SEVENTH FRAMEWORK PROGRAMME

European Commission

insight

Innovative
Policy Modelling and Governance Tools
for Sustainable Post-Crisis Urban Development

D5.3 Enhanced Version of the MARS Simulation Model

Project acronym :	INSIGHT
Project title :	Innovative Policy Modelling and Governance Tools for Sustainable Post-Crisis Urban Development
Grant Agreement number :	611307
Funding Scheme :	Collaborative project
Project start date / Duration:	01 Oct 2013 / 36 months
Call Topic :	FP7.ICT.2013-10
Project web-site :	http://www.insight-fp7.eu/
Deliverable :	D5.3 Enhanced Version of the MARS Simulation Model
Issue	1
Date	26/07/2016
Status	Approved
Dissemination Level :	Public

Authoring and Approval

Prepared by		
Name & Affiliation	**Position**	**Date**
Yang Wang (UPM)	Researcher	27/04/2016
María Henar Salas-Olmedo (UCM)	Researcher	27/04/2016
Andrea Alonso (UPM)	Researcher	27/04/2016
Andres Monzón (UPM)	Professor	27/04/2016
Juan Carlos García Palomares (UCM)	Professor	27/04/2016
Javier Gutiérrez Puebla (UCM)	Professor	27/04/2016

Reviewed by		
Name & Affiliation	**Position**	**Date**
Harry Timmermans (TU/e)	WP5 Leader	26/07/2016

Approved for submission to the European Commission by		
Name & Affiliation	**Position**	**Date**
Ricardo Herranz (Nommon)	Scientific/Technical Coordinator	26/07/2016
Iris Galloso (UPM)	Management Coordinator	26/07/2016

Record of Revisions

Edition	Date	Description/Changes
Issue 1 Draft 1	27/04/2016	Initial version
Issue 1	27/06/2016	Approval for submission to the EC

Table of Contents

Executive Summary

This report documents the enhanced version of MARS developed in the INSIGHT project sub-work *package WP5.3 Embedding new location sub-models into MARS*, which is framed in the *WP5 Model Integration and Software Implementation* work package.

MARS model is a dynamic and aggregate LUTI model that includes two main sub-models, transport and land use. A housing location sub-model and a workplace (including retail and production) location sub-model are part of the land use sub-model. Regarding the aim of the work package, the extensions of MARS model are four: (i) an up-to-date external scenario, (ii) a re-calibrated housing location model, (iii) new defined performance indicators based on policy decision makers' opinion, and (iv) the general accessibility indicator, which integrates the public service location choice into the MARS model.

The report introduces the structure of MARS model at the beginning and continues with the three model update processes. After that, this research explores the methodology of integrating the public choice model into MARS using a general accessibility indicator, creating new approach to estimate the coefficients of each public service section. The model update and MARS extension are all based on the Region of Madrid, Spain. The policy assessment using the enhanced version of MARS model will be given in work packages 6 and 7.

1. Introduction

The objective of WP5, as defined in the INSIGHT Description of Work, is to develop new versions of various LUTI simulation frameworks based on different modelling approaches to integrate the new sub models developed in WP4 and to demonstrate how new interactions within such models can be handled. Within the WP5, the specific objective of WP5.3, which corresponds to this report, is to embed the new housing, retail, and public services location models into a LUTI model built by integrating the MARS (Metropolitan Activity Relocation Simulator) dynamic model system .

The MARS model, unlike the other three micro LUTI simulation models (i.e., Albatross, SIMULACRA, UrbanSim), is a dynamic and aggregated LUTI model for strategic planning, formed by a transport sub-model and a land use sub-model. In addition, the current version of MARS model already includes a housing location sub-model and a workplace (including retail and production) sub-model as part of the land use sub-model. An extension of the model on the public service location-model is required.

The method to embed the public services location model into MARS is to re-develop the accessibility indicator, not only considering the capability to reach workplaces but also involving the ability to access certain public services (i.e., education, health and shops). Accessibility plays a major role to link the two main sub-models of MARS (Wang, et al., 2015). It is one of the outputs of the transport sub-model in year *n*, as well as the input to the land use sub-models in the year *n+1*. The new accessibility indicator is calculated by integrating a series of travel motives, which are then weighted using the results from a Geographical Weighted Regression (GWR) analysis. In this manner, the accessibility is evaluated as the key location factor to express the level of public services in land use, which in turn attracts travel demand.

The model update as a preparation is completed before the development of the accessibility indicator. The model update includes renewing the external scenarios, calibrating certain variables of the two main sub-models, and integrating the performance indicators designed in work package WP 2.2 (Romanillos et al., 2014) of INSIGHT.

This report demonstrates the development of a composite accessibility indicator in which the public service is embedded. The city of Madrid is used as the case study to illustrate the principles of the approach. The report therefore focuses on the principles of the implementation of the newly developed approach. A full application of the approach based on the MARS model system will be illustrated under the policy scenario studies in WP7.

The result of WP5.3 is the modified MARS model which embedded the new local sub models. It will be used a tool for the subsequent work packages in two dimensions: the provision of simulation results to feed visualization analysis (WP 6) and the policy assessment and model evaluation (WP 7).

The content of this report is organized in the following sections. After the introduction, Section 2 presents the background information of the MARS model in respect of the model structure, the qualitative and quantitative parts of the transport and land use sub models, and model update. Following that, Section 3 defines the methodology of embedding the public service into MARS model. And it demonstrates the definition of the new composite indicator of accessibility and the role of it in the MARS model. The document closes with some conclusions and the presentation of policy simulation using the modified model.

2. MARS model

2.1 Model description

MARS model is mainly developed to integrate forecasting, assessment and optimisation procedures (May et al., 2003). It owns a flexible platform to tailor and modify the conditions of analysis as required by planners and model users (Pfaffenbichler et al., 2008). It is also a Sketch Planning Model (SPM) embedded in an assessment and optimisation framework. The core concept of MARS is that it adopts the principles of System Dynamics (Sterman, 2000) and Synergetics (Haken, 1983). In particular it is developed in an SD (system dynamics) programming environment, based on the concept of Causal Loop Diagrams (CLD) and represents the relation of cause and effect of the variables in the model (Shepherd, et al., 2009). MARS model can simulate the interaction between land use and transport system that works with a significant level of aggregation and makes long-term assessments. It is important to clarify that MARS model does not include transport networks. Figure 1 shows the basic structure of MARS model, including the required ¨**input**¨ (such as the external variables and policy instruments) and ¨**output**¨ that are a series of performance indicators.

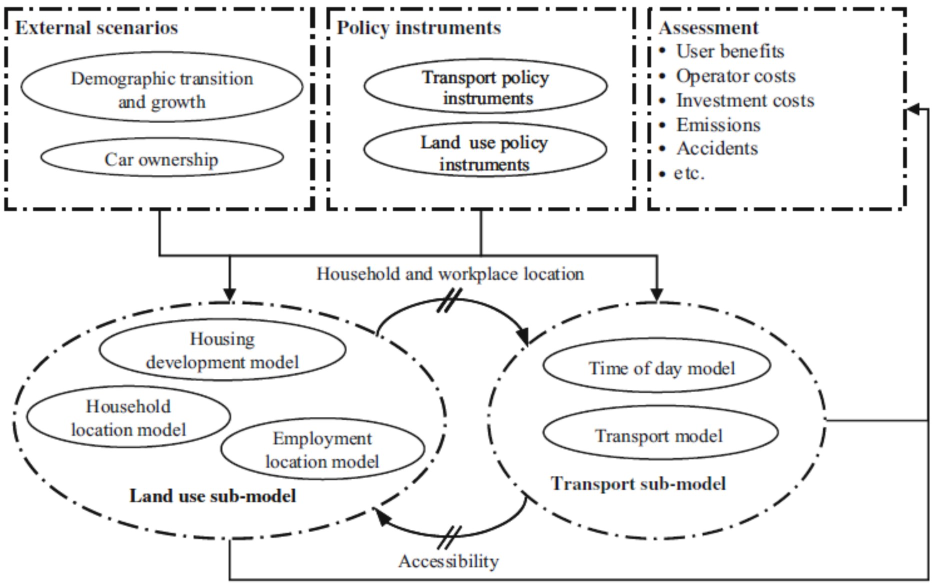

Figure 1 Basic structure of MARS model (Pfaffenbichler et al., 2008)

- The **external scenarios** as the **input** of MARS include a number of variables in relation to demographic indices, transport data and land use development that can be collected via the local statistic census or mobility survey.

- The **policy instruments** are another **input** of MARS which are a group of policy interventions. They can be divided into two categories i.e., transport policy measures and land use policy measures. The policy instrument needs to be defined in terms of the implementation time (in year), geographical scale and intensity. In this case, the implementation time frame and geographical scale are provided externally by modelers, while the intensity (like toll charging fees and bus frequency) is determined by the optimisation process.

- The **transport sub-model** in MARS is developed as an alternative to the traditional four stage model, working with speed-intensity ratios (Origin-Destination pairs) instead of an entire network. It includes a trip generation sub-model, trip distribution and mode choice sub-model. These sub-models use the highest possible level of simplification to represent the road and public transport network, i.e. the network is aggregated to one link per origin-destination (OD) pair.

- The **land use sub-model** comprises a residential location submodel and a workplace location submodel. The land use sub-models use in general LOGIT or gravity type models. The ratio of the exponential function value of utilities and dis-utilities of an alternative to the sum of all alternatives is used to distribute a potential to different locations. The detailed equations of the land use sub-model are presented in the next part.

- The **output** of MARS model is the result of policy simulation or optimization. It can be defined based on the requirements of the modelers. Two types of analysis- cost-benefit analysis and multi-criteria decision analysis- are developed and used to assess the impacts of policy instruments.

The MARS model can simulate the cause-effect-relations

1) between urban sprawl and the transport modal share, for example, urban sprawl leads to longer travel distance, thus increasing the use of the private car and decreasing the share of PT and non-motorized modes;
2) between economic development and travel demand: if the number of consumers increases, the travel demand increases, and vice versa, when travel demand increases, the potential profit increases.

A great advantage of this model is that it is supported by system dynamic software known as VENSIM®, where users can change the causal loop diagram and the variables as needed, instead of leaving aside the model as a 'black box'. This feature makes the model transparent and flexible and facilitates modellers' development and understanding. It is important to clarify that MARS model is not an equilibrium model. The following parts introduce the two location models of MARS in detail as well as the dynamic interaction between them.

2.2 Two location models

2.2.1 Transport sub-model

The transport sub-model of MARS includes the first stage of the traditional transport planning model, trip generation, trip distribution and modal split- while demographic trends and motorization rates are incorporated as background scenarios. Figure 2 illustrates the common transport model and the structure of the MARS transport sub-model.

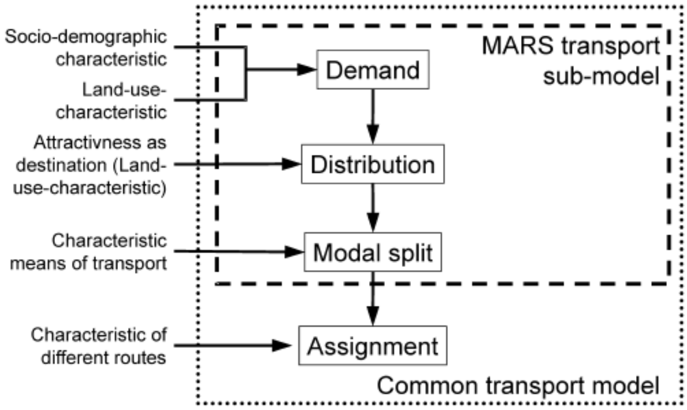

Figure 2. MARS transport sub-model and common four stage transport model

- Trip generation sub-model

The travel **Demand,** known as trip generation in the planning model, has two types in MARS. One is home-work-home and another is home-other-home. However, the method to predict the number of trips for these two motives of trips is different. Work oriented trips are influenced by the number of employed residents and by the average trip rate per person, as shown in Equ.1. Yet, the method to calculate home-other activities-home toursis different. The number of trips for home-work-home is calculated using the number of employed residents mulitipling the average number of trips/day directly (Pfaffenbichler, 2003).

$$P_i|_{HWH} = r|_{HWH} * E_i \quad (1)$$

Equation (1): Trip generation sub-model for tours home-work-home
$P_i|_{HWH}$: Production of trips at zone *i* for tours home-work-home
$r|_{HWH}$: Trip rate for tours home-work-home
E_i: Number of employed residents living in zone *i*

- Trip distribution and modal split

Equ.2 describes the whole trip **Distribution** and **Modal Split** part of the MARS transport sub-model. The trip distribution and modal split submodel uses a combination of the analogy to the law of gravity and Kirchoff's law from electrical engineering (Pfaffenbichler, 2008). The production of trips P_i, given by the trip generation sub-model, is distributed to the available destinations *j* and modes *m* according to the ratio of attraction to friction factor of destination *j* to the sum of attraction to friction factor over all destinations. The attraction A_j depends on the activity for which the destination is chosen. For tours home – work – home the attraction is equal to the number of workplaces in the destination zone. For tours home – other activities – home the attraction is the sum of the population living in the destination zone and the workplaces in retail trade. The first part should represent the attraction for the activity visit, while the second should represent the attraction for the activity shopping. Friction factors are indicators to measure the subjectively perceived effort in terms of time and money which is necessary to travel from origin *i* to destination *j*. Trip and tour matrices Tm *ij* are calculated separately for the activities work and other.

$$T_{ij}^m = \left[P_i * \frac{A_j/f(t_{ij}^m,c_{ij}^m)}{\sum_{mj} A_j/f(t_{ij}^m,c_{ij}^m)}\right]_{HWH} + \left[P_i * \frac{A_j/f(t_{ij}^m,c_{ij}^m)}{\sum_{mj} A_j/f(t_{ij}^m,c_{ij}^m)}\right]_{HOH} \quad (2)$$

Equation (2) Simultaneous trip distribution and mode choice
T_{ij}^{m}: Number of trips by mode *m* from zone *i* to destination *j*
P_i: Production of trips at zone *i*
A_j: Attraction of zone *j* as destination
$f(t_{ij}^{m}, c_{ij}^{m})$: Fraction factor for a trip by mode *m* from zone *i* to destination *j,* including travel time t_{ij}^{m} and travel costs c_{ij}^{m}
HWH: Tour home – work - home
HOH: Tour home – other activities – home
The fraction factor $f(t_{ij}^{m}, c_{ij}^{m})$: also known by trip impedance, is varied for different travel mode (i.e., car, bus, rail, and walking); the specific definition of this factor can be found in Pfaffenbichler (2003).

2.2.2 Land use sub-model

The land-use model consists of two sub-models: workplace and residential. These two location submodels have a similar principle system that involves four further submodels: a development model, a willingness to move-in model, a willingness to move-out model and a supply/demand redistribution model. The system diagram is given in Figure 3.

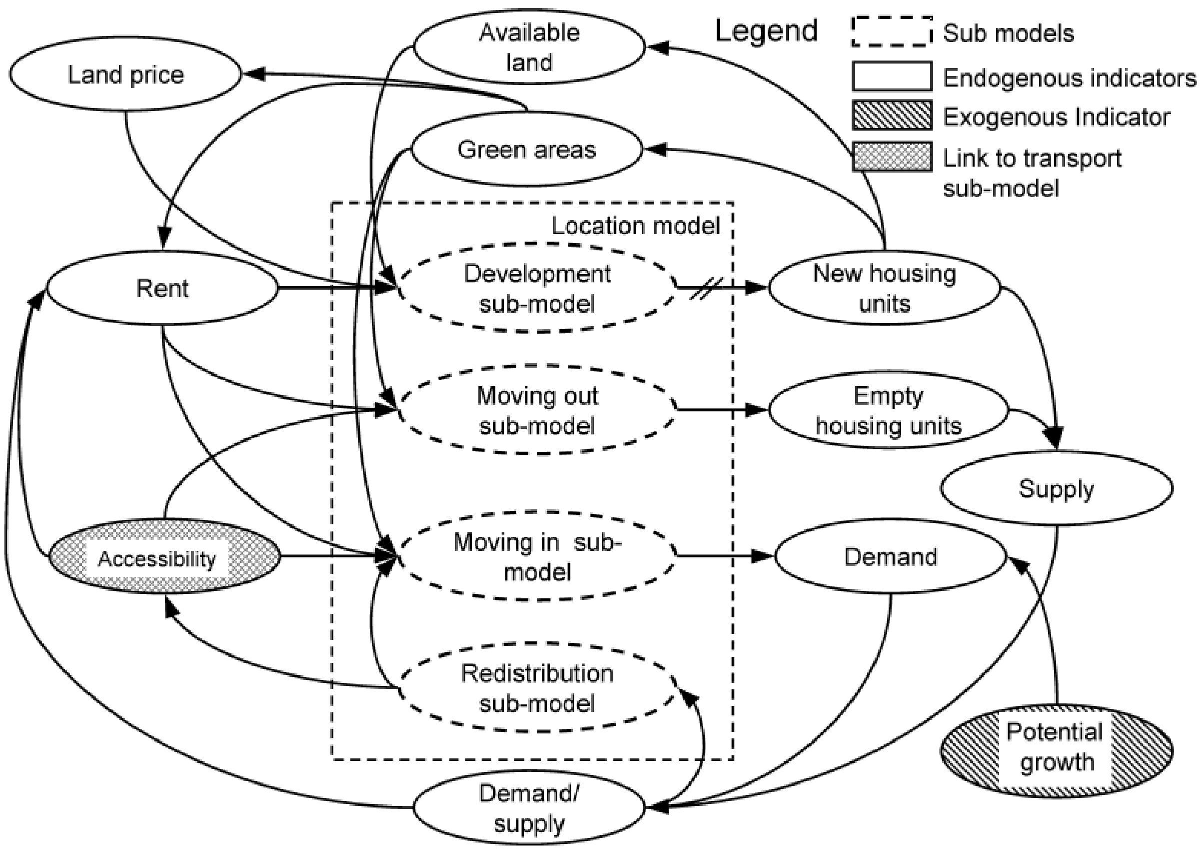

Figure 3. Sub-system diagram of land use sub-models

For example, the development submodel for resident decides whether, where and when to build new housings according to the renting prices, the land prices and the land availability in the decision year. The willingness to move in/out submodels is influenced by the rent price, share of green land and accessibility level. Based on these two submodels (move-in and move-out), the ratio of demanded/supplied housing utility for each zone can be obtained. Should the demand be higher than the supply, the demand would therefore be redistributed (Pfaffenbichler et al., 2010).

Equ.3 presents how to calculate the number of residents moving out from the indicator of attractiveness, whichwas derived from an analysis of observed data in the city of Vienna.

$$N_j^{mv}(t) = P^{mv}(t) * \frac{a^{mv} * e^{b^{mv} * {}^{WP}Acc_j^{PC(t)} + c^{mv} * shGr_j(t) + d^{mv} * R_j^D(t)}}{\sum_j a^{mv} * e^{b^{mv} * {}^{WP}Acc_j^{PC(t)} + c^{mv} * shGr_j(t) + d^{mv} * R_j^D(t)}} \tag{3}$$

$N_j^{mv}(t)$: Number of residents moving from zone *j* in the year *t*
$P^{mv}(t)$: Potential of moving residents in the year *t*
${}^{WP}Acc_j^{PC(t)}$: Accessibility of working places by private car from zone *j* in the year *t*
$shGr_j(t)$: Share of green land in zone j in the year t
$R_j^D(t)$: Monthly rent or mortgage from a domicile in zone j in the year t (€)
$a^{mv}, b^{mv}, c^{mv}, d^{mv}$: Parameter (derived from a regression analysis using observed data and the calibration)

The spatial distribution of people moving into new residential locations depends on the aggregated accessibility by public transport and car, the share of green land, and rent (Equation 4.). The accessibility by public transport and car reflects the utility from being able to reach employment opportunities. The share of green land is used as an indicator to measure the quality of life in a zone. A quadratic share of green land term was added to reflect the fact that high density, inner city locations are highly attractive to certain person groups. Rent measures again the cost of living in a zone. The basic form of Equation 4 was derived from an analysis of observed data in the city of Vienna.

$$N_j^{in}(t) = P^{in}(t) * \frac{A_j^{in}(t)/f(Z_j^{in}(t))}{\sum_j A_j^{in}(t)/f(Z_j^{in}(t))} = P^{in}(t) * \frac{a^{in} * e^{b^{in} * {}^{WP}Acc_j^{PC,PT}(t) + ShGr_j(t) * (c^{in} * shGr_j(t) + d^{in}) + e^{in} * R_j^D(t)}}{\sum_j a^{in} * e^{b^{in} * {}^{WP}Acc_j^{PC,PT}(t) + ShGr_j(t) * (c^{in} * shGr_j(t) + d^{in}) + e^{in} * R_j^D(t)}} \tag{4}$$

$N_j^{in}(t)$: Number of residents demanding a living space in zone *j* in the year *t*
$P^{in}(t)$: Potential of moving residents in the year *t*
$A_j^{in}(t)$: Attraction to move into zone *j* in year *t*
$f(Z_j^{in}(t)$: Friction factor to move into zone *j* in year *t* caused by impedance *Z*
${}^{WP}Acc_j^{PC(t)}$: Aggregate accessibility of working places from zone *j* in the year *t*
$shGr_j(t)$: Share of green land in zone j in the year t
$R_j^D(t)$: Monthly rent or mortgage from a domicile in zone j in the year t (€)
$a^{in}, b^{in}, c^{in}, d^{in}$: Parameter (derived from a regression analysis using observed data and the calibration)

2.2.3 Interaction between land use and transport model

The two submodels of MARS (transport and land use) are connected by a time interval that allows each submodel to work on two different time scales. The interactive process is modelled using time-lagged feedback loops between the transport and land use submodels over a long period (such as 30 years) in one year intervals. The land use model works as two location model of residential and workplace. It considers land use criteria for residential and employment location, such as accessibility, available land, rent price and the amount of parking place. It also allows modellers to add other submodels like energy consumption and emissions models. All these units are connected together. The transport model consists of commuting trips and non-commuting trips like leisure, shopping and sport, etc. The travel modes include motorised models (car, PT) and non-motorised modes (walking).

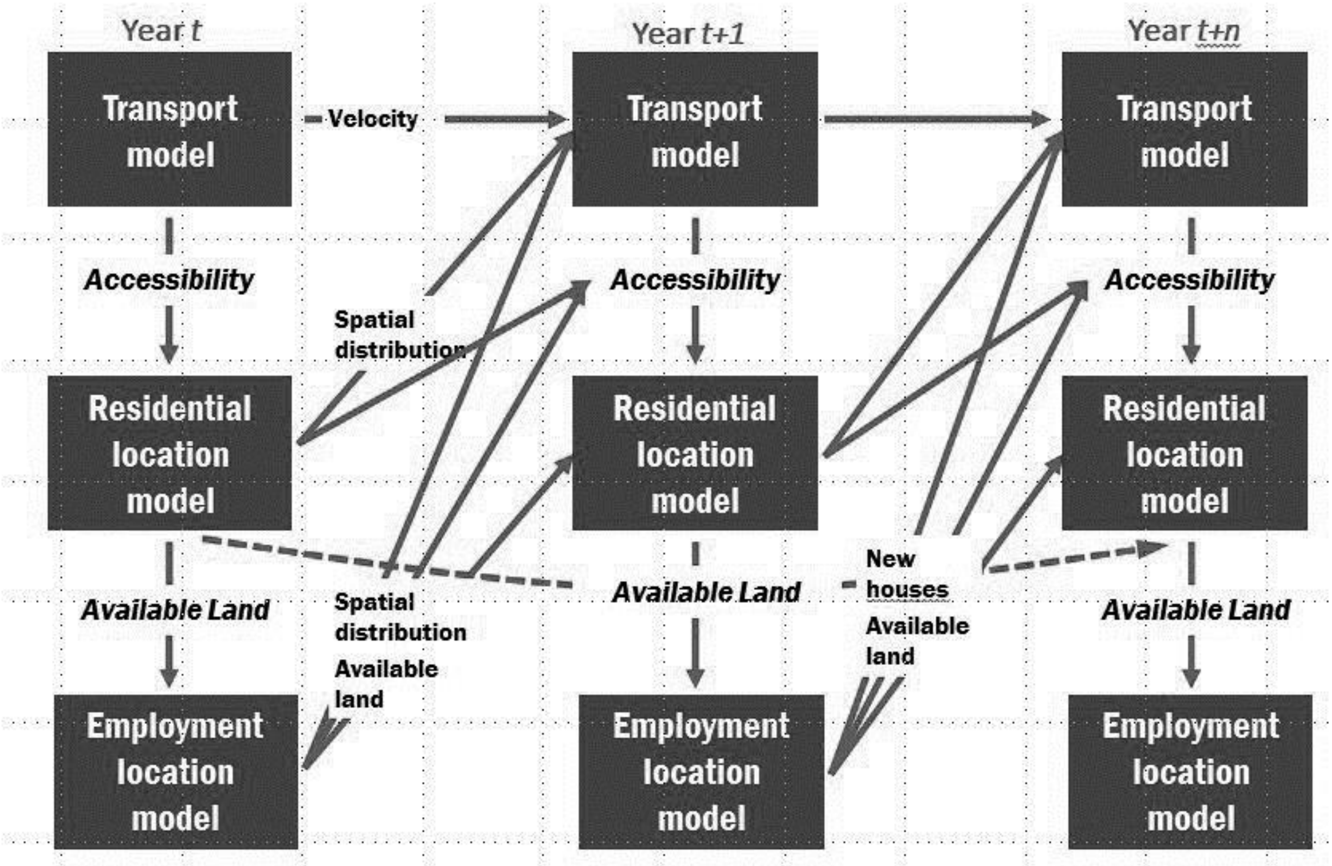

Figure 4. The iterations of MARS model over time

Figure 4 illustrates the iteration of MARS model as well as the interaction between transport and land use submodels. The model begins by calculating indicators in the transport model, like speed, accessibility, etc. The accessibility indicator then is an input data for the model of residential location. After that, the location of homes and the availability of land, which are input to the model location of jobs, are calculated. The transport model calculates the results of the speed of all OD pairs to the next iteration. The residential location model sends the distribution of such households to the transport model in the next iteration. The information in the new residences (homes) to residential location model is about a time delay (time lagged) $t + n$. The job location model passes the information related to its spatial distribution and land availability to the transport and residential location models in the next iteration.

The system accounts for interactions between transport and land-use that are modelled by using time-lagged feedback loops between the transport and land-use sub-models until the planning horizon of 2034 in one-year intervals.

2.3 MARS update

The main tasks to update MARS model followed in this research are three:

1. Updating the external scenario of MARS model with recent real-world data. The update uses all type of data sources, e.g., public institution, open data initiatives and non-conventional channels like Google.
2. Re-calibrating several MARS variables using the new mobility survey conducted in 2014.
3. Integrating new performance indicators that were defined in the INSIGHT project's D2.2 , in order to present the results of policy evaluation required in WP7.

2.3.1 External scenario update

One of the objectives of the INSIGHT project is to investigate how data from multiple available open data sources can be serviced as input for the modelling and simulation tasks. Moreover, input data for the previous version of MARS model was collected in 2004. Therefore, an update is also necessary in order to achieve better results. Thus, we collected a number of demographic indices, data of mobility and land use development along the period of the economic crisis of Spain from several sources.

Table 1 lists the data collected from national statistical census (INE: National Statistics Institute of Spain), the municipal register data (DUAE: Directory of Economic Activities; ALMUDENA: Municipal Data Bank; Nomecalles database) from Regional Statistics Institute of the Community of Madrid, local data bank and local census from Madrid City Hall, mobility data from the Metropolitan Mobility Observatory (OMM) and synthetic survey of mobility of Madrid region (ESM 2014), and data from private companies like Google, Idealista and Fotocasa.

The external scenario update is based on the MARS zoning, which aggregates the 199 municipalities of Madrid into 90 modelling zones (Guzman, 2011). The zoning was carried out following parameters of homogeneity in socioeconomic characteristics and mobility, plus correspondence with the transport zones of the regional transport consortium, as well as regional rings. Thus, the data collected at district level are directly used for the model, and the data gathered at municipalities' level are aggregated to the MARS zoning of MARS.

The mobility data collected from Google are travel time and travel distance of three different modes (i.e., car, bus and rail) both for peak hour and non-peak hour.

Table 1. List of data update of MARS

Indicator	Update year	Data source
Residents growing	2012	INE
Workplace (service, production) growing	2012	INE, ALMUDENA
Average number of trips per employed and workday	2014	ESM2014
Average daily travel time budget	2014	ESM2014
Average household moves every X year	2012	Local census
Housing unit planned in base year	2012	ALMUDENA
Car occupancy rate (commute/non-commute)	2014	ESM2014
Driving license % (employed/all)	2012	ALMUDENA ,ESM2014
Number of residents	2012	INE, ALMUDENA, local census
Number of employee	2012	INE, ALMUDENA, local census
Household income	2012	INE, ALMUDENA, local census
Nº person per household	2012	INE

Indicator	Update year	Data source
Average rent price	2012	Idealista and Fotocasa
living space per flat	2012	ALMUDENA, local census
Free flats	2012	INE, ALMUDENA, local census
Number of jobs (production, services)	2012	INE, ALMUDENA, local census
Number of schools	2014	Nomecalles
Number of health centres	2014	Nomecalles
Share of sector (production/service)	2012	ALMUDENA, local census
Workplace per premise (production/service)	2012	ALMUDENA, local census
Space per premise (production/service)	2012	ALMUDENA, local census
Car ownership	2014	ESM2014
Moto ownership	2014	ESM2014
Area m2 Of which is undeveloped of which is developed (residential/economic/protected)	2012	ALMUDENA, local census
Bussines development allowed in zone (production/service)	2012	ALMUDENA, local census
Land price	2012	ALMUDENA, local census, Idealista and Fotocasa
Slow model distance per OD	2014	ESM2014
Car distance per OD (peak/off peak)	2014	ESM2014, Google Maps
Car travel time per OD (peak/off peak)	2014	ESM2014, Google Maps
Parking place searching time (peak/off peak)	2014	ESM2014, Google Maps
Distance from Parking place to home (peak/off peak)	2014	Google Maps
Average parking costs (peak/off peak)	2014	OMM 2014
Car free flow speed (peak/off peak)	2014	Google Maps
Car speed (peak/off peak)	2014	Google Maps
Bus distance pear OD (peak/ off peak)	2014	ESM2014, Google Maps
Bus access time (peak/off peak)	2014	Google Maps
Bus headway time (peak/off peak)	2014	Google Maps
Bus changing time (peak/off peak)	2014	Google Maps
Bus speed (peak/ off peak)	2014	Google Maps
Bus fare	2014	OMM 2014
Rail distance pear OD (peak/ off peak)	2014	ESM2014, Google Maps
Rail access time (peak/off peak)	2014	Google Maps
Rail headway time (peak/off peak)	2014	Google Maps
Rail changing time (peak/off peak)	2014	Google Maps
Rail speed (peak/ off peak)	2014	Google Maps
Rail fare	2014	OMM 2014

2.3.2 Model re-calibration

The previous version of MARS model was calibrated using the two mobility surveys of Madrid (1996 and 2004) by Guzmán (2011). As a result of the external scenario update, it is essential to re-calibrate a series of parameters in order adjust the model to the real system.

The model re-calibration in this research consists in adjusting two groups of parameters that are involved both in transport and land use sub-models of MARS. MARS considers the journey from home to work as a shift, and it is calculated based on the number of jobs in each area. Thus, the first variable to calibrate is the friction factor (also called impedance) of the four modes of transport considered in the model, its costs and operating time (in the case of motorized transport), availability of car as well as factors in rush hour. And the second calibration consists in modifying the average time living at the same household that is used as a key factor in the resident development sub-model. Figure 5 illustrates the CLD of the average time living at the same household.

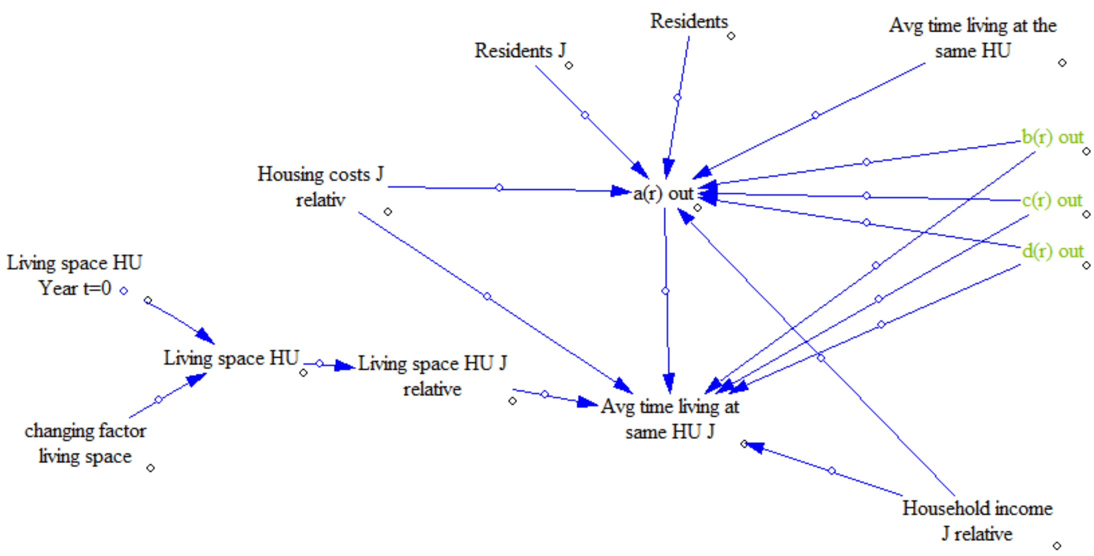

Figure 6. CLD of average living at same HU in the MARS model

Equ. 5 shows the average time living in the same household T^{MV} defined in the MARS model. The calibration uses real data to adjust the constants (i.e., b, c d) used involved in the variable T^{MV}. The base year of the calibration is 2011 in which the latest information is available from the local census.

$$T^{mv} = \max[1, a_{out}^{r} + b_{out}^{r} * HC_j^R(t) + c_{out}^{r} * HI_j^R(t) + d_{out}^{r} * LS_j^R(t) + e_{out}^{r} * SO_j^R(t) \quad (5)$$

Where,

$HC_j^R(t)$= Relative housing cost in zone *j* in year *t*

$HI_j^R(t)$= Relative average household income in zone *j* in year *t*

$LS_j^R(t)$ = Relative living space of housing in zone *j* in year *t*

$SO_j^R(t)$ = Relative share owner occupied housing in zone *j* in year *t*

$b_{out}^r, c_{out}^r, d_{out}^r, e_{out}^r$ = constants (equals to -10, 1, 23.98, 7.718 respectively)

And a^r_{out} is calculated by the following equation:

$$a^r_{out} = T^{mv} - \frac{\sum_j b^r_{out} * HC^R_j(t) * N_j(t) + \sum_j c^r_{out} * HI^R_j(t) * N_j(t) + \sum_j d^r_{out} * LS^R_j(t) * N_j(t) + \sum_j e^r_{out} * SO^R_j(t) * N_j(t)}{\sum_j N_j(t)} \quad (6)$$

$N_j(t) =$ Number of residents in zone *j* in year *t*

Table 2 presents the calibration factor used in Equ5. Table 3 lists the results of calibration in respect of four territorial areas.

Table 2 Factors of calibration

Factor	Value
b^r_{out}	-10
c^r_{out}	1
d^r_{out}	1.309
e^r_{out}	0

Table 3 Comparison of average time living in the same household

	Census 2011	MARS 2011	Difference
Madrid center	9.70	13.36	3.66
Madrid Metropolitan ring	12.79	12.74	-0.05
Madrid regional ring	14.57	11.53	-3.04
Whole Madrid Region	12.66	12.48	-0.18

As shown in the Table 3, the difference between the model results and the real data in respect to the whole region is very small (0.18, less than 1 year). However, we found the big difference occurred both in the city center and the regional ring. The difference in the area like city or region ring is a result of the model definition on the residents in MARS, which does not distinguish permanent from renting residents. Permanent residents, who normally own the house in the city center, are much more resistant to move than renting residents. On the contrary, most of the permanent residents in the region ring stay fewer years than the renting residents.

2.3.3 Indicators integration

After the re-calibration process we reformulated and/or extended the MARS causal loop diagrams and the associated stock and flow diagrams to integrate the new performance indicators, to optimise the implementation of transport policy strategies, and to assess their derived effects on transport and land use. The performance indicators include economic, environmental and social performance indicators that were proposed in the survey about the capacity of each indicator to measure a stated objective as well as the importance of the objective itself (see D2.2- Romanillos et al., 2014). In the case of MARS model, most of the performance indicators were developed and integrated within the correspondent sub-model. However, there are some of them (like Share of GGE by sector or proportion of population living in households considering that they suffer from noise) that cannot be included in MARS as the result of data unavailability. Table 4 lists all the indicators defined in D2.2 of INSIGHT project, their related objective as well as the integration method.

Table 4 - Indicators to assess the policy measure - MARS for Madrid case study

Performance Indicators	Related Objective	Capability to model the indicator	Integration Method
Unemployment	Economic growth	Yes	In workplace sub-model
Land prices	Economic growth	Yes	Updated
Job creation	Economic growth	Yes	In workplace sub-model
Unoccupied flats and buildings	Economic efficiency	Yes	Updated
Time spent travelling	Economic efficiency	Yes	Updated
Congestion levels	Economic efficiency	Yes	It simply considers the current speed is less than 50% of free flow speed as congestion.
Vulnerable users injured by traffic accidents	Liveable streets and neighbourhoods	Yes	Updated
Share of the budget devoted to fundamental needs	Equity and social inclusion	Yes	Extended calculation
Accessibility to main services in each zone	Equity and social inclusion	Yes	Updated with GWR in GIS.
PT supply	Equity and social inclusion	Yes	As an input indicator
Traffic accidents with casualties	Safety and security	Yes	Updated
Fatalities occurred in traffic accidents	Safety and security	Yes	Updated
% active population	Stop demographic decline	Yes	Extended calculation
% population > 60 years	Stop demographic decline	No	Could be added as an input indicator
% population < 25 years	Stop demographic decline	No	Could be added as an input indicator
Energy consumption	Reduce energy consumption	Yes	Only for transport section
Share of energy consumption by sector	Reduce energy consumption	No	Extended calculation
Greenhouse Gases Emissions	Reduce contribution to climate change	Yes	Only for transport section
Share of GGE by sector	Reduce contribution to climate change	No	Extended calculation

Performance Indicators	Related Objective	Capability to model the indicator	Integration Method
Emissions of NOx and particles generated by transport modes	Reduce air pollution	Yes	Only for transport section
Trends in air concentration of NOx and particles	Reduce air pollution	Yes	Could be calculated externally.
Noise intensity levels	Reduce noise pollution	Yes	Only for transport section
Proportion of population living in households considering that they suffer from noise	Reduce noise pollution	No	Extended calculation
Urban density	Reduce urban sprawl	Yes	As an input indicator
Share of the metropolitan area living in the central city	Reduce urban sprawl	No	Extended calculation
Land occupied by transport infrastructures	Reduce urban sprawl	Yes	As an input indicator
Share of jobs in the CBD	Reduce urban sprawl	Yes	Extended calculation

3. Methodology

As the key connection of land use and transport sub-model, the accessibility indicator is influenced by a series of factors, like the number of jobs or job centers, schools, health centers, parks and gardens or retail. The influence of these factors varies between different population groups. These differences must be taken into account when computing land use and transport impacts.

The proposed methodology consists of linking land-use and transport submodels by means of a new defined accessibility indicator. In order to plan the optimum policy strategies, the new accessibility indicator of MARS considers both accessibility to workplaces as well as to public facilities which determines the quality of the service or the possibility of choice between different services. The single accessibility indicator that only considers people accessibility to workplaces is not sufficient to account for land-use/ transport interactions because it leads to a substantial underestimation in policy effects. For example, increasing the public transport fare affects the accessibility to other activities (like shopping or leisure) rather than the accessibility to jobs (Wang, et al., 2016). Therefore, further development on a general accessibility indicator is required.

This chapter presents the methodology of developing and integrating the general accessibility indicator that considers both access to jobs and to public facilities into the MARS model. It firstly introduces the definition and the old and new accessibility indicators respectively, and then it describes the method of calculating the weights of each factor of public service using a Geographically Weighted Regression (GWR). Finally, it explains the method of integrating the new accessibility indicator with the transport and land use submodels of MARS. A comparison analysis by using the two accessibility indicators is given in the end.

3.1 The definition of two accessibility indicators in MARS

3.1.1 Traditional potential accessibility indicator

The traditional potential accessibility (also referred to as the old accessibility indicator in the text) is widely used to measure the aggregate level of job accessibility, (Geurs, K, et al., 2010), and it is estimated regarding personal perceptions of transport by using a function that decreases with distance or time (Geurs & Van Wee, 2004). Equ.7 shows the potential accessibility to workplaces ${}^{WP}Acc_j^{PC(t)}$ that uses a negative exponential cost function in MARS model.

$$ {}^{WP}ACC_j(t) = \sum_t \sum_{jm} W_{jm}(t) * F(t_{ijm,}\, c_{ijm}) \tag{7} $$

Where ${}^{WP}ACC_j(t)$ is the potential accessibility to working places from zone *i* and *j* by mode *m* in year *t;* $W_{jm}(t)$ is the number of jobs in the destination zone *j* by mode *m* in year *t*; $F(t_{ijm,}c_{ijm})$ is a function of the average generalised travel cost associated with travel time and costs between *i* and *j* by mode *m*. For this study, the $F(t_{ijm,}c_{ijm})$ is defined in Equ. 8 (Guzmán et al., 2013):

$$ F(t_{ijm,}c_{ijm}) = 0.16 * Exp[-0.0163 * (c_{ijm}(t) + t_{ijm}(t) * VOT] \tag{8} $$

where $t_{ijm}(t)$ is the total travel time between *i* and *j* by mode *m* in year *t*; $c_{ijm}(t)$ is the total travel cost between *i* and *j* by mode *m* in year *t*; *VOT* is the value of time (€10.45 /hour during peak hours and €5.7

/hour during non-peak hours). The parameters in Equ. 8 were calibrated by Guzmán (2011) on the basis of two household mobility surveys in Madrid (CTRM, 1998 and 2006).

3.1.2 General potential accessibility indicator

Accessibility refers to the number of opportunities available within a certain travel distance. Those opportunities also called activity sites are not only jobs, but also other sites like schools, hospitals, shops and parks, etc. In a LUTI model, a single accessibility indicator is not sufficient to represent the influence of transport changes to land use changes. People choose where to live and work according to endogenous (like age, income, ethnicity, etc.) and exogenous factors (green zone, school, job preference, etc.). In the case of an aggregated LUTI model, we develop a general accessibility indicator considering both the accessibility to jobs as well as to other public services. Moreover, the combination of the general accessibility for each area (like municipality or district) is different in respect of the characteristics of the area. For example, the accessibility to school is more important than the accessibility to shops for those people who live in a commercial area of the city. This is because they can easily reach a shop close to their home, but not a school. Therefore, the general accessibility indicator in MARS model is defined in Equ. 9 consisting of all factors varied by different zones.

$$GACC_j(t) = \sum_t \sum_{jm} [a_j * W_{jm}(t) * F(t_{ijm}, c_{ijm})_{work} + b_j * Edu_{jm}(t) * F(t_{ijm}, c_{ijm})_{edu} + c_j * Hea_{jm}(t) * F(t_{ijm}, c_{ijm})_{health} + d_j * Park_{jm}(t) * F(t_{ijm}, c_{ijm})_{park} + e_j * Shop_{jm}(t) * F(t_{ijm}, c_{ijm})_{shop}] \quad (9)$$

$GACC_j(t)$ is the general accessibility to working places and public services (i.e., education, health, park and shops) from zone *i* to *j* by mode *m* in year *t*;
$W_{jm}(t)$ is the number of jobs in the destination zone *j* by mode *m* in year *t*;
$Edu_{jm}(t)$ is the number of schools in the destination zone *j* by mode *m* in year *t*;
$Hea_{jm}(t)$ is the number of hospitals and health centers in the destination zone *j* by mode *m* in year *t*;
$Park_{jm}(t)$ is the number of parks in the destination zone *j* by mode *m* in year *t*;
$Shop_{jm}(t)$ is the number of shops in the destination zone *j* by mode *m* in year *t*,
$F(t_{ijm}, c_{ijm})_x$ is the generalized cost to reach jobs or the respective public service.
a_j, b_j, c_j, d_j, e_j: coefficients for zone *j*, weighting the importance of accessibility to each activity, the sum of them equals to 1.

It is crucial to properly define the weights of the each part of the general accessibility, since the result identifies different people preferences that can contribute to the manifestation of public services imbalances. The method to estimate these local coefficients consists on a geographical weighted regression with the use of network based distances, which is explained in detail in part 3.2.

3.2 Coefficients estimation

We applied Geographical Weighted Regression (GWR) to generate local models in which specific coefficients are computed for each observation (i.e. spatial unit) and for each significant variable. The calculation of these local coefficients is based on the values of the corresponding independent variables in nearby locations, giving more weight to close locations, thus establishing an inverse distance relationship.

Unlike most studies, distance is computed through the street network. The origin-destination matrix of generalized travel cost, computing the shortest path between each pair of locations, was computed with ArcGIS Network Analyst extension. This matrix was used as input in GWmodel R package in order to consider network distance in the computation of the model.

Population data was obtained from National Statistics Institute of Spain (INE) at the census tract level for the whole study area. The number of job centres as well as the number of health, education and retail activities for each census tract was computed from the geo-localized units available from the Directory of Economic Activities (DUAE) of the Regional Statistics Institute of the Community of Madrid with the use of a Geographic Information System (GIS). The number of jobs in each activity was estimated from the number of units in each job range. The location of parks and gardens was obtained from the Nomecalles database (Regional Statistics Institute of the Community of Madrid). We also obtained the location of education and health centres from Nomecalles, which is a dataset more accurate than the DUAE, but lacking any reference to the number of employees or any other proxy to its size. An origin-destination matrix of minimum generalized travel cost between all census tract centroids was computed using TomTom's road network.

The correlation matrix (Table 6, next page) evidences the relationship between the dependent (population) variable and some of the candidate variables, while discarding collinearity issues between the latter. It also allows the reduction of candidate variables to the most suitable in each topic: number of work places, Nomecalles' education centres, Nomecalles' primary health centres, and number of shops are the most suitable variables of each corresponding topic (i.e. jobs, education, health and retail, respectively).

Continuing with the global analysis, Ordinary Least Squares (OLS) yielded poor results, with adjusted r^2 values below 0.2 in any of the 9231 possible models with up to 5 explanatory variables (table 5).

Table 5. Top 10 best fit OLS models

Run ID	Adj R2	AICc	Max VIF	Num Vars	X1	X2	X3	X4	X5
7072	0.158	66210	3.956	5	JOBS	WORKPLACES	EDU_06	HEALTH_05	EDU_01
7075	0.158	66210	4.004	5	JOBS	WORKPLACES	EDU_06	HEALTH_07	EDU_01
4038	0.158	66213	3.938	5	HEALTH_03	JOBS	WORKPLACES	HEALTH_05	EDU_01
4041	0.157	66213	3.986	5	HEALTH_03	JOBS	WORKPLACES	HEALTH_07	EDU_01
7096	0.157	66215	3.954	5	JOBS	WORKPLACES	HEALTH_05	HEALTH_04	EDU_01
7101	0.157	66216	4.003	5	JOBS	WORKPLACES	HEALTH_07	HEALTH_04	EDU_01
7059	0.157	66217	3.940	5	JOBS	WORKPLACES	EDU_09	HEALTH_05	EDU_01
7062	0.157	66217	3.987	5	JOBS	WORKPLACES	EDU_09	HEALTH_07	EDU_01
7078	0.156	66220	3.602	5	JOBS	WORKPLACES	EDU_06	HEALTH_04	EDU_01
5099	0.156	66222	4.122	5	HOSPITAL	JOBS	WORKPLACES	HEALTH_05	EDU_01

Table 6. Correlation matrix

	Population	Workplace	Jobs	Edu_01	Edu_02	Edu_03	Edu_04	Edu_05	Edu_06	Edu_07	Edu_08	Edu_09	Edu_10	Edu_11	Health_01	Health_02	Health_03	Health_04	Health_05	Health_06	Health_07	Health_08	Health_09	Health_10	Retail shop	Retail job	Parks
Population	1.00																										
Workplace	0.18	1.00																									
Jobs	0.14	0.85	1.00																								
Edu_01	0.36	0.19	0.22	1.00																							
Edu_02	0.28	0.08	0.10	0.73	1.00																						
Edu_03	0.25	0.20	0.22	0.75	0.09	1.00																					
Edu_04	0.18	0.26	0.30	0.58	0.32	0.53	1.00																				
Edu_05	0.27	0.12	0.13	0.62	0.42	0.50	0.60	1.00																			
Edu_06	0.11	0.22	0.20	0.45	0.22	0.45	0.60	0.18	1.00																		
Edu_07	0.00	0.17	0.24	0.13	0.04	0.15	0.72	0.05	0.16	1.00																	
Edu_08	0.06	0.11	0.21	0.30	0.17	0.28	0.78	0.19	0.34	0.87	1.00																
Edu_09	0.15	0.10	0.13	0.48	0.37	0.34	0.47	0.68	0.19	0.08	0.27	1.00															
Edu_10	0.11	0.10	0.11	0.42	0.22	0.39	0.42	0.15	0.71	0.08	0.38	0.19	1.00														
Edu_11	0.00	0.07	0.17	0.10	0.04	0.11	0.62	0.02	0.10	0.92	0.93	0.04	0.04	1.00													
Health_01	0.08	0.08	0.09	0.18	0.22	0.05	0.15	0.07	0.04	0.15	0.17	0.07	0.04	0.16	1.00												
Health_02	0.07	0.10	0.18	0.15	0.09	0.13	0.30	0.05	0.12	0.36	0.38	0.09	0.11	0.37	0.44	1.00											
Health_03	0.10	0.03	0.02	0.10	0.14	0.02	0.05	0.10	0.02	0.00	0.01	0.07	0.02	0.00	0.66	0.00	1.00										
Health_04	-0.02	0.03	0.00	0.07	0.14	-0.03	-0.04	-0.02	-0.04	-0.01	-0.02	-0.03	-0.03	-0.01	0.58	-0.01	-0.04	1.00									
Health_05	0.00	0.37	0.25	0.07	-0.03	0.13	0.21	0.05	0.17	0.18	0.13	0.07	0.10	0.09	0.17	0.31	0.08	-0.04	1.00								
Health_06	0.03	0.24	0.29	0.12	0.04	0.13	0.26	0.06	0.14	0.27	0.27	0.11	0.11	0.24	0.26	0.58	0.02	-0.01	0.42	1.00							
Health_07	0.00	0.36	0.22	0.06	-0.04	0.12	0.18	0.04	0.16	0.15	0.09	0.06	0.08	0.06	0.14	0.24	0.09	-0.04	0.99	0.30	1.00						
Health_08	0.05	0.18	0.26	0.14	0.07	0.13	0.33	0.05	0.12	0.41	0.42	0.10	0.09	0.41	0.38	0.75	0.08	-0.01	0.38	0.57	0.31	1.00					
Health_09	0.05	0.12	0.23	0.14	0.08	0.13	0.34	0.04	0.10	0.45	0.46	0.09	0.09	0.46	0.35	0.80	-0.01	0.00	0.27	0.61	0.20	0.89	1.00				
Health_10	0.01	0.16	0.15	0.05	0.01	0.06	0.08	0.04	0.06	0.06	0.05	0.05	0.03	0.03	0.18	0.15	0.19	-0.02	0.31	0.12	0.31	0.53	0.08	1.00			
Retail shop	0.11	0.68	0.46	0.04	0.00	0.06	0.09	0.03	0.10	0.06	0.02	0.01	0.02	0.01	0.04	0.01	0.05	-0.01	0.25	0.10	0.24	0.07	0.03	0.10	1.00		
Retail job	0.10	0.63	0.65	0.11	0.06	0.10	0.11	0.06	0.10	0.05	0.03	0.05	0.04	0.01	0.03	0.06	0.01	-0.01	0.14	0.17	0.12	0.12	0.08	0.10	0.66	1.00	
Parks	0.05	0.08	0.13	0.10	0.09	0.06	0.16	0.03	0.08	0.18	0.18	0.04	0.05	0.18	0.04	0.08	0.00	0.00	0.02	0.07	0.02	0.12	0.12	0.05	0.00	0.02	1.00

Code key (data source): Population: Total population (INE); Workplace: Number of workplaces (DUAE); Jobs: Number of jobs (DUAE); Edu_01: Education centres (Nomecalles); Edu_02: Public education centers (Nomecalles); Edu_03: Private education centres (Nomecalles); Edu_04: Education centres (DUAE); Edu_05: Primary schools (DUAE); Edu_06: Secondary schools (DUAE); Edu_07: Third cycle education centres (DUAE); Edu_08: Number of employees at education centres (DUAE); Edu_09: Number of employees at primary schools (DUAE); Edu_10: Number of employees at secondary schools (DUAE); Edu_11: Number of employees at education centresthird cycle education centres (DUAE); Health_01: All health centres (Nomecalles); Health_02: Hospitals (Nomecalles); Health_03: Primary health centres (Nomecalles); Health_04: Rural health centres (Nomecalles); Health_05: All health centres (DUAE); Health_06: Hospitals (DUAE); Health_07: Health activities (DUAE); Health_08: Number of employees in health centres (DUAE); Health_09: Number of employees in hospitals (DUAE); Health_10: Number of employees in health activities (DUAE); Retail shop: Retails shops (DUAE); Retail job: Number of employees in retail shops (DUAE); Parks: Number of parks and gardens (Nomecalles).

We aimed to explore local models to see whether any of these variables configure an explanatory model of population location considering their different intensities that might get masked in the global model. For this, we first computed local correlation statistics between population data and the highest correlated variables for each topic, as mentioned before. Figure 7 shows the variability of the Pearson correlation between the dependent and the candidate variables. There is a center-periphery pattern in which the candidate variables have stronger explanation power in areas where they are scarce, whereas in the city center the ubiquity of most variables downgrades the coefficients. Of them, education centers seems the strongest variable in all the study area, while the presence of parks and gardens does not follow a logic pattern, which might be due to data being limited to official parks and gardens. Based on a previous study (INSIGHT Deliverable 3.2); we applied a 5 km bandwidth to incorporate the values of nearby locations using a Gaussian function. In this case, the origin-destination matrix reflects network-based distances, as well as the further GWR models. And the final result of the local coefficients is given in Annex II.

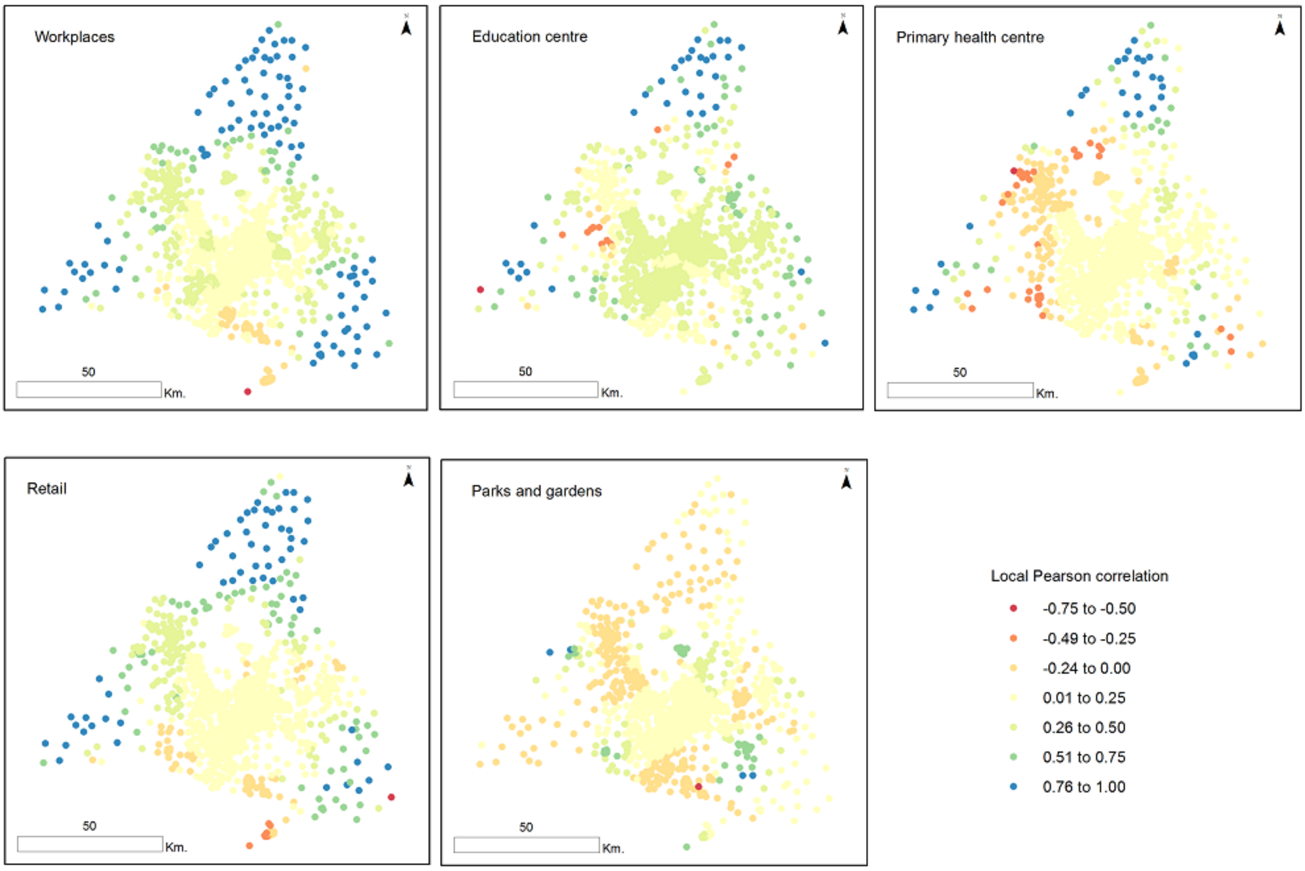

Figure 7. Local Pearson correlation statistics between population and the candidate variables

We then performed a model selection process based on the spatial relationships of the observations within 5 km. During this process, the variable 'parks and gardens' was dropped due to "reciprocal condition number" (not surprisingly in view of the local coefficients). The following table illustrates the main evidence ratios of the most suitable potential geographically weighted models.

Table 7. Model selection

Model	bw	AIC	AICc	RSS	deltaAIC	AICweight	AICevid
1	5	65316	65459	942802439	246.89	2.4E-54	4.1E+53
2	5	65536	65671	993717564	459.01	2.1E-100	4.7E+99
3	5	65183	65335	912522266	122.40	2.6E-27	3.8E+26
4	5	65472	65613	978100549	400.79	9.3E-88	1.1E+87
5	5	65017	65212	870331540	0.00	1.0E+00	1.0E+00
6	5	65149	65341	898157086	128.95	9.9E-29	1.0E+28
7	5	65081	65274	883828161	61.95	3.5E-14	2.8E+13
8	5	64990	65225	858180891	12.99	1.5E-03	6.6E+02
9	5	64988	65225	857660242	12.74	1.7E-03	5.8E+02
10	5	64957	65231	845489357	18.42	1.0E-04	1.0E+04

We chose models 5, 8 and 9 as the most likely to explain the spatial distribution of population in the study area. We then estimated the best bandwidth in terms of distance (fixed) and number of neighbors (adaptive) both for distance along the road network and for private motor vehicle travel time. In all cases, a 5-neighbor adaptive bandwidth provided the best fitted models, with distance along the network performing better than travel time. Therefore, we re-run the model selection tool with the 5-neighbors adaptive bandwidth, and then run the most likely models in order to choose the final one.

Table 8. Best-fit models after bandwidth selection

Model	RSS.gw	AIC	AICc	gw.R2	gwR2.adj
1	552193804	63639	64729	0.611	0.483
5	513738740	63527	65040	0.638	0.485
6	464867520	63227	65057	0.672	0.500
7	484644807	63327	64959	0.658	0.497
8	431978657	63094	65438	0.695	0.501
9	411869765	62936	65428	0.710	0.508

The best-fitted model is the one considering the number of workplaces, education centers and retail. Figure 8 shows the standardized local coefficients once aggregated at the MARS zoning. The intensity and sign of the relationship between each factor and population location have a great variety across space, especially in the case of education centers. Population figures predicted with our model are consistent with real figures, with discrepancies below +- 0.5 Standard Deviation in the most populated areas.

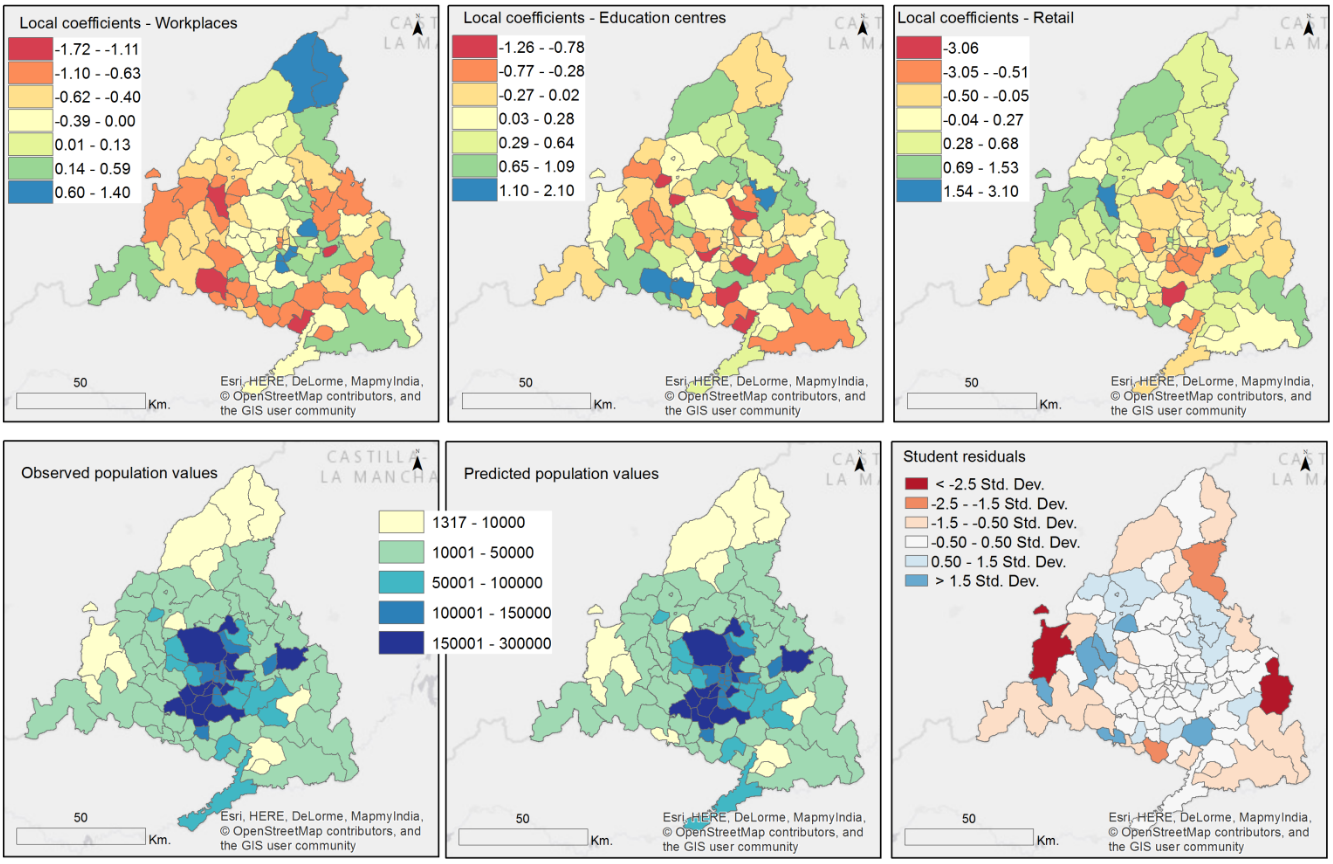

Figure 8. Mean standardized local coefficients, total observed and predicted population values and studenti residuals of Model 9 aggregated by MARS zones

3.3 Comparison analysis

3.3.1 Integration of the general accessibility indicator in MARS

The accessibility indicator acts as an output of the transport sub-model and as an input of the land use sub-model. Thus, the integration consists of two parts: one is linking the new indicator with the generalized travel costs that were calculated from transport sub-model, and another is to replace the old accessibility indicator both in the residential and workplaces location sub-model. Figure 9 shows the simplified CLD of the single potential accessibility (the old one) and the general potential accessibility indicator (the new one) within MARS model, as defined in this study. The old accessibility indicator (Equ.5) is decided by the number of jobs and the generalized travel cost. The number of jobs is determined by the input/output flow of jobs in zone *j* (i.e. the difference between the jobs attracted to zone *j* and the jobs that migrate from zone *j* to other zones). There is a mutual influence between job supply and accessibility indicator, as the job supply in each zone is also influenced by its accessibility, in addition to the variables in land-use submodels (such as land price, land-use development opportunities, and employment sector growth rate). With the job supply, there is a mutual influence between job demand (number of employees) (i.e., the input/output flow of employees) and accessibility, because accessibility is one of the main determinants of job demand and residential growth (Wang, et al., 2015).

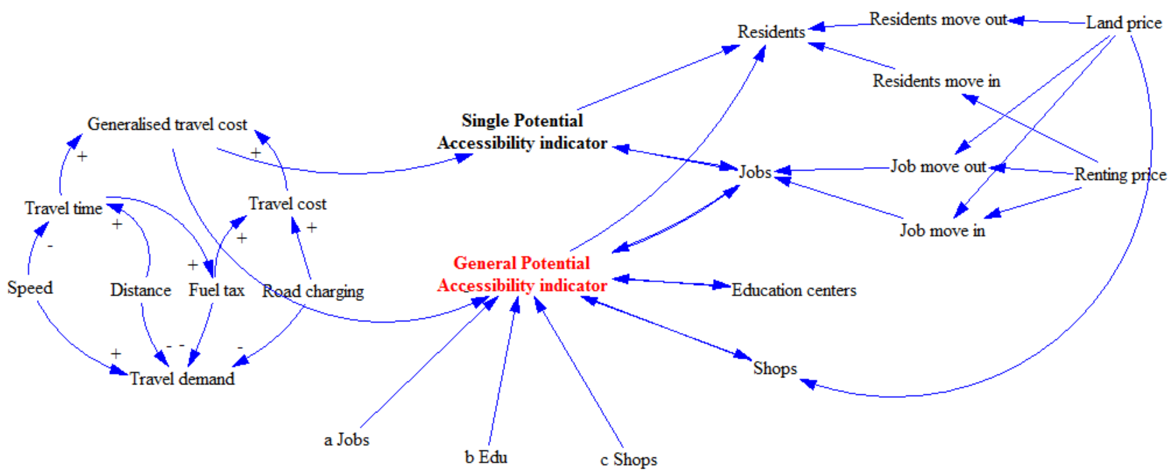

Figure 9. Simplified CLD of accessibility indicators in the MARS model

As seen in Figure 9, the new accessibility indicator consists of accessibility to jobs and to two other public services e.g., education and retail shops. Hospital and parks are dropped through the coefficients estimation procedure. The number of education centres and shops are defined as a data variable using the data collected from the local census. The negative exponential cost function to schools and shops considers all four travel modes, e.g., car, bus, rail and slow modes using Equ. 8, but the parameters vary on the basis of the new household mobility surveys in Madrid (CTRM, 2006 and 2014).

The general accessibility indicator is implemented in the MARS model using the interaction between transport and the different land-use submodels. It improves the accessibility characterization of the MARS model (expand MARS model objective) and brings out a more accurate indicator than the single one for representing the public facility locations among zones.

3.3.2 Comparison analysis with the two accessibility indicators

We replaced the old potential accessibility indicator with the new one in MARS model and we then conducted the simulation using the two indicators respectively in the condition of no policy intervention (do-nothing scenario). The outputs of the model are many. The Comparison then is based on two selected variables which are strongly influenced by the accessibility changes, e.g., the number of workplaces and the number of residents. The real data used in the comparison are collected from the Municipal Data Bank in 2015. The model outputs on the two variables are obtained from the same year.

The results of the comparison of the number of workplaces are illustrated in Figure 10. The left chart is the correlation of Nº of workplaces predicated using the old accessibility indicator and the real data, and the right chart shows the same using the new accessibility indicator. As seen, the ordinary Least Squares (OLS) yielded better results by using the new accessibility indicator (0.9733 comparing with 0.9596). In particular, the old accessibility leads an under estimation of the workplaces in the zones which have between 60,000 to 100,000 workplaces; and overestimations in the zones which have more than 120,000 workplaces (basically the city center).

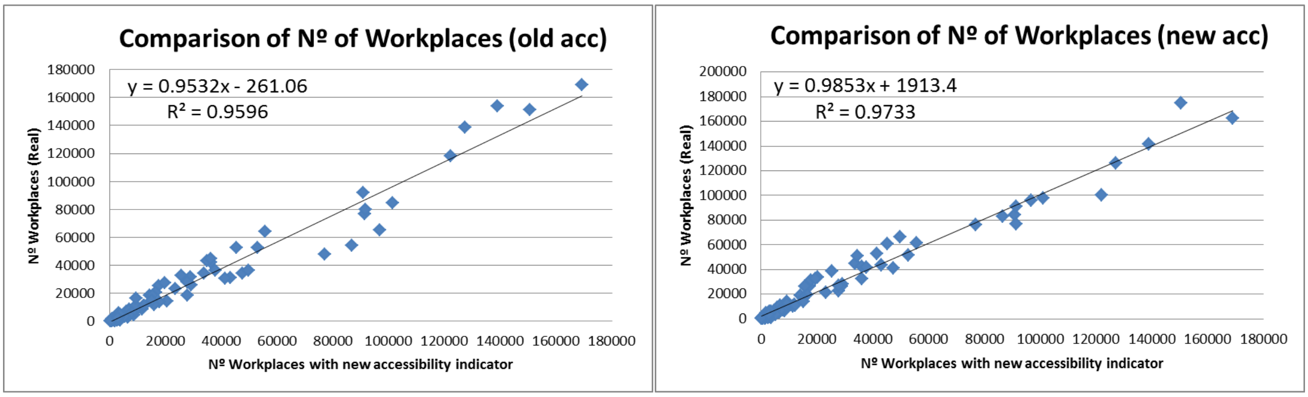

Figure 10. Comparison of Nº of workplaces using new and old accessibility indicator

We conducted the comparison also for the number of residents, and the results are shown in Figure 11. Similarly, the correlation using the new accessibility (right chart) is higher than the one using the old accessibly indicator. Moreover, the predication using the new indicator achieves better results for the whole area whatever the zone is small or large.

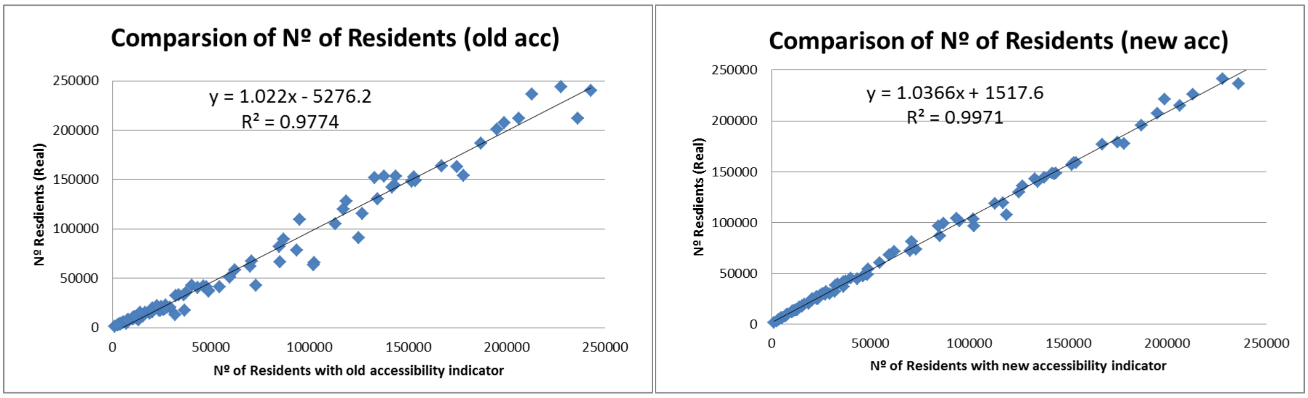

Figure 11. Comparison of Nº of Residents using new and old accessibility indicator

4. Conclusions

The aim of the work package 5.3 is to integrate the theoretical location model to enhance the existing MARS model. The main objective has been achieved in four aspects: (i) updating the external scenario, (ii) re-calibrating the housing location sub-model, (iii) integrating and tailoring the performance indicators based on the policy decision makers' opinion, and (iv) re-developing the accessibility indicator which integrates the public service location choice into MARS model.

With respect to the model update, we would like to underline that:

- The update of the external scenario and model re-calibration are realized throughout a number of data sources, public and private. The model update captures the trends on demographic, economic and land use changes of Madrid region during the economic crisis.
- The model re-calibration improves the housing location model in terms of the variable of resident's attractiveness. The updated model now fits better with the real data.
- The integration of performance indicators is an extension of the existing model, and more importantly it makes the policy assessment available in respect to the urgent required objectives (D2.2).
- The accessibility indicator has been re-developed in a more complex manner. More specifically, three single accessibility indicators have been combined using the estimated weights and integrated into transport and land use sub-model of MARS respectively. The new indicator includes the accessibility to jobs, schools and shops, while the calculation is straightforward by using generalized travel costs as decay function multiplying the number of the opportunities.

Regarding the comparison of the number of workplaces and residents from MARS model and from the local census using the two accessibility indicators, some considerations and findings are highlighted:

- The comparison of real data and the model results is an important analysis in order to evaluate the level of correlation.
- The analysis also evidences the integration of the new accessibility improving the model accuracy and precision. Using the new accessibility indicator, MARS model fits better with the real data in respect of the number of workplaces and residents, which are the key variables of the land use sub-model.
- The general accessibility indicator combining the accessibility to jobs as well as to other public services complements the MARS model that now includes the public service choice.
- At the same time, calculating the weights of different public services in different urban areas is important in order to identify possible people´s preference that can contribute to the manifestation of public services imbalances.

However, the last step of this work package is to make the model ready for the WP6 and WP7. The new MARS model should be extended and integrated in WP6, and be used to investigate specific problems of activity location in Madrid in WP7. Therefore, specific modifications are expected to fulfill these goals.

5. References

Geurs, K. T., Zondag, B., De Jong, G. C., & De Bok, M. (2010). Accessibility appraisal of land use/transport policy strategies: More than just adding up travel-time savings. Transportation Research Part D, 15(7), 382–393

Guzmán, L. A., De la Hoz, D., & Monzón, A. (2011). Optimal and long-term dynamic transport policy design. Seeking maximum social welfare through a pricing scheme. Sustainable Transportation, 12, 34-42

Haken, H. (1983). Advanced synergetics instability hierarchies of self-organizing systems and devices. Berlin: Springer (chap. 2)

May, A. D., Karlstrom, A., Marler, N., Matthews, B., Minken, H., Monzón, A & Shepherd, S. (2003). Developing Sustainable Urban Land Use and Transport Strategies-A Decision Makers' Guidebook. Institute for Transport Studies, University of Leeds, Leeds.

Pfaffenbichler, P. (2003). The strategic, dynamic and integrated urban land use and transport model MARS (metropolitan activity relocation simulator) Institut für Verkehrsplanung und Verkehrstechnik der Technischen Universität Wien.

Pfaffenbichler, P., Emberger, G., & Shepherd, S. (2008). The integrated dynamic land use and transport model MARS. Networks and Spatial Economics, 8(2), 183-200.

Pfaffenbichler, P., Emberger, G., & Shepherd, S. (2010). A system dynamics approach to land use transport interaction modelling: The strategic model MARS and its application. System Dynamics Review, 26(3), 262-282.

Romanillos, G., Alonso, A., Wang, Y., (2014). D2.2 *Urban planning and governance: current practices and new challenges*. INSIGHT 7FP – EC

Shepherd, S., Koh, A., Balijepalli, C., Liu, R., Pfaffenbichler, P., Emberger, G. (2009). Overcoming barriers to model use. *Ejtir*, 3(9)

Sterman, J. D. (2000). Business dynamics: Systems thinking and modeling for a complex world (Vol. 19). New York: Irwin/McGraw-Hill.

Train, K.E., 2009. Discrete choice methods with simulation. Cambridge university press.

Wang, Y., Monzon, A. and Di Ciommo, F., 2015. Assessing the accessibility impact of transport policy by a land-use and transport interaction model–The case of Madrid. Computers, Environment and Urban Systems, 49, pp.126-135.

Wang, Y., and Monzón, A. (2016). Economic crisis and its influences on the interaction between land use and transport in Madrid Region. Valencia, 7-9, junio.

Wen, C.H., and Koppelman, F.S., 2001. The generalized nested logit model. Transportation Research Part B: Methodological, 35(7), 627-641.

Wegener, M. (2004), Overview of land use transport models. In: D.A. Hensher and K. Button (eds.), Transport Geography and Spatial Systems. Handbook in Transport. Pergamon Press, Kidlington, UK., pp. 127-146.

Annex 1. Abbreviations and Acronyms

CLD: Causal loop diagrams

DUAE: Directory of Economic Activities

ESM: Synthetic survey of mobility of Madrid region

GIS: Geographic Information Systems

GWR: Geographical Weighted Regression

INE: National Statistics Institute of Spain

LUTI: Land use and transport interaction model

MARS: Metropolitan Activity Relocation Simulator

OD: Origin Destination

OLS: Ordinary Least Squares

OMM: Metropolitan Mobility Observatory

SD (system dynamic)

SPM: Sketch Planning Model

VOT: Value of time

Annex 2. Results of coefficients of the general accessibility indicator

MARS ZONE	a_j	b_j	c_j
1	0.205	0.586	0.209
2	0.354	0.310	0.336
3	0.574	0.291	0.135
4	0.241	0.610	0.149
5	0.325	0.610	0.065
6	0.216	0.660	0.124
7	0.151	0.281	0.568
8	0.235	0.258	0.508
9	0.313	0.106	0.582
10	0.371	0.082	0.547
11	0.343	0.208	0.449
12	0.373	0.084	0.543
13	0.398	0.093	0.509
14	0.437	0.084	0.479
15	0.365	0.042	0.594
16	0.307	0.102	0.591
17	0.338	0.128	0.534
18	0.223	0.089	0.688
19	0.246	0.147	0.607
20	0.349	0.321	0.330
21	0.332	0.185	0.483
22	0.362	0.029	0.609
23	0.394	0.152	0.454
24	0.080	0.710	0.210
25	0.148	0.398	0.455
26	0.163	0.333	0.505
27	0.110	0.719	0.172
28	0.424	0.348	0.228
29	0.323	0.204	0.473
30	0.112	0.707	0.182
31	0.246	0.452	0.302
32	0.229	0.152	0.619
33	0.047	0.160	0.794
34	0.175	0.323	0.502
35	0.258	0.290	0.451
36	0.394	0.356	0.250
37	0.316	0.291	0.393
38	0.213	0.008	0.779
39	0.249	0.508	0.242
40	0.203	0.628	0.169
41	0.064	0.208	0.729
42	0.236	0.637	0.127
43	0.262	0.097	0.642
44	0.233	0.521	0.246
45	0.160	0.600	0.240
46	0.125	0.485	0.390

MARS ZONE	a_j	b_j	c_j
47	0.125	0.017	0.858
48	0.463	0.008	0.530
49	0.372	0.183	0.445
50	0.152	0.413	0.435
51	0.324	0.146	0.530
52	0.628	0.131	0.240
53	0.004	0.047	0.949
54	0.108	0.047	0.845
55	0.024	0.311	0.665
56	0.390	0.589	0.021
57	0.457	0.476	0.068
58	0.201	0.337	0.461
59	0.428	0.452	0.120
60	0.474	0.360	0.166
61	0.042	0.636	0.323
62	0.133	0.182	0.686
63	0.251	0.148	0.601
64	0.018	0.501	0.481
65	0.120	0.517	0.364
66	0.037	0.769	0.194
67	0.172	0.176	0.652
68	0.109	0.573	0.318
69	0.080	0.767	0.153
70	0.791	0.128	0.081
71	0.277	0.560	0.163
72	0.008	0.099	0.893
73	0.276	0.046	0.677
74	0.251	0.372	0.377
75	0.305	0.162	0.533
76	0.666	0.056	0.278
77	0.941	0.055	0.003
78	0.181	0.303	0.515
79	0.357	0.199	0.444
80	0.099	0.706	0.195
81	0.196	0.404	0.400
82	0.462	0.029	0.508
83	0.177	0.464	0.359
84	0.099	0.453	0.448
85	0.154	0.348	0.498
86	0.083	0.329	0.589
87	0.472	0.313	0.214
88	0.433	0.028	0.540
89	0.067	0.458	0.475
90	0.191	0.462	0.347