

Addressing the spatial nonstationarity in the MCI's parameters using Geographically Weighted Regression

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In this paper, a Multiplicative Competitive Interactive Model (MCI) is treated. Although several papers have addressed this type of model, including different ways for estimating the parameters involved, a very few documents have faced the spatial nonstationarity problem that may arise. Nakanishi and Cooper (1974) proposed one of the most used procedures for estimating the MCI parameters. They suggested some transformation in order to estimate the parameters by means ordinary least squares (OLS). This method does not take into account the possible variation of the parameters because they are constant along the working space. Therefore, in order to consider the spatial nonstationarity we propose the use Geographically Weighted Regression (a local lineal regression method) instead the global ordinary least square. An application revealing the spatial nonstationarity of the OLS parameters is presented. This example is also used to show how the local regression model predicts data better than the OLS model.

1. MCI models:

Different location models and procedures for calculating trading areas have been proposed in the specialized literature. The gravity models has widely used within the field of the retail distribution. These models are based on the assumption that individual movements between points are inversely proportional to the distance between them. Multiplicative Interactive Models (MCI) are a generalization of the gravity models to the case where the attraction perceived by the customers from the facilities depends on other variable in addition to the distance. For MCI models, the probability that a customer at i buys at a facility j is given by

$$p_{ij} = \frac{U_{ij}}{\sum_{j=1}^n U_{ij}},$$

$$U_{ij} = \prod_{k=1}^K (X_{kj}^{\alpha_k}) d_{ij}^{\lambda},$$

where U_{ij} is the utility of facility j to customers at point i , X_{kj} is the k th of K variables measuring characteristics of facility j , α_k are the parameters reflecting the effect of k th store characteristics, and λ is the parameter reflecting the transportation cost effect.

Nakanishi and Cooper (1974) proposed the following log-transformed-centered form to obtain least squares estimates of the parameters:

$$\ln(p_{ij} / \tilde{p}_{ij}) = \sum_{k=1}^K \alpha_k \ln(X_{kj} / \tilde{X}_{kj}) + \lambda \ln(d_{ij} / \tilde{d}_{ij})$$

where \tilde{p}_{ij} , \tilde{X}_{kj} , \tilde{d}_{ij} are the geometric means of p_{ij} , X_{kj} and d_{ij} over j , respectively.

These parameters are influenced by socio-demographic characteristics of the market. Local differences in this aspect (changes in density population or income ratios) may produce local differences in customers' perception of the facilities attraction. (See Gosh (1984) for a deeper discussion about nonstationarity in MCI models)

2. Using GWR for estimating MCI parameters

GWR (Brunsdon et al. (1996) and Fotheringham et al. (1996, 1997)) is based on the assumption that closer customers present closer preferences. Following this method, parameters for a particular location must be estimated under the assumption that nearby observed data are more influent than those located further away. So the traditional OLS can be rewritten as

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^K \beta_k(u_i, v_i)x_{ik} + \varepsilon_i$$

where (u_i, v_i) represents the coordinates of the i th point in space and $\beta_k(u_i, v_i)$ is a realization of the continuous function at point i .

Let X be the matrix of explanatory variables (including the constant) and Y the vector of dependent variable, the estimation of the vector β of coefficients regressors is

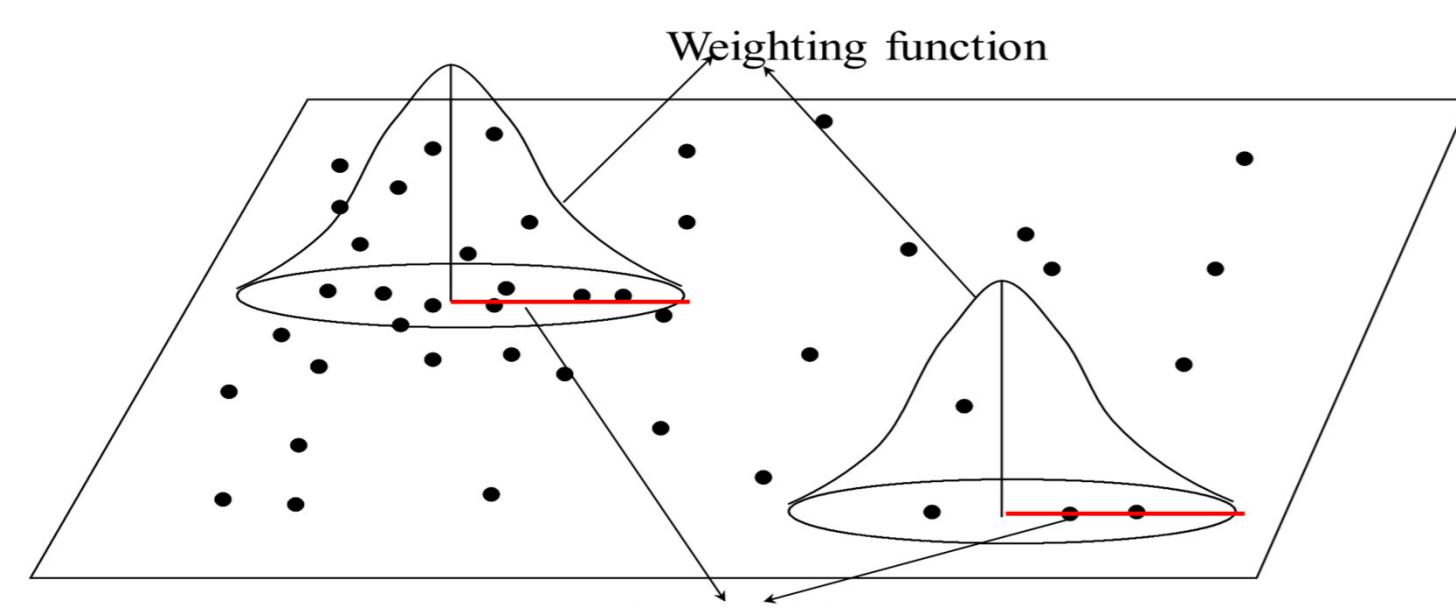
$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) Y,$$

with $W(u_i, v_i)$ a weight matrix where each element w_{jj} in the diagonal represents the weight of the observation j ($j = 1, 2, \dots, n$) for estimating the parameters in location (u_i, v_i) .

The function used for obtaining $W(u_i, v_i)$ is named kernel. In this application a bi-square (kernel) was selected

$$w_{jj} = w_j(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h}\right)^2\right)^2, & \text{if } d_{ij} < h, \\ 0, & \text{if } d_{ij} > h \end{cases}$$

where h is the bandwidth.



(Imagen taken from "Geographically weighted regression", Yu and Wei (2004))

6. References

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3. Particular case: Huff model

If spatial variation for the parameters model in Huff (Huff (1964)) is taken into account, probabilities p_{ij} can be reformulated as:

$$p_{ij} = \frac{S_j^{\alpha_j}}{\sum_{j=1}^n S_j^{\alpha_j}}$$

where α_j and λ_j are the estimated parameters reflecting the effect of the sales surface and the distance for customers located at demand node i .

Steps given for estimating α_j and λ_j :

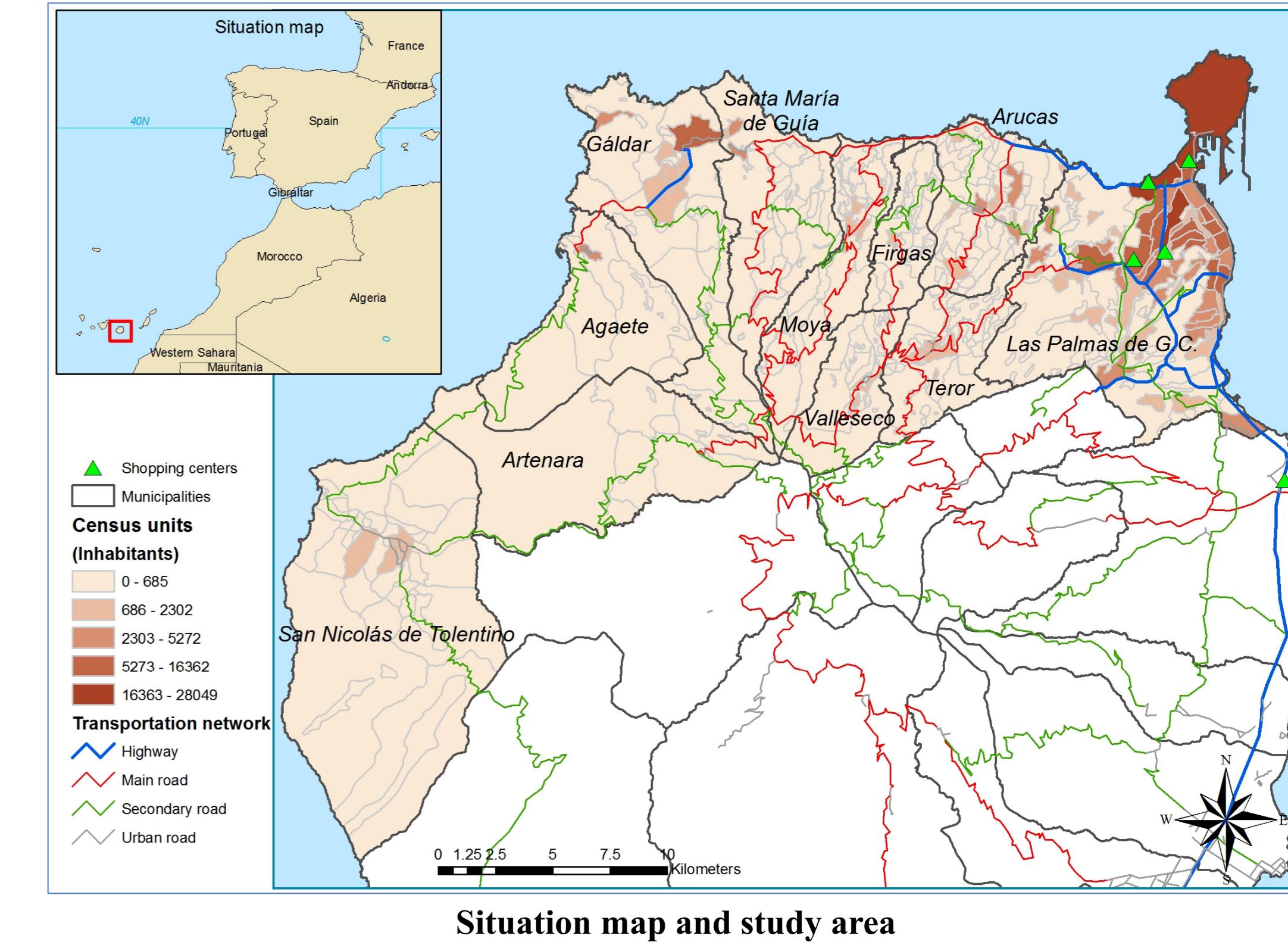
- Obtain revealed probabilities p_{ij} from a survey.
- Select the kernel and the bandwidth for the GWR model that better fits the sample data.
- Estimate using this settlement parameters α_j and λ_j for the demand point.

Given the parameters, the probabilities that customers at i purchase at a new facility with sales surface S and located at P is given by:

$$p_{ip} = \frac{S^{\alpha_p}}{\sum_{j=1}^n S_j^{\alpha_j}}$$

Therefore, if w_i is the buying power at demand node i , the estimated capture for the new facility is

$$MS(P) = \sum_{j=1}^n w_i p_{jp}$$



4. Application

In this study we have analyzed the potential market share of a new grocery store considering the market formed by the north part of the island, the capital (Las Palmas de Gran Canaria) and nine municipalities which form the Northwest Community. This study area presents the particularity that there exists a significant socio-demographic difference between the capital of the island, an urban municipality with a population of 381114 inhabitants, and the rest of municipalities which are mainly rural areas with a total population of 119536.

The figure above shows the population distribution by census units for the study area and the shopping centers considered. The population of each census unit was allocated to the gravity center of the housing units sited in it.

Grocery stores, shopping centers, population gravity centers and polls were georeferenced in order to calculate transports costs and estimated the GWR parameters.

5. Results

For calibrating the Huff model, a survey formed by 726 valid questionnaires was used. People were asked about the proportion of food purchase they made in the five shopping centers considered in the study. The remaining purchase power was considered as proximity purchase. The proximity purchase was allocated to the closest grocery store.

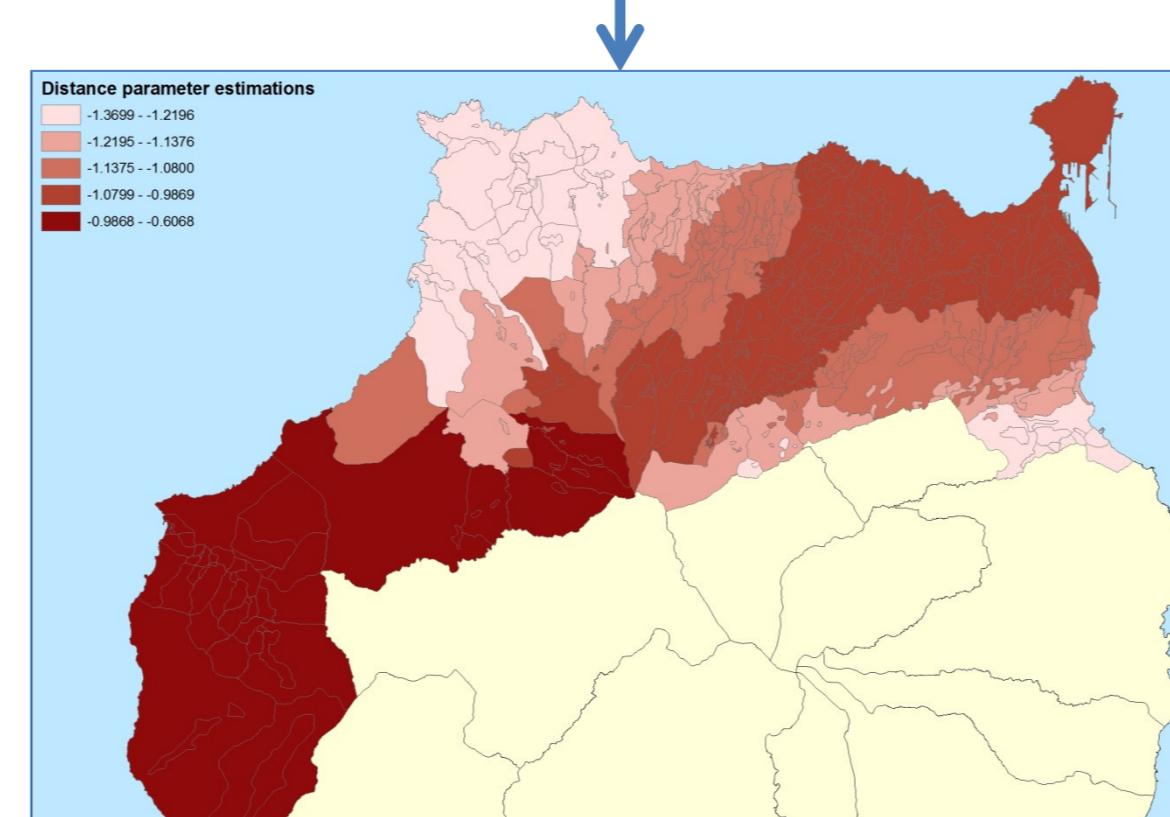
GWR over sample data

(A bi-square kernel with a 12000 m. fixed bandwidth was selected for being the settlement that better fits the sample data)

	OLS		GWR				
	Estimated	p-value	Average	Min	Max	STD	p-value
α	-0.573	0.0000	-0.5387	-0.9675	-0.3410	0.1246	0.0018
λ	-1.083	0.0000	-1.1067	-1.3180	-0.8155	0.1008	0.0168
AICc	18792			18770			
	0.3859			0.3898			
Improvement F-test p-value: 0.018							

Results for OLS and GWR estimations for the sample data

GWR over demand points



Estimated parameters for the demand node

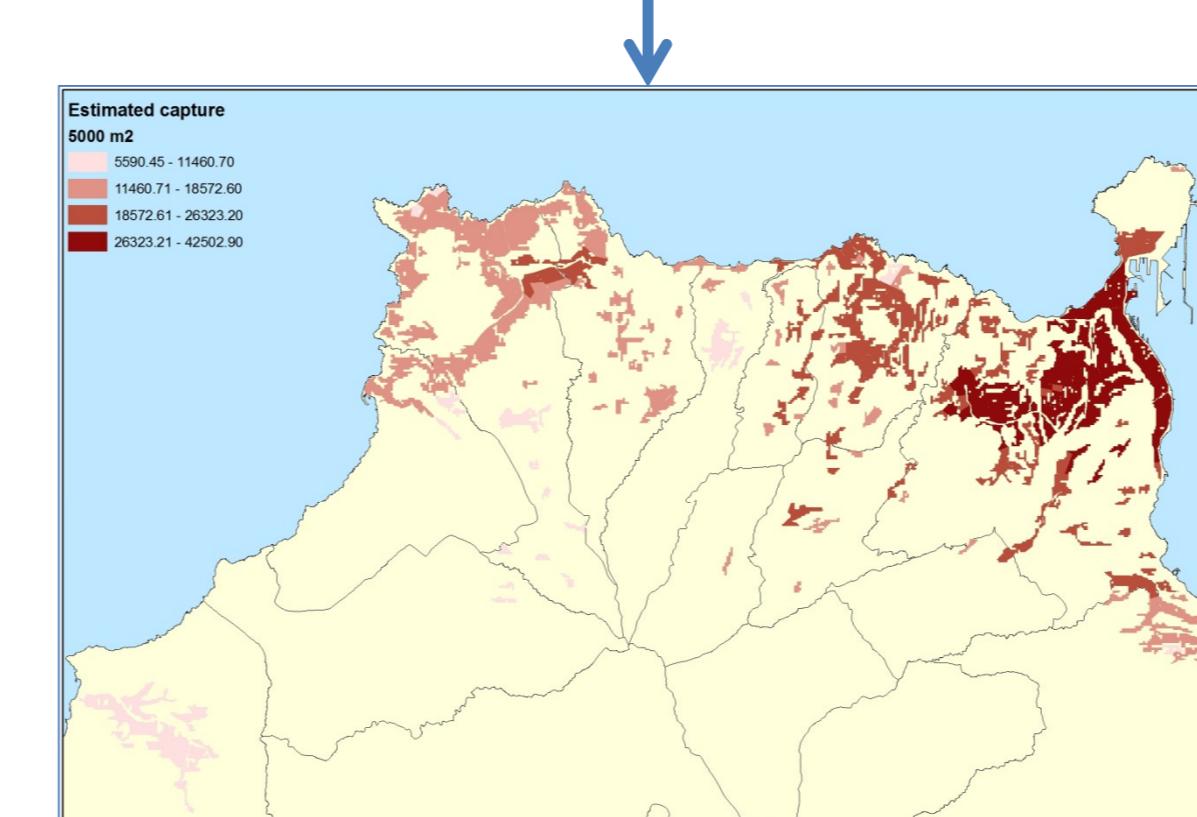
Spatial nonstationarity exists for the two parameters (F-test proposed by Leung et al. (2000)). It is most significant for the parameter associated to the size.

GWR model better fits data sample than OLS model (F-test proposed by Fotheringham et al. (2002))

	Average est.	Min.	Max.	STD
α	-0.5617	-1.1781	-0.3405	0.1440
λ	-1.0945	-1.3699	-0.6068	0.1040

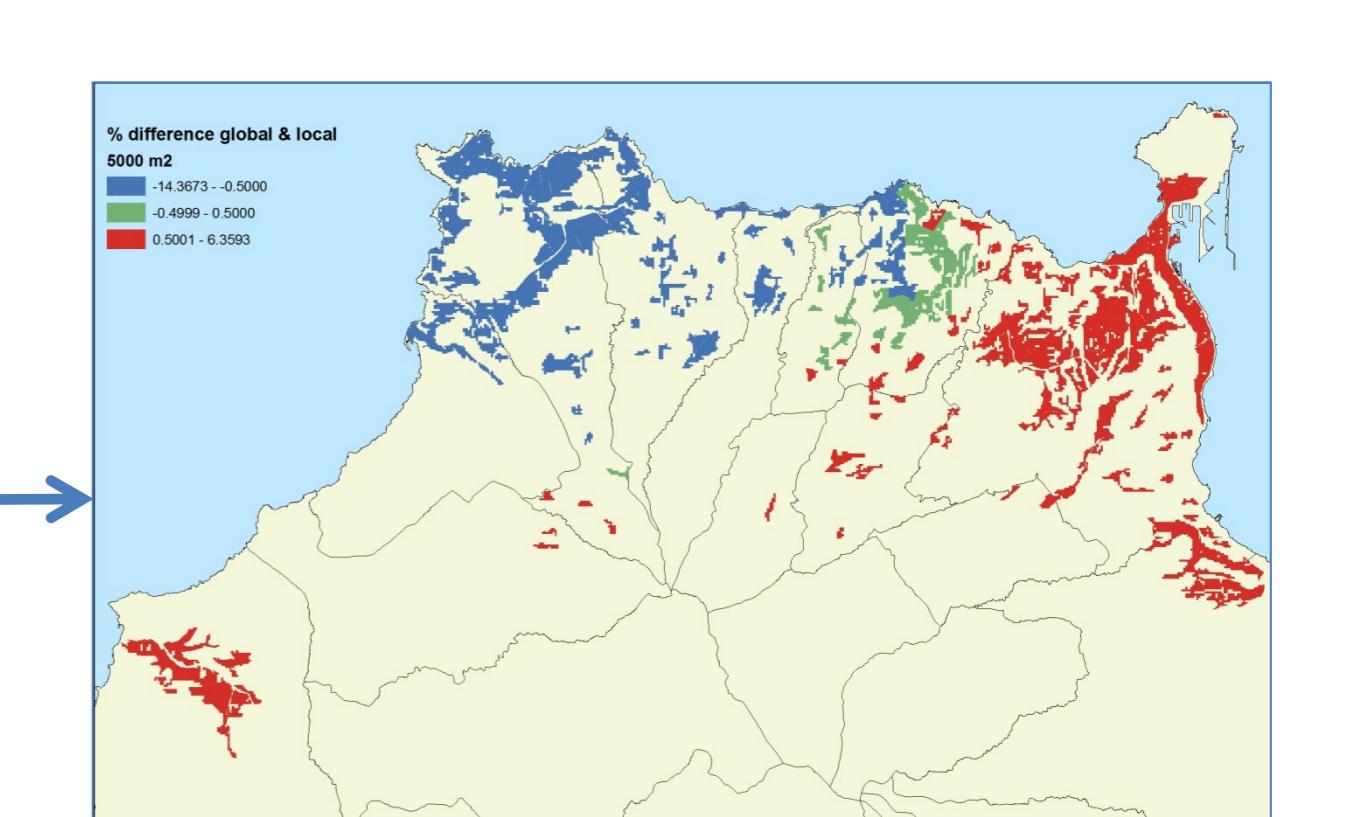
GWR parameters estimations for the demand points

These estimations were obtained using the kernel and bandwidth selected for estimating the sample data.



Using the estimated capture map not only the site with the maximum capture can be identified but also an overall vision of the profitability of the different zones in the feasible area is obtained.

$$100 * \frac{(GC - LC)}{GC}$$



Percentage difference between global capture (GC) and local capture (LC)

The map shows as the OLS model overestimates the capture for the new store in the most populated area and in the most remote zone (the western part of the feasible region). Nevertheless, in the more accessible zone out of the capital, the GWR model obtains higher capture estimations than OLS model.