4th AIEAA Conference - June 11th - 12th, 2015, Ancona (Italy)
**Innovation, productivity and growth:
towards sustainable agri-food production**

Spatial Heterogeneity in Production Functions Models

Salvioni C.[1], Billé AG.[2] and Benedetti R.[1]

[1] DEC, University of Chieti-Pescara, Pescara, Italy
[2] DEF, Tor Vergata University, Rome, Italy

Objective

In this paper we extend the literature on production functions by taking explicitly into account the inherent

spatial heterogeneity in technologies.

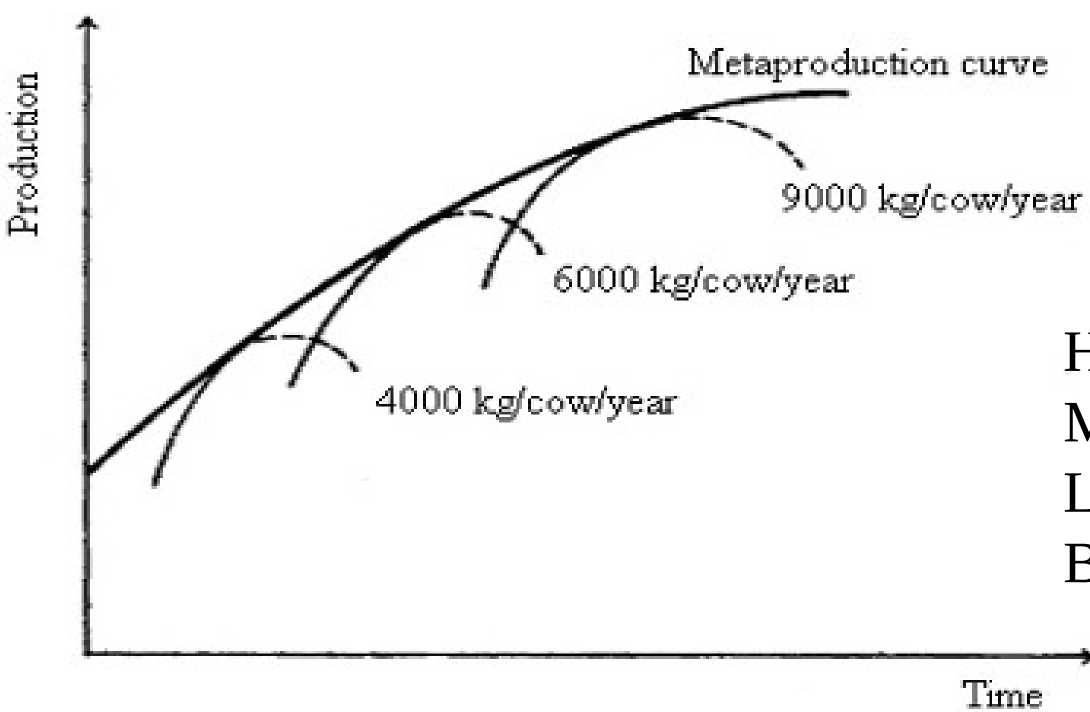
Heterogeneity in technologies

Although theory supports firms do not operate on a **common production function** (homogeneous technology), in most empirical literature a **global** production function is proposed that **assumes production technology is invariant** over space and across firms.

Assuming a common production function encompassing every sample observation, i.e. failing to recognize the geographical variations in technology, leads to **biased estimates**.

Modeling heterogeneous technologies 1

1. Classify sample observations into categories defined on the basis of *a priori* sample separation (regions) … **estimate a production function for each group** …



results used to build a **meta-production** (envelope of the production points of the most efficient groups).

Hayami and Ruttan, 1971;
Mundlak and Hellinghausen, 1982;
Lau and Yotopoulos ,1989;
Battese and Rao, 2002.

Modeling heterogeneous technologies 2

2. When categories cannot be defined *a priori*
   - **state-dependent production functions** (Mundlak, 2012) continuous parameter variation;
   - **latent class model**, also referred to as finite **mixture model** (Orea and Kumbakhar, 2004; O'Donnell and Griffith 2006;), which treat heterogeneity in technology as generated by a latent discrete distribution.

   - IGWR to *control for spatial heterogeneity*

Spatial heterogeneity

- The same stimulus has different response in different parts of the study region … values of β are different over space.
- Variations in relationship over space are referred to as a particular case of **non-stationarity.**
- If a spatial non-stationary relationship is modeled using **global** models, possible wrong conclusions might be drawn (model misspecification - biased results).

Geographically Weighted Regression - IGW

GWR, a local form of linear regression used to model spatially varying relationships. **... with the estimator**

$$\beta'(i)=(XW X) XW Y$$

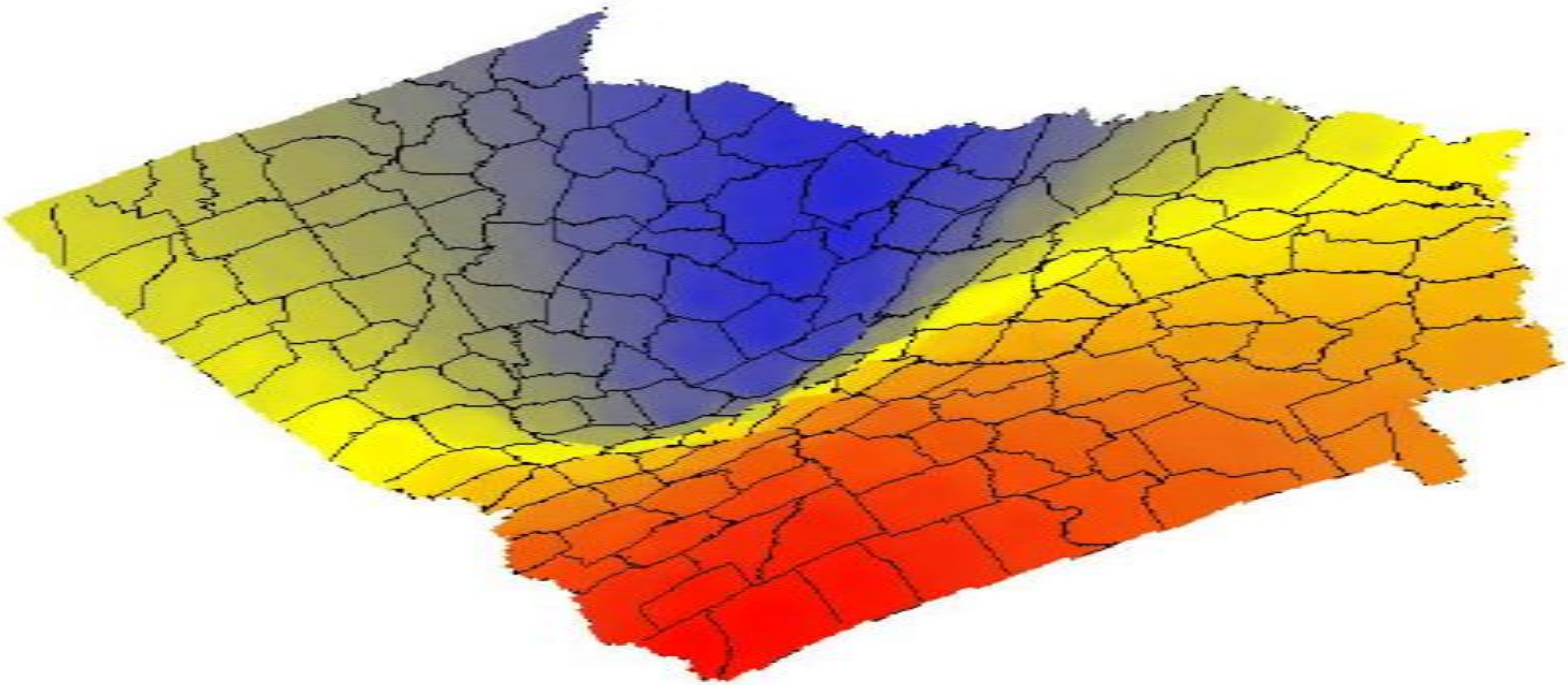
where

- **W(i)** is a matrix of weights specific to location i such that observations nearer to i are given greater weight than observations further away.
- w_{in} is the weight given to data point n for the estimate of the local parameters at location i.

Fotheringham et al. (2002) Geographically Weighted Regression: The Analysis of Spatially Varying Relationship, published by Wiley.

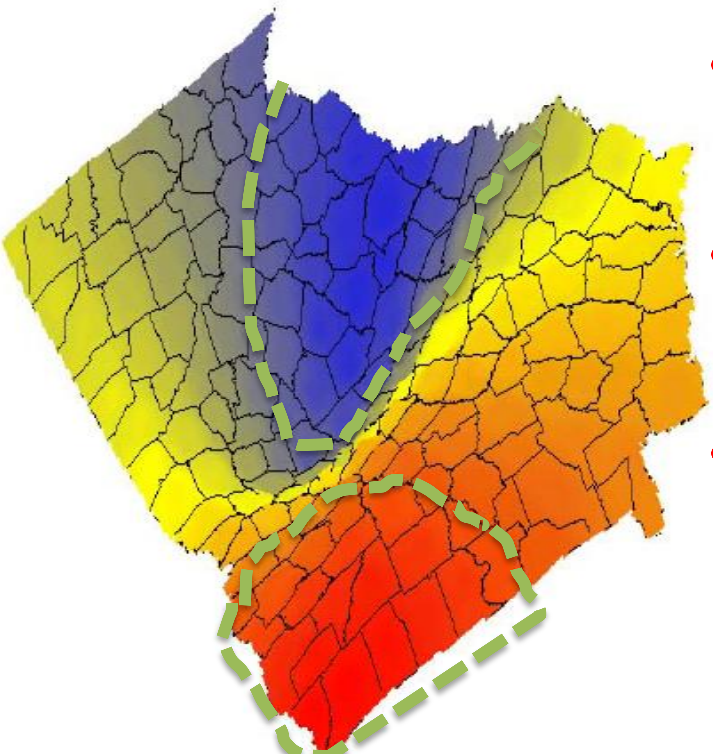
Output from GWR

Main output from GWR is a set of **location-specific parameter estimates** which can be mapped and analysed to provide information on spatial non-stationarity



Iterative Geographically Weighted Regression - IGW

Our aim: to identify spatial **clusters of farms** in which a single local econometric model is justified (fix the borders).



We **iteratively extend the GWR approach:**

- new weights computed in the main diagonal of at each iteration;
- estimated beta coefficients are compared by using distance criteria;
- Iterations stop when all the observations with similar beta coefficients belong to the same homogeneous cluster.



An application to olive farms in Italy 1

Italian Farm Accountancy Data Network (FADN) survey 2012

3 Regional samples of olive-growing farms:

- Apulia (270)
- Marche (268)
- Tuscany (317).


AN APPLICATION TO OLIVE FARMS IN ITALY 2

Dependent variable: olive production (kg)

Explanatory variables:

- **Land** grown to olive-tree cultivation (ha);
- **Labor**: hired and family labor (hours);
- **Capital**: proxied by mechanical work (hours);
- **Other inputs:** water, fertilizers, pesticides, fuel and electric power and other miscellaneous expenses, augmented with expenses for contract work (euros);

We use the **Cobb–Douglas** (CD) functional form:

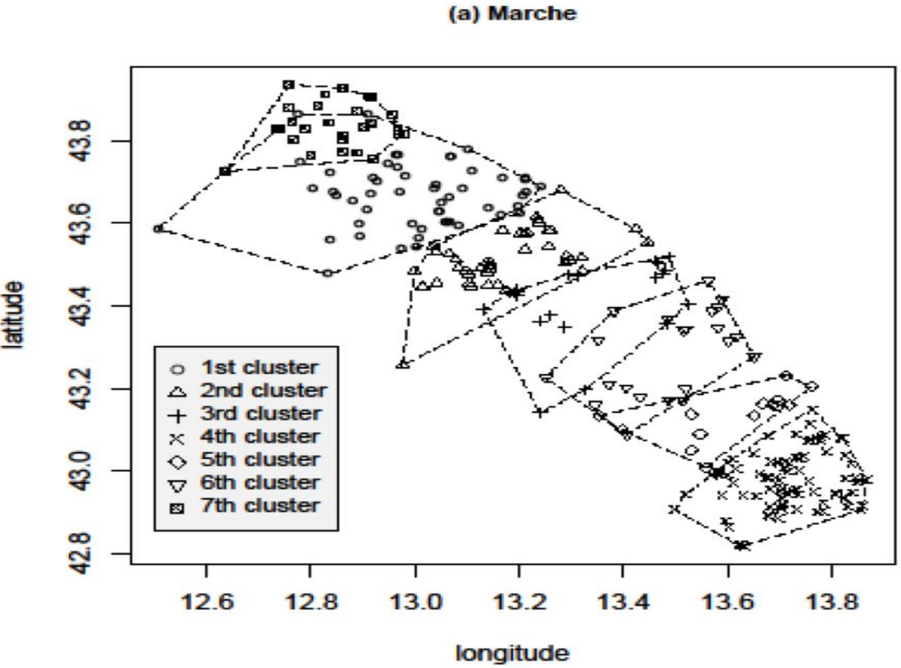
- Coefficients are easy to interpret;
- CD avoids the multicollinearity problem that arises with more flexible functional forms;
- flexibility is not an issue in our case given our coefficients are local specific .

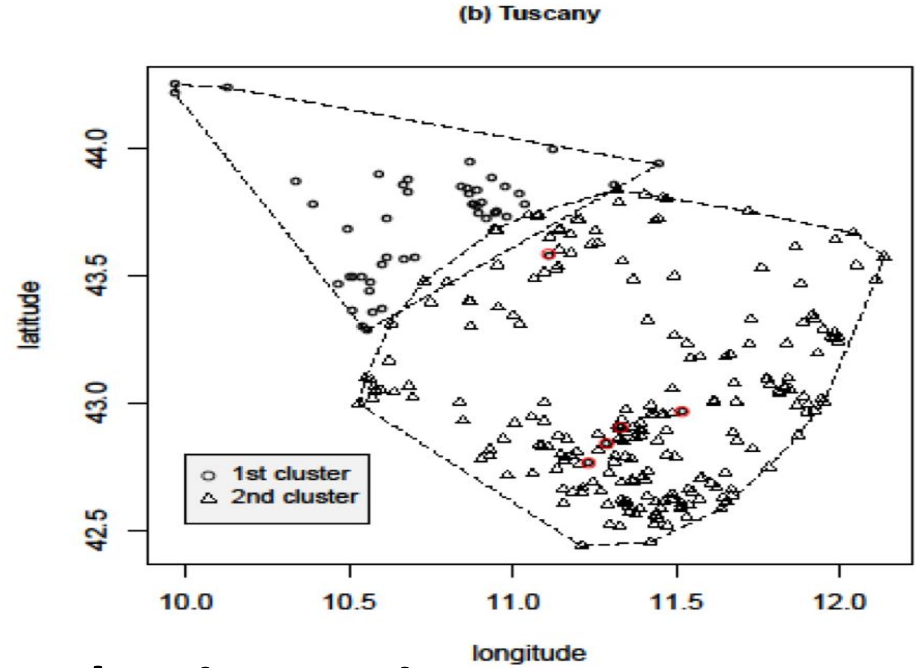
	Global Model	Spatial Global Model	Model with spatially varying param.s	Spatial Model with spatially varying parameters
Intercept	-1.641***	-1.478***	-	-
Intercept (1)	-	-	-2.791***	-3.229***
Intercept (2)	-	-	1.304*	1.380**
Land	0.167***	0.168***	-	-
Land (1)	-	-	0.108	0.119
Land (2)	-	-	0.175***	0.166***
Labour	0.273***	0.281***	-	-
Labour (1)	-	-	0.277*	0.244
Labour (2)	-	-	0.309***	0.327***
Capital	0.179***	0.176***	-	-
Capital (1)	-	-	0.182·	0.173·
Capital (2)	-	-	0.168**	0.153**
Other inputs	0.337***	0.336***	-	-
Other inputs (1)	-	-	0.570***	0.595***
Other inputs (2)	-	-	0.281***	0.275***
rho	-	-0.056	-	0.12
lambda	-	-0.028	-	-0.974
AIC	565.735	569.472	560.494	562.319

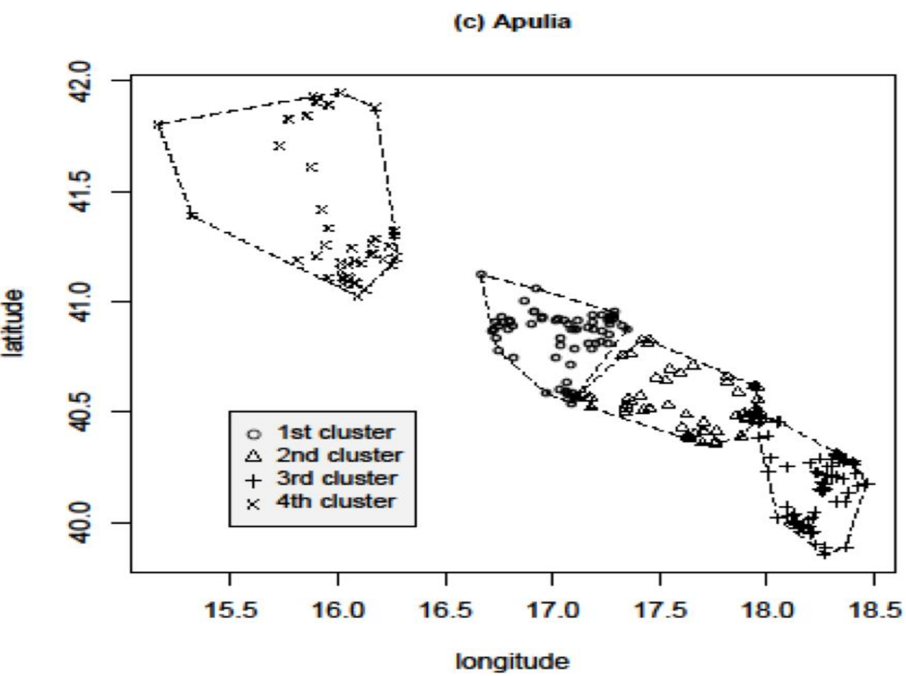
lowest AIC

- the model with spatially varying coefficient **fits the data best**,
- existance of technological heterogeneity;

effects of farm localization on production technology are mainly due to **heterogeneity** **not** to **spatial autocorrelation**.







Production regimes are **related** to the existence of some **latent,** not observed**, factors** that are closely **related to the spatial position** of the observed farms …. **climate, soil type, cultivars and** social factors.

high degree of overlapping between
- our map of clusters,
- map of varieties (available only at the **territorial level)**

Empirical results

- Confirmed <u>the existance of technological heterogeneity</u>; therefore empirical analysis that fails to incorporate parameter heterogeneity can produce misleading results.

- Once partitioned the study area we observed that the spatial interaction between farms belonging to the same cluster is not anymore significant, giving rise to the hypothesis that the effects of farm localization on production technology are mainly represented by heterogeneity, and not by the presence of spatial autocorrelation.

- The presence of different production regimes is related to the existence of some **latent, not observed, factors that are closely related to the spatial position** of the observed farms **climate, soil type, cultivars and** social factors.

Conclusions

Results are encouraging even if some additional research is needed

- the proposed strategy performs very well with large datasets, but we **need to explore the computational burden when huge sample sizes are used**
- the conditions under which the proposed partitions imply a better fit of the regression model, should be better investigated.

The end

Thank you for your attention