
Montgat	MOG	Y	Y	Y
Santa Coloma de Gramenet	SCG	Y	Y	Y
Sant Andreu de la Barca	SAB	Y	Y	N
El Papiol	PAP	Y	Y	N
Molins de Rei	MDR	Y	Y	N
Corbera de Llobregat	CLL	Y	N	N
Palleja	PJ	Y	Y	N
Sant Adriá de Besos	SAB	Y	Y	Y
la Palma de Cervelló	PLM	N	N	N
Sant Feliu de Llobregat	SFLL	Y	Y	Y
Cervelló	CEV	Y	N	N
Sant Vicent dels Horts	SVH	Y	Y	N
Sant Just Desvern	SJDE	Y	Y	Y
Esplugues de Llobregat	ELL	Y	Y	Y
Santa Coloma de Cervelló	SCC	Y	Y	N
l'Hospitalet de Llobregat	HLL	Y	Y	Y
Sant Joan Despí	SJDI	Y	Y	Y
Torrelles de Llobregat	TLL	Y	Y	N
Cornellá de Llobregat	CLL	Y	Y	Y
Sant Boi de Llobregat	SBLI	Y	Y	Y
Begues	BG	N	Y	N
Sant Climent de Llobregat	SCLL	Y	Y	N
el Prat de Llobregat	PLL	Y	Y	Y
Viladecans	VIL	Y	Y	Y
Gavá	GV	Y	Y	Y
Castelldefels	CASF	Y	Y	Y
Barcelona	BCN	Y	Y	Y

3. Methods

Our general approach was to generate the geographic distributions of human time devoted to different activities in the area of study from data having a geographic support, and to improve this support through (i) the compatibility of human activities with land cover types, and (ii) by defining a common geographic unit for all variables considered. The set of categories of human time was defined according to the hierarchical partitioning proposed in MuSIASEM (Giampietro et al. 2009), which we reproduce in Figure 2.

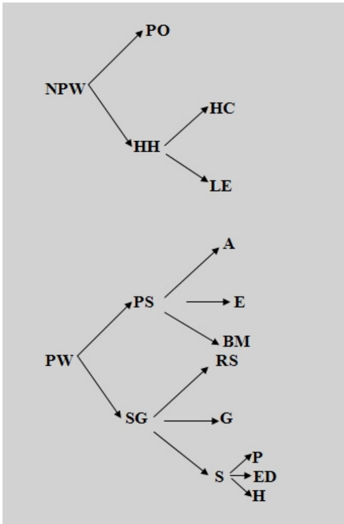


Figure 2. Hierarchical partitioning of human time into categories, (Giampietro et al. 2009). NPW, not paid work; PW, paid work; PO, physiological overhead; HH, household activities; PS, paid work in productive sectors; SG, services and government. HC, household chores; LE, leisure and education; A, agriculture; E, energy; BM, building and manufacturing; RS, retail sector; G, government; S, services; P, police and army; ED, education; H, health services.

3.1 Data Sources

We derived the basic information on land cover from the *Mapa de Cobertes de Sol de Catalunya v3* (Burriel et al. 2005, http://www.creaf.uab.es/MCSC/), a map generated by interactive contouring and photo-interpretation on orthophotomaps 1:5000, which are acquired and processed by the *Institut Cartogràfic de Catalunya*. Table A1 in the Appendix lists the relevant land cover categories for the area of study.

In order to estimate human time spent in the household, we used data from the Continuous Register of Population of 2006, which were facilitated by IDESCAT, the agency of statistics of the Catalan Government. These data were in tabular form, including, for each census tract, tract code and population values by sex and age class (segments of 5 y). IDESCAT also made a vector layer of census tracts available for this study.

For estimating time spent on paid work in the productive sectors (PS), we used the DUNS 50000 database (Dun & Bradstreet International, 2003), which holds data on the 50,000 main companies of Spain, including fields such as zip code, activity and number of employees. We checked the completeness of these data by comparing the total number of employees for all recorded companies in the city of Barcelona (401,260) to the figure provided by the municipality of Barcelona according to data from the 2001 census (724,246 workers, of which 645,682 were actually employed). Considering that the figure derived from DUNS 50000 does not include employees in retail, administration, educational sectors, etc., we considered the figure derived from DUNS 50000 to be a very good approximation (62%).

Information on the number of employees in the retail sector (part of Service and Government) was provided by the *Ajuntament de Barcelona* on neighbourhoods, but is still lacking for the rest of municipalities of the area of study. Data on employees in Government, education, health and other services has been made available to us by municipalities, and we are currently working on a finer geographic distribution for these data. Therefore, we are not including data on Service and Government in this article.

3.2 Methodological Problems

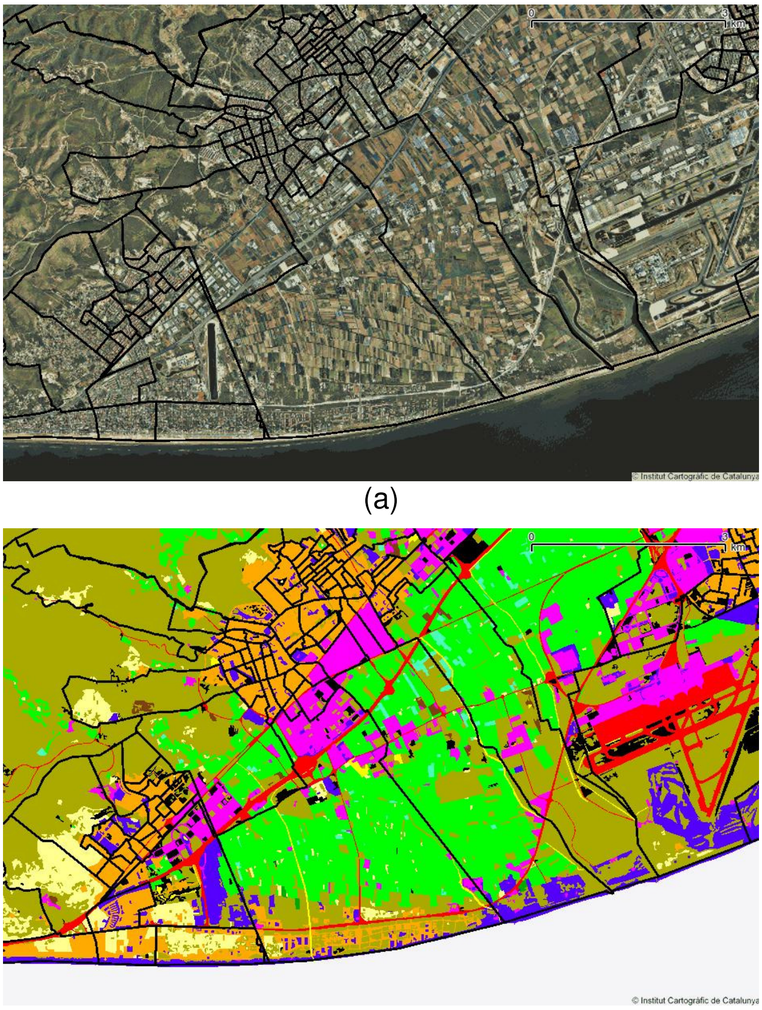
3.2.1 Arbitrary (administrative) spatial units

As is commonly the case, the geographic support of the socio-economic data that we have used in our study is based on pre-existing units that are not necessarily appropriate for geographic analysis. For example, census data are provided by census tracts, which in some cases are evenly residential but that in other cases can include large zones with actually no population (Fig. 3).

This is even more serious a problem for zip codes, neighbourhoods, municipalities etc. Since our goal is to produce an unbiased representation of the geographic distribution of different human activities, we have used a Land Cover map to exclude, for a given activity, those areas whose LC makes it unlikely that the given activity could be actually performed there. For example, we restrict the population of a census tract to that part of the tract with buildings. The resulting choropleth maps are most often very different from the original ones, as well exemplified by the maps of Serra Batiste and Ruiz Almar (2008) reproduced in Figure 4. The misleading information provided by choropleth maps of non-uniform spatial units is actually the graphic consequence of the MAU problem (i.e., Green and Flowerdew, 1996). Thus, increasing the homogeneity of the spatial unit decreases the MAU problem for ulterior statistical analysis.

3.2.2 Different spatial units for each data set

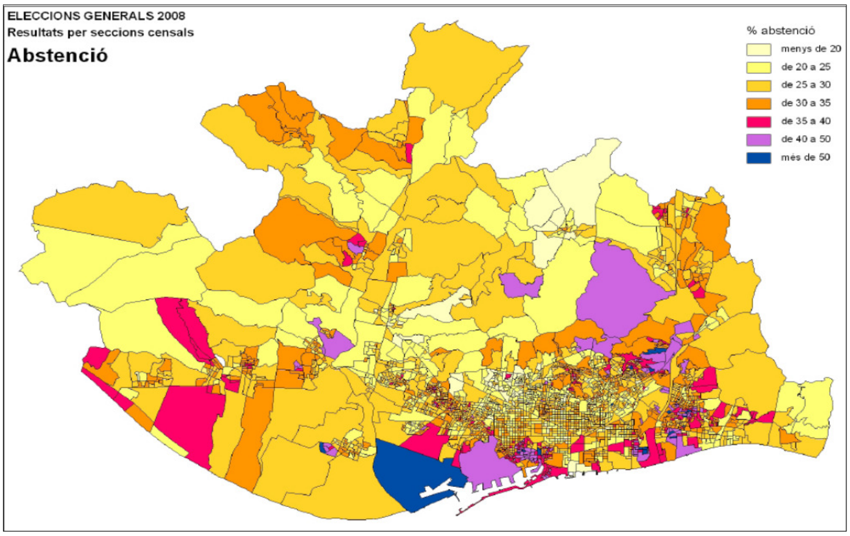
An important practical problem is that virtually each source of data uses a different geographic partition: census data are provided by tracts, jobs by zip codes, retail shops by neighbourhoods and many government data by municipalities and/or county.



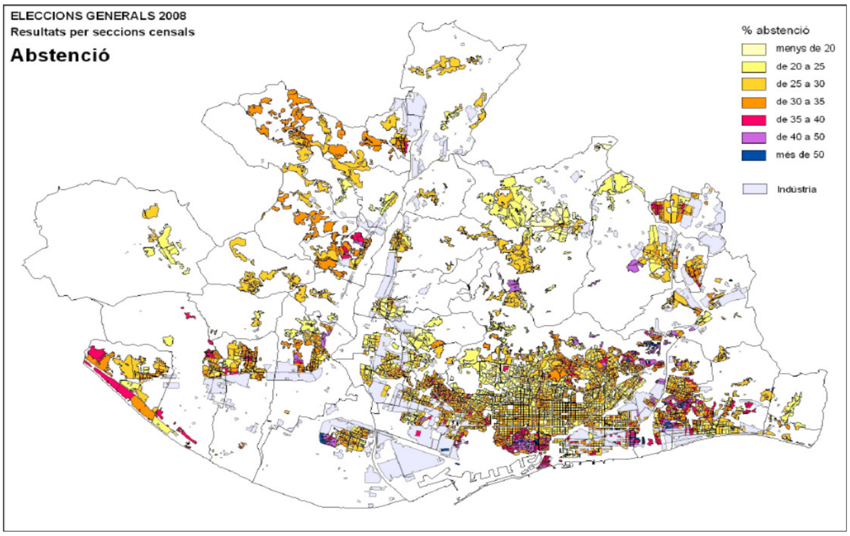
(a)

(b)

Figure 3. Example of a census tract in which the residential use is actually concentrated into a small part of the total area of the tract. (a) boundary of the census tract overlaid on a 1:5000 orthophotomap (ICC); (b) boundary of the census tract overlaid on the Land Cover Map (CREAF).



(a)



(b)

Figure 4. Choropleth maps of the percent of non-participation in the general elections of Spain 2008. (a) colour-coding by census tracts; (b) colour-coding by actual residential areas. (Serra Batiste and Ruiz Almar, 2008)

3.3 Common Geographic Units (CGU)

As our focus is on mapping human time, we created a subset of polygons of LC (henceforth named Urban Land Cover, ULC) disregarding those labelled as Not Colonized Land (NCL) and Agriculture. As an initial step, we did not include agricultural land in our study because of the lack of data on human time invested in agricultural activities and because we assumed that the fraction of human time allocated to agriculture is proportionally very low in this metropolitan area. We thus kept categories "compact urban", "loose urban", "industrial urban" and "urban plots", according to legend level LU in Table A1. We defined CGUs as the intersection of the vector layers Census Tracts (2537 polygons), Urban Land Cover (5049 polygons) and zip codes (1124 polygons). In this way, each polygon is defined by:

- ID
- Area
- ULC category
- Census tract code
- Area of tract
- Zip code
- Area of Zip Code

After cleaning spurious polygons (very small or very elongated polygons, see Fig 5), the resulting layer of CGUs had 7978 polygons. These geometric operations were conducted using the functions "Intersect", "Multipart to Single part", "Dissolve" and "Merge" in Arc-Gis (ESRI (2004).

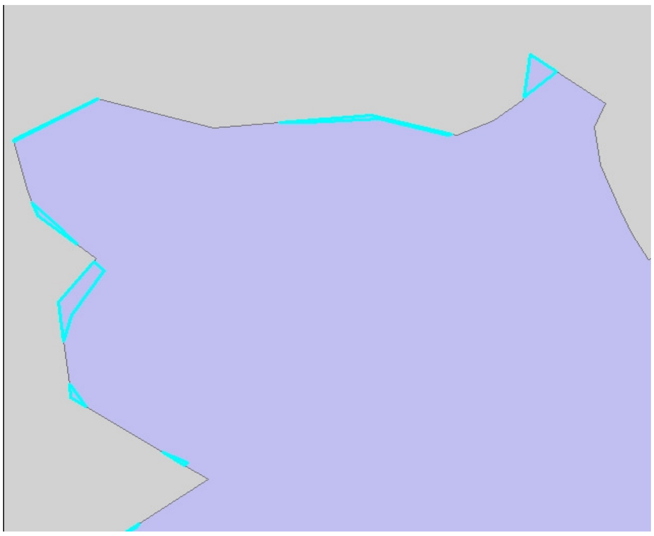


Figure 5. Detailed view of spurious polygons produced by the intersection operations.

3.4 Estimates of human time devoted to different activities

We ignored time spent in transportation in this initial approach, as the geographic support for this activity (transportation network) requires specific treatment. For the rest, we proceeded as follows.

For each tract, we processed the information from the census data in the following way:

- THT = P * 365* 24 h (where THT stands for Total Human Time and P for population)
- Aggregate the original 5 y age intervals in 3 categories (C, children; A, adults; R, retired):
  - C = P younger than 20 y old
  - A = P with age between 20 and 65 y
  - R = P older than 65 y old
- Disaggregating A (adults) into D (women) and H (men), and D into Dw (women having a job) and Dhh (housewives), assuming Dw = 0.46*D and Dhh = 0.44*D (according to the average data for Catalonia, as data on the actual labour situation of adult women for each tract were not available for this study).

We assumed the following time partitioning for the different human types (units are h in all cases)

- Physiological Overhead (PO)
  - PO = P*365*10
- Leisure and Education (LE)
  - LE(C) = (365*14)*C
  - LE(R) = (365*14)*R
  - LE(H) = (ld*3 + vd*12) * H
  - LE(Dw) = (ld*1 + vd*8) * Dw
  - LE(Dhh) = (ld*3 + vd*8) * Dhh

(where *ld* stands for labour days (ld = 365-30-52*2) and *vd* stands for vacation days (*vd* = 30 + 52*2)

  - LE = LE(C) + LE(R) + LE(H) + LE(Dw) + LE(Dhh)
- House Hold activities (HH):
  - HH(H) = (ld *1 + vd*1) * H
  - HH(Dw) = (ld*3 + vd*5) * Dw
  - HH(Dhh) = (ld*10 + vd*5) * Dhh
  - HH = HH(H) + HH(Dw) + HH(Dhh)
- Time spent in Paid Work (PW) is divided into time spent in the Productive Sectors (PS) and in Service and Government (SG).
  - For PS, we extracted the information on the number of workers (W) from the DUNS 50000 data set for each zip code of the area of study
    PS = (ld*8) * W_{PS}

- ◦ Time spent in Government and Service (GS)[1] is being derived from different sources but cannot be referred to CGUs yet:

- Time spent in the Retail Sector: for each neighbourhood, we derived RS (time spent on PW in the retail sector) from the information from the *Ajuntament de Barcelona* on the number of employees in the retail service (W_{RS}):

  $RS = (ld*8) * W_{RS}$

- Time spent in the Administration: for each municipality, we derived the rest of GS from information on the number of employees (W_G):

  $G = (ld*8) * W_G$ and $G = (ld*8) * W_G$

3.5 Geographic distribution of human time

Each CGU was initially populated with the data on HH, LE and AWF corresponding to its tract, and with the data on PS corresponding to its zip code. In a second step, these figures were modified according to the land cover (LC) type according to the compatibility table (Table 2):

• All kinds of human activities were set to 0 for those CGUs of land cover type "urban plot", for obvious reasons.
• PS on CGUs of land cover type "loose urban" were set to 0 (we considered "loose urban" to have residential use only).
• LE, HH, PO and APW on CGUs of "industrial" land cover type were set to 0 (we considered "industrial urban" to have no residential use at all).

Table 2. Compatibility matrix between human activities and Land Cover

	Human Activity			
Land Cover	**PS**	**PO**	**HH**	**LE**
NCL	0	0	0	0
A	0	0	0	0
Ui	1	0	0	0
Ul	0	1	1	1
Uc	1	1	1	1
Us	0	0	0	0

1 *On going work, not included in the Results*

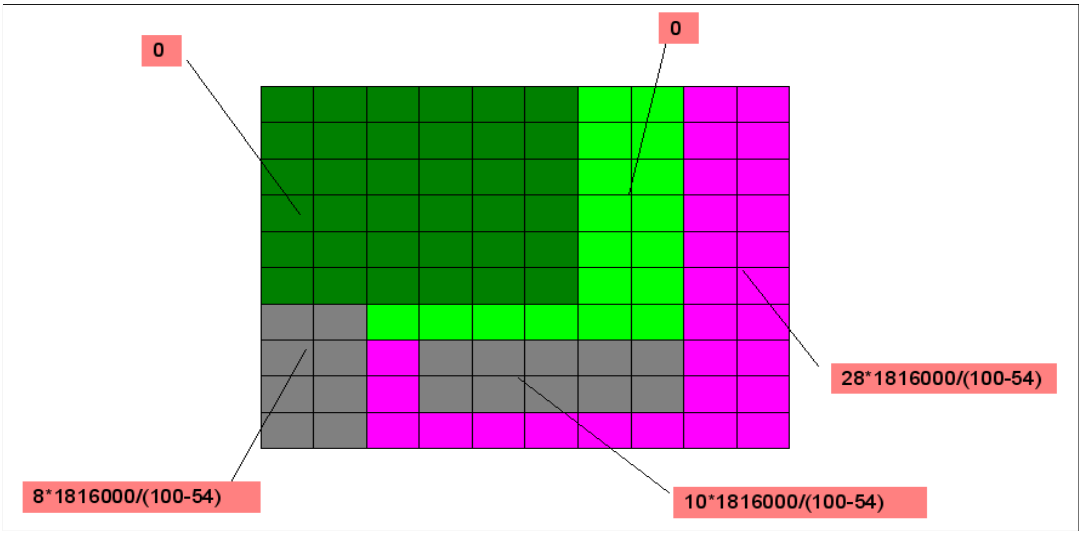


Figure 6. Idealized example of the stratified estimate of human time invested on a given activity in a given CGU. In this case, the total grid represents a Zip Code of 100 ha in which, according to the data, there is a total of 1816000 h invested on working in the Productive Sector (excluding Agriculture). Colours represent Land Cover, where each colour patch represents a CGU and each cell one ha. For CGUs of Non Colonized Land (dark green) and Agriculture (light green), the estimate is set to 0. For CGUs of Industrial (grey) and Compact Urban (pink), the estimate is proportional to the area of each CGU divided by the surface of the Zip Code which is compatible with the land use "Working in the Productive Sector" (100 – 54 = 46 ha in this example).

In a third step, the estimate of time spent on a given activity in a given CGU with a compatible LC, was calculated by weighting the initial estimate by a factor proportional to the ratio of the area of the CGU and the area of the original unit (tract or zip code) that had compatible LCs. That is (Fig. 6):

- PS on CGUs of land cover type "compact urban" and "industrial urban" were weighted proportionally to the ratio S(CGU)/S(Z'), where S(CGU) stands for the area of the CGU and S(Z') stands for the area of the zip code that is either "compact urban" or "industrial urban".

- PS, LE, HH, PO and APW on CGUs of land cover type "compact urban" and "loose urban", were weighted proportionally to the ratio S(CGU)/S(T'), where S(CGU) stands for the area of the CGU and S(T') stands for the area of the census tract that is either "compact urban" or "loose urban".

These computations were done in R (R Development Core Team, 2009) using packages "rgdal" (Keitt et al. 2009) and "sp" (Pebesma and Bivand, 2005). Geographic display and analysis has been done using QGIS (Quantum GIS Development Team, 2009) and GeoDa (Anselin et al. 2006).

3.6. Spatial segregation

We measured spatial segregation between human time devoted to household activities and time devoted to paid work in the Productive Sectors by means of the Local Index of Spatial Association (LISA, Anselin 1995). LISA values are standardized individual components of the Moran's I index (Moran, 1950), and thus measure the spatial autocorrelation of the variable in a given position with its values on a surrounding area. “Hot spots” for the variable are identified by clusters of significantly high LISA values produced in areas in which high values of the variable are surrounded by high values, while “cold spots” are also clusters of significantly high LISA values but in which low values of the variable are surrounded by low values. LISA maps of time devoted to household activities and time devoted to paid work in the Productive Sectors indicate, respectively, areas in which high (and low) values are significantly concentrated for these two variables.

3.7 Estimates and geographic distribution of Energy throughput

As a first approximation, we estimated the geographic distribution of energy consumption by simply multiplying HH and PS time at each CGU by the average values of Exosomatic Metabolic Rate (EMR) according to Ramos-Martin et al. (2009), 2.70 MJ/h and 343 MJ/h for, respectively, HH and PS in 2003. This procedure obviously ignores the relevant effect of the non-uniform spatial distribution of the variance and is presented here both as an example of the interest on generating actual maps for this variable based on data with geographic support, and to compare to the conventional method of multiplying the aggregated 162.32 MJ/hab (resulting from the ratio 1120/6.9 PJ/Mhab) of Catalonia by the population of each municipality.

4. Results

The different variables of human time have log-normal distributions, with the skew towards lower values (Fig. 7). Frequencies are calculated by the area covered (in ha), as the number of polygons would be misleading because of the variability in size. Histograms of log-transformed human time reveal bi-modal distributions, with a first mode for very low values.

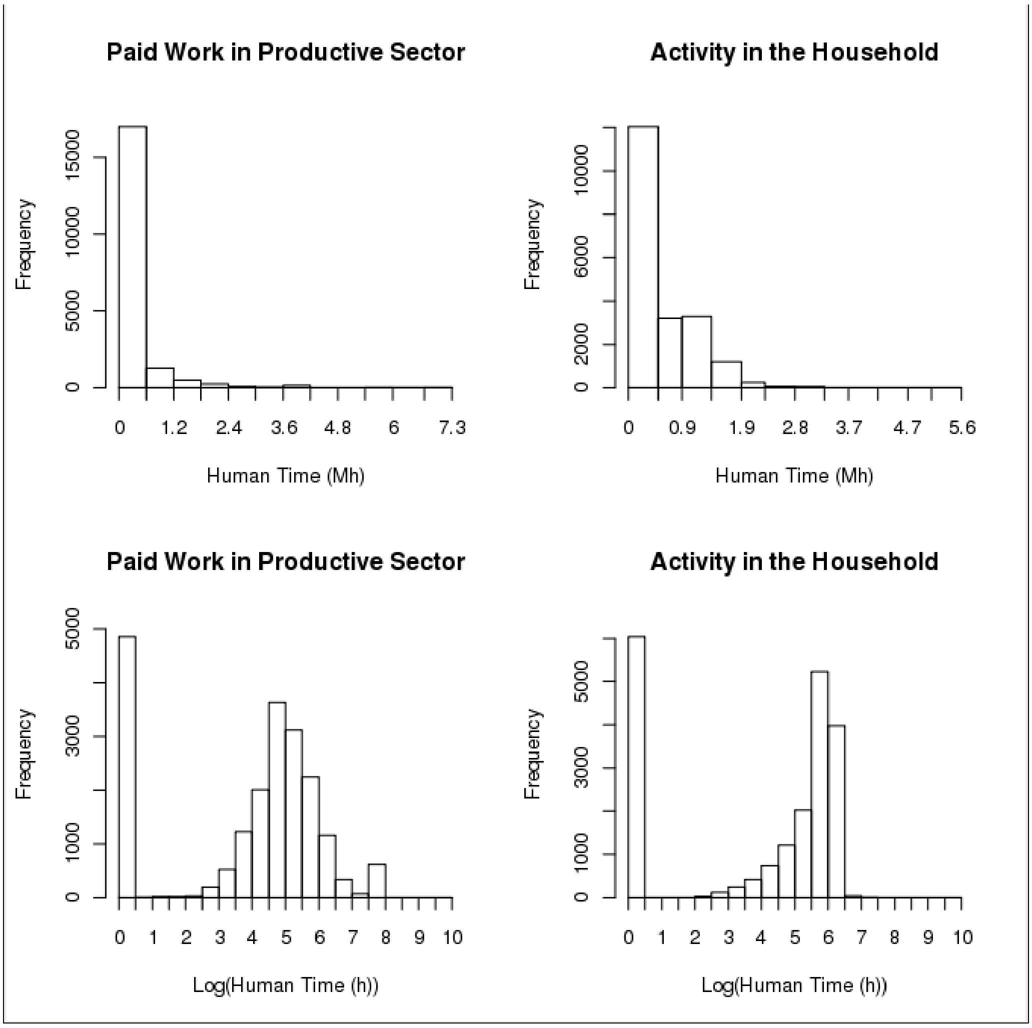


Figure 7. Histograms of human time (h) devoted to paid work in the productive sectors and to household activities. Time is in logarithmic scale as the original histograms are very skewed. Frequency is measured as area (ha) because individual CGUs greatly vary in terms of size.

Figures A1 to A3 in the Appendix display maps of log-transformed human time spent on, respectively, Physiological Overhead (PO), Household activities (HH) and paid work in Productive Sectors (PS). Figure A4 displays the map of Available Working Force, which is a virtual magnitude representing "how many hours of potential work are living in a given site", thus the map of AWF/PS (Fig. A5) represents the differential distribution of the source of the working force and the actual investment in work. Figure A6 displays the sum PO + HH, to represent the total amount of time that is invested by the society in its maintenance ("Physiological + Societal overhead").

The bi-modal distributions observed in the histograms become three-modal in bi-variate histograms (Fig. 8), putting in relevance a clear pattern. Metropolitan Barcelona can be divided in 3 types of zones. Zones essentially devoted to PO + HH, zones essentially devoted to PS and zones of multiple uses. This distribution is mapped in Figures 9 and A7 through the values of the log-transformed ratio HH/PS. Note the clear three-modal distribution of the histogram and its clumped geographic mapping. Figures A8 and A9 in the Appendix represent the geographic distribution of the Local Index of Spatial Aggregation (LISA, Anselin), in which the actual clumping of the variable is displayed (red represents areas where high values significantly correlate with high values in the neighbourhood, while blue areas represent clumps of low values correlating with low values in the neighbourhood).

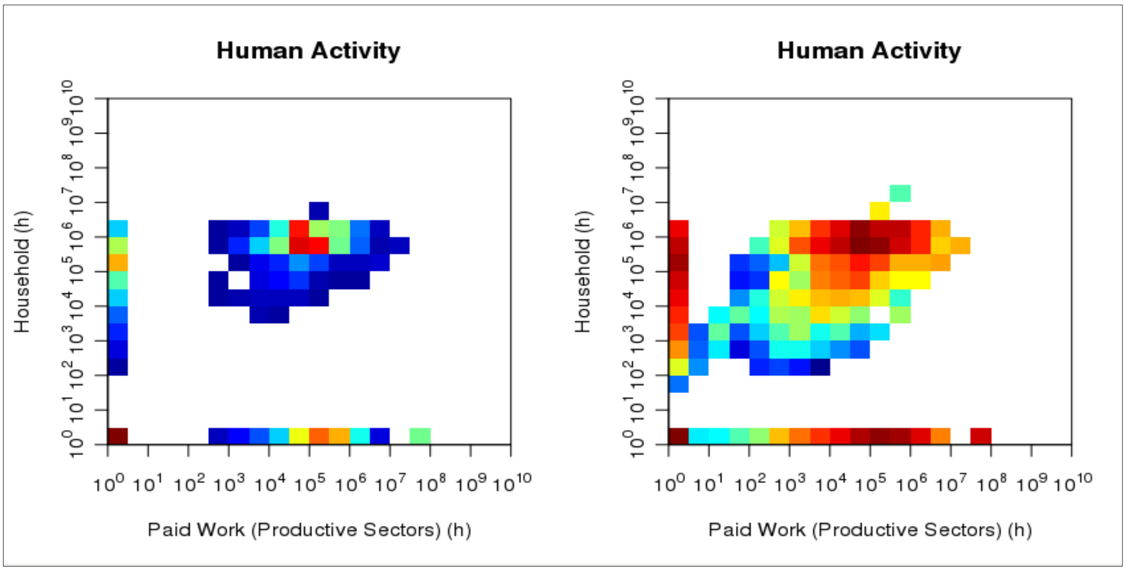


Figure 8. Bi-variate histogram of human time devoted to household activities and to paid work in the productive sectors. Frequency of the histogram is computed as area; therefore colours are proportional to the area covered by each pair of intervals. Left, frequency in number of ha; Right, frequency in logarithmic scale.

Finally, our first estimate of total energy throughput, calculated as the sum of energy throughput in the household and productive sectors, is represented both in absolute values and per ha (Figs. 10 and Figs. A10 and A11 in the Appendix). Note that the geographic pattern is entirely driven by values of human time as this is just calculated from average ETRs for HH and PS, but the result puts in evidence the interest of providing the actual geographic distribution for this variable. In fact, the local anomalies of actual values to this average approach would be very relevant.

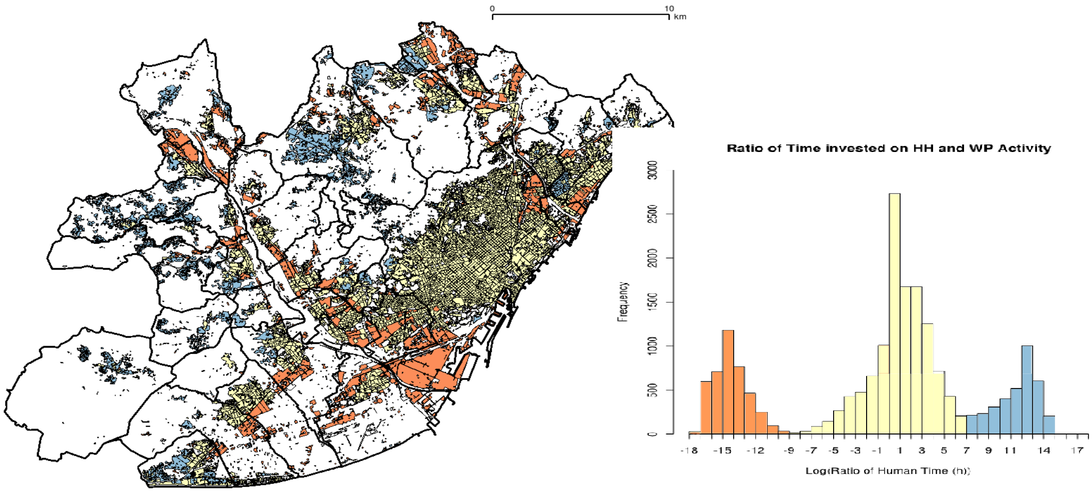


Figure 9. Map of the logarithm of the ratio of human time devoted to household activities and to paid work in the productive sectors. Colours identify the three gaussian distributions identified in the histogram.

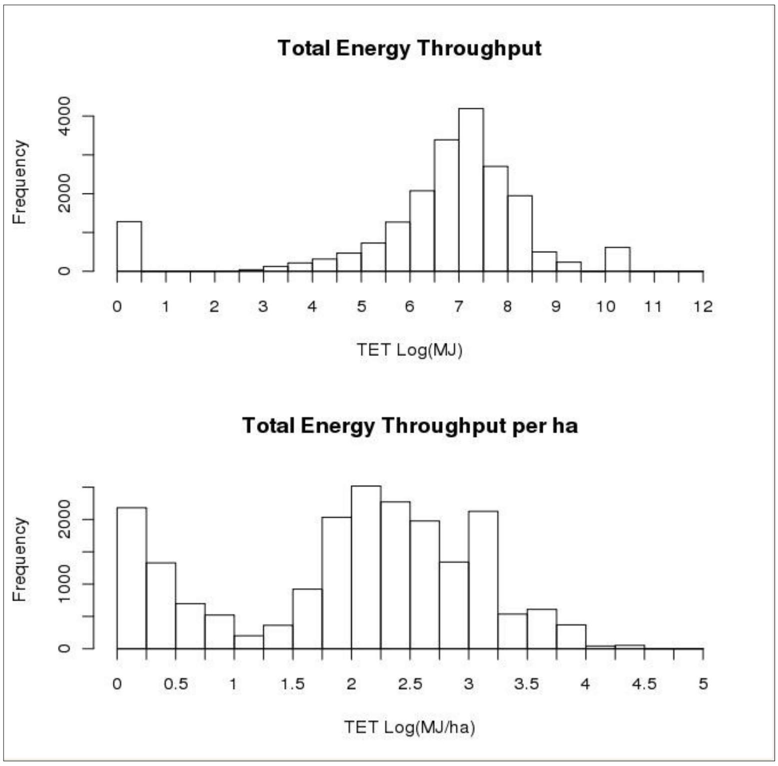


Figure 10. Histograms of Total Energy Throughput (logarithmic scale)

5. Conclusions

Human time devoted to different activities tends to be spatially clumped in specialized areas in urban systems. In our area of study, household activities and paid work (the two main categories in the hierarchical scheme of Giampietro et al., 2009), are distributed in three main types of clusters: two of them mutually exclusive and a third large region in which both types of activities co-occur. We conjecture that large areas of exclusivity, either for paid work or for residence, tend to appear in zones of fast growth, responding to sudden increases in industrial activity, thus in exosomatic energy flow. Areas of slow growth tend to do so by making both types of activities compatible (and also increasing the diversity of sub-activities, although we are not including evidence of this fact in this article.) Areas of slow growth channel a lower flux of exosomatic energy (which is not demonstrated in this article either as we have used a lumped EMR for all productive sectors). In the future we intend to test our conjectures by comparing to other urban and rural areas.

Our approach also let us put in evidence the double interest of a correct disaggregation in order to obtain a correct scaling and to compare different cases of study at equivalent scales. A traditional approach would have addressed the problem of the geographic representation of exosomatic energy throughput by simply multiplying the average TET/inhabitant of the country by the number of inhabitants of each census tract or, worse, each municipality. The result of this approach is reproduced in Figure A12 as a reference. By comparison, our estimate (Fig. A11) has a completely different spatial structure. The conceptual difference between both approaches arises from two characteristics of the analysis. First, the MuSIASEM-based approach implies using a stratified EMR, with different values of MJ/h for household activities and for the productive sectors. The same stratification is applied to human time, which implies that the demographic structure is taken into account, superseding the oversimplification of equating population to the number of inhabitants. Second, we use a geographic segmentation, restricting the different activities to the spaces in which they effectively take place. We claim that this multi-scale approach, based on a hierarchical partitioning of variables and geographic space, is required for an effective representation of the reality, able to be compared across different cases of study and, thus, able to enlighten both the understanding of the processes and the tasks of policy makers.

6. Improvements

Work presented here still requires addressing a number of issues, some of them in the near future:

- Geographically-distributed data on unemployment should be used for a more appropriate computation of total time spent in the household.
- A weight for taking population density into account should be used to distribute household time between compact and loose residential areas.
- The current geographical distribution of time invested on leisure and education should be improved. Note that in the current approach time spent on leisure and education is derived from census data by assuming that all these activities take

place in the household. While this is partially true, future approaches must include location and use of educational, sports, entertainment buildings, as well as the beach.

- Our current work on the distribution of the retail sector should be extended beyond the municipality of Barcelona.
- Government buildings should be located to accurately distribute the data on public services that we have at the municipality level.
- Inclusion of agricultural land is possible as we have obtained data on the number of farmers at the municipality level.

Future work could address more involved but important improvements:

- Improving detail in the spatial distribution of industrial buildings and industrial complexes, as well as taking the height of the buildings (multi-layering) into account. Correcting for the area of streets will be important to refine the assessment of energy flux per ha.
- Including the transport network and transport time is of major interest, but also very involved both in terms of data acquisition and data handling.
- An analysis of the relationship of structural characteristics of buildings using a random sample of sites could open the way to techniques based on pattern recognition for estimating building typologies, in the way this is being done by G. Meinel (2008) in Germany.

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