Hedonic Housing Prices in Corsica: A hierarchical spatiotemporal approach

WORKSHOP: THEORY AND PRACTICE OF SPDE MODELS AND INLA

LING Yuheng¹

30 Oct. 2018

¹PhD student in Economics - University of Corsica - CNRS UMR LISA
6240, France.
Location, location, location

**Corse Matin, May 17, 2012**

"Une nouvelle exception corse: Les prix de l’immobilier flambent”.

**Corse Matin, Auguste 28, 2012**

"Aussi, que vaut aujourd’hui un appartement dans la cité impériale ? Tout dépend du quartier.”

"On language: location, location, location” in The New York Times, June 28, 2009

When asking a real estate professional about the three most important characteristics of a house, the likely answer will be ”location, location, location”.
Economist’s words


- Neighborhood effects

Potential spatial autocorrelation
Economist’s words


- Neighborhood effects
- Adjacent effect

Potential spatial autocorrelation
Data

**Housing transaction data (collected over time)**

Cross section? Panel? Repeated cross section?

Spatiotemporal geostatistical/point-referenced data

**Tools**

The tools to analyze geo-referenced house transaction data are very limited. *(Dubé and Legros, 2013)*

- Pooling cross-sectional data
- Using a pooled OLS regression *(Palmquist, 2005)*
- Biased coefficients? *(Clark and Linzer, 2015)*
Literature on Corsican property market

Corsican property market studies

Corsican housing market has not been fully explored in literature.

- Spatial inequality, as well as on land-use pressure (*Furt and Tafani, 2014; Kessler and Tafani, 2015; Prunetti et al., 2015*)

- A recent research (*Giannoni et al., 2017*) focuses on the phenomenon that non-local house buyers drive out local house buyers.
A twofold objective

First
We propose a model which can explicitly capture dependences in space and over time simultaneously.

Second
The proposed model is applied to study the Corsican housing market. We intend to investigate the determinants of Corsican apartment prices; in particular, we would like to highlight the impacts of time and space on apartment prices.
Economic cornerstone: Hedonic price theory (HPM)

A New Approach to Consumer Theory

"The good, per se, does not give utility to the consumer; it possesses characteristics, and these characteristics give rise to utility.” (Lancaster, 1966, p134)

Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition

"A class of differentiated products is completely described by a vector of objectively measured characteristics. Observed product prices and the specific amounts of characteristics associated with each good define a set of implicit prices.” (Rosen, 1976, p34)
Empirical definition of HPM

Empirical representation of a house price  

\[ P = f(S, N, L, C, T, \beta) \]  

(Malpezzi, 2008)
Dealing with Space

Spatial regression models *(Anselin, 1988)*

\[ y = \beta Wy + X\beta + u \] (2)

\[ y = X\beta + \varepsilon \] (3)

\[ \varepsilon = \lambda W \varepsilon + u \] (4)
Dealing with Space

Multilevel modeling/hierarchical models (*Raudenbush and Bryk, 2002*)

\[ Level 1: y = \Delta \alpha + X\beta + \varepsilon, \varepsilon \sim N(0, \sigma^2) \] (5)

\[ Level 2: \alpha = Z\gamma + u, u \sim N(0, \tau^2) \] (6)

- *Goodman and Thibodeau (1998)*
- *Goodman and Thibodeau (2003)*
Special issues on applying HPM

Space and time
Housing transaction data are collected over time.

Tools
The tools to analyze geo-referenced house transaction data are very limited. *(Dubé and Legros, 2013)*
State-of-the-art models dealing with dependences in space and over time

Spatial econometrics and the hedonic pricing model: what about the temporal dimension?

"...the STAR specification outperforms the SAR specification; the STAR specification, with a small good threshold distance value outperforms the OLS specification;" (Dubé and Legros, 2014, p355)

Drawbacks
Specification
State-of-the-art models dealing with dependences in space and over time

Hedonic Housing Prices in Paris: An Unbalanced Spatial Lag Pseudo-Panel Model with Nested Random Effects


- Turning repeated cross-sectional data into pseudo-panel data
State-of-the-art models dealing with dependences in space and over time

Hedonic Housing Prices in Paris: An Unbalanced Spatial Lag Pseudo-Panel Model with Nested Random Effects


- Turning repeated cross-sectional data into pseudo-panel data
- N-way nested error component disturbances models (Baltagi and Chang, 1994) with a spatial lag term
State-of-the-art models dealing with dependences in space and over time

Hedonic Housing Prices in Paris: An Unbalanced Spatial Lag Pseudo-Panel Model with Nested Random Effects


- Turning repeated cross-sectional data into pseudo-panel data
- N-way nested error component disturbances models (Baltagi and Chang, 1994) with a spatial lag term
- Spatial nested random effect model allowing spatial lag effects $\lambda$ to vary by year.
State-of-the-art models dealing with dependences in space and over time

Hedonic Housing Prices in Paris: An Unbalanced Spatial Lag Pseudo-Panel Model with Nested Random Effects

\[ y_{taqif} = \lambda_t \tilde{y}_{taqif} + X_{taqif} \beta + u_{taqif}; \]
\[ \tilde{y}_{taqif} = \sum_{a=1}^{N} \sum_{q=1}^{Q_{ta}} \sum_{i=1}^{M_{taq}} \sum_{p=1}^{F_{taqi}} w_{taqip} y_{taqip}; \]
\[ u_{taqif} = \delta_{ta} + \mu_{taq} + \nu_{taqi} + \varepsilon_{taqif} \] (7)

Drawbacks

Temporal dependence
A two-level hierarchical spatio-temporal model (Banerjee and al. 2014; Cressie and Wikle, 2011; Cameletti and al., 2013).
A two-level hierarchical spatio-temporal model (Banerjee and al. 2014; Cressie and Wikle, 2011; Cameletti and al., 2013).

\[ y(s_i, t) = z(s_i, t) \beta + \xi(s_i, t) + \varepsilon(s_i, t) \]  

(8)
Hierarchical spatio-temporal model

A two-level hierarchical spatio-temporal model (Banerjee and al. 2014; Cressie and Wikle, 2011; Cameletti and al., 2013).

\[ y(s_i, t) = z(s_i, t) \beta + \xi(s_i, t) + \varepsilon(s_i, t) \]  

(8)

\( y(s_i, t) \) is a realization of the underlying spatio-temporal process \( Y (\cdot, \cdot) \) representing house prices measured at apartment unit \( i = 1, \cdots, d \) located at site \( s_i \) and time \( t = 1, \cdots, T \).
Hierarchical spatio-temporal model

- A two-level hierarchical spatio-temporal model (Banerjee and al. 2014; Cressie and Wikle, 2011; Cameletti and al., 2013).

\[ y(s_i, t) = z(s_i, t) \beta + \xi(s_i, t) + \varepsilon(s_i, t) \]  

(8)

- \( y(s_i, t) \) is a realization of the underlying spatio-temporal process \( Y(\cdot, \cdot) \) representing house prices measured at apartment unit \( i = 1, \cdots, d \) located at site \( s_i \) and time \( t = 1, \cdots, T \).

- \( z(s_i, t) \beta \) represents all covariates referring to fixed effects
Hierarchical spatio-temporal model

- $\xi(s_i, t)$ is a so-called spatiotemporal random effects term.
Hierarchical spatio-temporal model

- $\xi(s_i, t)$ is a so-called spatiotemporal random effects term.

$$\xi(s_i, t) = a\xi(s_i, t - 1) + \omega(s_i, t) \quad (9)$$
Hierarchical spatio-temporal model

- $\xi(s_i, t)$ is a so-called spatiotemporal random effects term.
  
  \[
  \xi(s_i, t) = a\xi(s_i, t - 1) + \omega(s_i, t)
  \]  

- $a$ is the first-order autoregressive (AR1) coefficient.
Hierarchical spatio-temporal model

- $\xi(s_i, t)$ is a so-called spatiotemporal random effects term.

$$\xi(s_i, t) = a\xi(s_i, t - 1) + \omega(s_i, t)$$  \hspace{1cm} (9)

- $a$ is the first-order autoregressive (AR1) coefficient.
- $\omega(s_i, t)$ is a time-independent random field (RF).
Hierarchical spatio-temporal model

- $\xi(s_i, t)$ is a so-called spatiotemporal random effects term.

\[
\xi(s_i, t) = a\xi(s_i, t - 1) + \omega(s_i, t)
\]  \hspace{1cm} (9)

- $a$ is the first-order autoregressive (AR1) coefficient.
- $\omega(s_i, t)$ is a time-independent random field (RF).

\[
\omega(s_i, t) \sim N(0, \sum = \sigma^2_\omega \sum)
\]  \hspace{1cm} (10)
Hierarchical spatio-temporal model

- $\xi(s_i, t)$ is a so-called spatiotemporal random effects term.

  \[ \xi(s_i, t) = a\xi(s_i, t - 1) + \omega(s_i, t) \]  

- $a$ is the first-order autoregressive (AR1) coefficient.
- $\omega(s_i, t)$ is a time-independent random field (RF).

  \[ \omega(s_i, t) \sim N(0, \sum = \sigma^2 \omega \sum) \]  

- $\text{cov}(\omega(s_i, t), \omega(s_j, t')) = \begin{cases} 
0 & \text{if } t \neq t' \\
C_\theta(h) & \text{if } t = t' 
\end{cases}$

  where $h = \|s_i - s_j\|$ is the Euclidean distance.
Hierarchical spatio-temporal model

• $\xi(s_i, t)$ is a so-called spatiotemporal random effects term.

$$\xi(s_i, t) = a\xi(s_i, t - 1) + \omega(s_i, t) \tag{9}$$

• $a$ is the first-order autoregressive (AR1) coefficient.
• $\omega(s_i, t)$ is a time-independent random field (RF).

$$\omega(s_i, t) \sim N(0, \sum = \sigma_\omega^2 \sum) \tag{10}$$

$$\text{cov} \left( \omega(s_i, t), \omega(s_j, t') \right) = \begin{cases} 0 & \text{if } t \neq t' \\ C_\theta(h) & \text{if } t = t' \end{cases} \tag{11}$$

where $h = \|s_i - s_j\|$ is the Euclidean distance.

• Gaussian white noise

$$\varepsilon(s_i, t) \sim N\left(0, \sigma_\varepsilon^2 I_d\right) \tag{12}$$
As a grouped model

\[ \xi \] represents grouped random effects

- a within group correlation structure \( \omega (s_i, t) \)
As a grouped model

\( \xi \) represents grouped random effects

- a within group correlation structure \( \omega(s_i, t) \)
- a between group correlation structure measured by \( a \)
As a grouped model

\[ \xi \text{ represents grouped random effects} \]

- a within group correlation structure \( \omega(s_i, t) \)
- a between group correlation structure measured by \( a \)
- If \( \xi_{s_i, t} \) is the \( i \)th element in the domain \( S \) in time period \( t \), we have

\[
Cov(\xi_{s_1, t}, \xi_{s_2, t'}) = \sum ar_1 \otimes \sum \omega \quad (13)
\]
Fitting the model

- Matérn correlation function
Fitting the model

- Matérn correlation function
- Gaussian Markov random field (GMRF)
Fitting the model

- Matérn correlation function
- Gaussian Markov random field (GMRF)
- SPDE approach
Fitting the model

- Matérn correlation function
- Gaussian Markov random field (GMRF)
- SPDE approach
- INLA algorithm
Corsica
"PERVAL" database from "Notaries de France"

- The "PERVAL" database records all type of property transactions in France.
Data

"PERVAL" database from "Notaries de France"

- The "PERVAL" database records all type of property transactions in France.
- High-quality and high-reliability
Data

"PERVAL" database from "Notaries de France"

- The "PERVAL" database records all types of property transactions in France.
- High-quality and high-reliability
- Transaction ID
Data

"PERVAL" database from "Notaries de France"

- The "PERVAL" database records all type of property transactions in France.
- High-quality and high-reliability
- Transaction ID
- Transaction date
Data

"PERVAL" database from "Notaries de France"

- The "PERVAL" database records all type of property transactions in France.
- High-quality and high-reliability
- Transaction ID
- Transaction date
- Transaction price
Data

"PERVAL" database from "Notaries de France"

- The "PERVAL" database records all type of property transactions in France.
- High-quality and high-reliability
- Transaction ID
- Transaction date
- Transaction price
- Characteristics of the property
Our dataset

- The used dataset are extracted from the ”PERVAL” database.
Our dataset

- The used dataset are extracted from the "PERVAL" database.
- We are interested in apartment prices.
Data

Our dataset

- The used dataset are extracted from the "PERVAL" database.
- We are interested in apartment prices.
- 7634 observations.
Our dataset

- The used dataset are extracted from the "PERVAL" database.
- We are interested in apartment prices.
- 7634 observations.
- Transactions from 2006 to 2017
### Independent variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description/Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROOM</td>
<td>Number of rooms</td>
</tr>
<tr>
<td>BATH</td>
<td>Number of bathrooms</td>
</tr>
<tr>
<td>GAR</td>
<td>Number of garages</td>
</tr>
<tr>
<td>FLOOR</td>
<td>Number of floors</td>
</tr>
<tr>
<td>SURF</td>
<td>Living area (square meters)</td>
</tr>
<tr>
<td>TYPE</td>
<td>Dummy (=1 if the apartment pertains to this type and 0 otherwise)</td>
</tr>
<tr>
<td>SA</td>
<td>Standard apartment (referenced)</td>
</tr>
<tr>
<td>DU</td>
<td>Duplex apartment</td>
</tr>
<tr>
<td>ST</td>
<td>Studio apartment</td>
</tr>
<tr>
<td>CONSTRUCTION</td>
<td>Dummy (=1 if the apartment was built during this period and 0 otherwise)</td>
</tr>
<tr>
<td>PERIOD</td>
<td>Time of building 1850-1913 (referenced)</td>
</tr>
<tr>
<td>PERIOD A</td>
<td>Time of building 1914-1947</td>
</tr>
<tr>
<td>PERIOD C</td>
<td>Time of building 1948-1969</td>
</tr>
<tr>
<td>Variable</td>
<td>Description/Unit</td>
</tr>
<tr>
<td>-------------</td>
<td>-------------------------------------------------------</td>
</tr>
<tr>
<td>PERIOD G</td>
<td>Time of building 2001 / 2010</td>
</tr>
<tr>
<td>PERIOD H</td>
<td>Time of building 2011 / 2020</td>
</tr>
<tr>
<td>DBEAD</td>
<td>Distance to the nearest beach (kilometers)</td>
</tr>
<tr>
<td>DPuHigSch</td>
<td>Distance to the nearest public high school (kilometers)</td>
</tr>
<tr>
<td>DHealFac</td>
<td>Distance to the nearest health facility (kilometers)</td>
</tr>
<tr>
<td>DPuHigSch</td>
<td>Distance to the nearest public primary school (kilometers)</td>
</tr>
</tbody>
</table>
## Descriptive statistics

**Table:** Descriptive statistics for hedonic housing prices in Corsica

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Pctl(25)</th>
<th>Pctl(75)</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transaction Price</td>
<td>149467.08</td>
<td>58483.01</td>
<td>57445.76</td>
<td>100000</td>
<td>185347.95</td>
<td>325431.67</td>
</tr>
<tr>
<td>log(Transaction Price)</td>
<td>11.84</td>
<td>0.39</td>
<td>10.96</td>
<td>11.55</td>
<td>12.13</td>
<td>12.69</td>
</tr>
<tr>
<td>ROOM</td>
<td>2.672</td>
<td>0.967</td>
<td>0</td>
<td>2</td>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>BATHROOM</td>
<td>1.053</td>
<td>0.259</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>PAK</td>
<td>0.795</td>
<td>0.712</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>FLOOR</td>
<td>1.849</td>
<td>1.731</td>
<td>-3*</td>
<td>1</td>
<td>3</td>
<td>12</td>
</tr>
<tr>
<td>SURF</td>
<td>59.315</td>
<td>22.191</td>
<td>6</td>
<td>43</td>
<td>73</td>
<td>197</td>
</tr>
<tr>
<td>DBEAD</td>
<td>3.782</td>
<td>7.153</td>
<td>0.001</td>
<td>1.040</td>
<td>3.561</td>
<td>52.008</td>
</tr>
<tr>
<td>DHealFac</td>
<td>10.421</td>
<td>12.099</td>
<td>0.051</td>
<td>1.636</td>
<td>16.461</td>
<td>72.244</td>
</tr>
<tr>
<td>DPuPriSch</td>
<td>1.347</td>
<td>1.698</td>
<td>0.0001</td>
<td>0.469</td>
<td>1.544</td>
<td>39.513</td>
</tr>
<tr>
<td>DPuHigSch</td>
<td>9.914</td>
<td>10.689</td>
<td>0.001</td>
<td>1.434</td>
<td>15.809</td>
<td>78.978</td>
</tr>
<tr>
<td>SVI</td>
<td>11.653</td>
<td>11.237</td>
<td>0.000</td>
<td>1.503</td>
<td>19.906</td>
<td>47.923</td>
</tr>
</tbody>
</table>
Models

- **Classical linear regression model (M0)**

\[
ln y(s_i, t) = z(s_i, t) \beta + \varepsilon(s_i, t); \quad \varepsilon(s_i, t) \sim N(0, \sigma^2_{\varepsilon})
\] (14)
Models

- **Classical linear regression model (M0)**

\[
\ln y(s_i, t) = z(s_i, t) \beta + \varepsilon(s_i, t); \quad \varepsilon(s_i, t) \sim N(0, \sigma^2_{\varepsilon}) \quad (14)
\]

- **Classical linear regression with space fixed effects (M1)**

\[
\ln y(s_i, t) = z(s_i, t) \beta + 112 \text{ municipality dummies} \\
+ \varepsilon(s_i, t); \\
\varepsilon(s_i, t) \sim N(0, \sigma^2_{\varepsilon}) \quad (15)
\]
Models

- Classical linear regression model (M0)
  \[ \ln y(s_i, t) = z(s_i, t) \beta + \varepsilon(s_i, t); \varepsilon(s_i, t) \sim N(0, \sigma^2_{\varepsilon}) \] (14)

- Classical linear regression with space fixed effects (M1)
  \[ \ln y(s_i, t) = z(s_i, t) \beta + 112 \text{ municipality dummies} + \varepsilon(s_i, t); \varepsilon(s_i, t) \sim N(0, \sigma^2_{\varepsilon}) \] (15)

- Classical linear regression with space and time fixed effects (M2)
  \[ \ln y(s_i, t) = z(s_i, t) \beta + 112 \text{ municipality dummies} + 48 \text{ quarter dummies} + \varepsilon(s_i, t); \varepsilon(s_i, t) \sim N(0, \sigma^2_{\varepsilon}) \] (16)
Fixed effects Models

- Advantages
  - Economic perspective
Fixed effects Models

- Advantages
  - Economic perspective
  - Spatial analysis

- Disadvantages
  - Spatial autocorrelation
Motivation

Objective

Literature review

Methodology

Empirical analysis

Findings

Conclusion

Conclusion

END

Mixed effects Models

- **Hierarchical spatial model (M3)**

\[
\ln y(s_i) = z(s_i) \beta + \xi(s_i) + \varepsilon(s_i) ;
\]

\[
\xi(s_i) = \omega(s_i) ;
\]

\[
\varepsilon(s_i) \sim N(0, \sigma^2_{\varepsilon}) ;
\]

\[
\omega(s_i) \sim N(0, \sum = \sigma^2_{\omega} \sum) \quad (17)
\]
Mixed effects Models

- **Hierarchical spatial model (M3)**

\[
\ln y(s_i) = z(s_i) \beta + \xi(s_i) + \varepsilon(s_i) ;
\]

\[
\xi(s_i) = \omega(s_i) ;
\]

\[
\varepsilon(s_i) \sim N\left(0, \sigma_\varepsilon^2\right) ;
\]

\[
\omega(s_i) \sim N\left(0, \sum = \sigma_\omega^2 \sum\right) \quad (17)
\]

- **Hierarchical spatiotemporal model: AR1 (M4)**

\[
\ln y(s_i, t) = z(s_i, t) \beta + \xi(s_i, t) + \varepsilon(s_i, t) ;
\]

\[
\xi(s_i, t) = a \xi(s_i, t - 1) + \omega(s_i, t) ;
\]

\[
\varepsilon(s_i, t) \sim N\left(0, \sigma_\varepsilon^2\right) ;
\]

\[
\omega(s_i, t) \sim N\left(0, \sum = \sigma_\omega^2 \sum\right) \quad (18)
\]
Implementing details

- R-INLA
Implementing details

- R-INLA
- Vague prior to hyperparameters
Implementing details

- R-INLA
- Vague prior to hyperparameters
- Mesh (3237 triangles)
Model selection

Table: Results of DIC

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC values</th>
<th>Elapsed Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLRM</td>
<td>2009.37</td>
<td>6</td>
</tr>
<tr>
<td>CLRM + Space fixed effects</td>
<td>-1123.87</td>
<td>6</td>
</tr>
<tr>
<td>CLRM + Space and time fixed effects</td>
<td>-1204.59</td>
<td>7</td>
</tr>
<tr>
<td>Spatial hierarchical model</td>
<td>-3867.65</td>
<td>43</td>
</tr>
<tr>
<td>Spatiotemporal hierarchical model</td>
<td>-4460.54</td>
<td>17287</td>
</tr>
</tbody>
</table>

- M4 is deemed the best model.
# Posterior estimates of covariate coefficients

<table>
<thead>
<tr>
<th></th>
<th>Model 4</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>quant</td>
<td>quant</td>
</tr>
<tr>
<td>Intercept</td>
<td>10.981</td>
<td>10.886</td>
<td>11.075</td>
</tr>
<tr>
<td>ROOM</td>
<td>0.033</td>
<td>0.024</td>
<td>0.042</td>
</tr>
<tr>
<td>BATHROOM</td>
<td>0.017</td>
<td>-0.001</td>
<td>0.035</td>
</tr>
<tr>
<td>GAR</td>
<td>0.050</td>
<td>0.041</td>
<td>0.059</td>
</tr>
<tr>
<td>FLOOR</td>
<td>0.019</td>
<td>0.016</td>
<td>0.022</td>
</tr>
<tr>
<td>SURF</td>
<td>0.010</td>
<td>0.010</td>
<td>0.011</td>
</tr>
<tr>
<td>DU</td>
<td>0.028</td>
<td>0.002</td>
<td>0.054</td>
</tr>
<tr>
<td>ST</td>
<td>-0.190</td>
<td>-0.209</td>
<td>-0.170</td>
</tr>
<tr>
<td>PERIOD B</td>
<td>0.000</td>
<td>-0.065</td>
<td>0.065</td>
</tr>
<tr>
<td>PERIOD C</td>
<td>-0.006</td>
<td>-0.068</td>
<td>0.056</td>
</tr>
<tr>
<td>PERIOD D</td>
<td>0.031</td>
<td>-0.032</td>
<td>0.094</td>
</tr>
<tr>
<td>PERIOD E</td>
<td>0.047</td>
<td>-0.016</td>
<td>0.110</td>
</tr>
<tr>
<td>PERIOD F</td>
<td>0.107</td>
<td>0.038</td>
<td>0.175</td>
</tr>
<tr>
<td>PERIOD G</td>
<td>0.219</td>
<td>0.154</td>
<td>0.284</td>
</tr>
<tr>
<td>PERIOD H</td>
<td>0.234</td>
<td>0.169</td>
<td>0.299</td>
</tr>
<tr>
<td>DBEAD</td>
<td>-0.016</td>
<td>-0.021</td>
<td>-0.011</td>
</tr>
<tr>
<td>DHealFac</td>
<td>-0.005</td>
<td>-0.008</td>
<td>-0.003</td>
</tr>
<tr>
<td>DPuHigSch</td>
<td>0.002</td>
<td>-0.001</td>
<td>0.005</td>
</tr>
<tr>
<td>DPuPriSch</td>
<td>0.007</td>
<td>-0.001</td>
<td>0.015</td>
</tr>
</tbody>
</table>
Posterior estimates of the variance parameters

**Table:** Posterior mean estimates of the variance parameters

<table>
<thead>
<tr>
<th>Model</th>
<th>$\sigma_e^2$</th>
<th>$\sigma_w^2$</th>
<th>AR1 coef</th>
<th>Range Km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model0</td>
<td>0.076</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model1</td>
<td>0.050</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model2</td>
<td>0.049</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model3</td>
<td>0.032</td>
<td>0.108</td>
<td></td>
<td>1.582</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.090,0.129)</td>
<td></td>
<td>(1.369,1.831)</td>
</tr>
<tr>
<td>Model4</td>
<td>0.028</td>
<td>0.106</td>
<td>0.990</td>
<td>1.503</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.090,0.123)</td>
<td>(0.987,0.993)</td>
<td>(1.289,1.711)</td>
</tr>
</tbody>
</table>

**Main findings**
Spatiotemporal random effects visualization
Spatiotemporal random effects visualization
Spatiotemporal random effects visualization

Easting (UTM/Km)
Northing (UTM/Km)
4600 4650 4700 4750
480 500 520 540

-0.8 -0.6 -0.4 -0.2 0.0 0.2 0.4 0.6

Festing (UTM/Km)
Spatiotemporal random effects

\[ \ln y(s_i, t) = z(s_i, t) \beta + \xi(s_i, t) + \varepsilon(s_i, t) \] (19)

\[ y(s_i, t) = \exp^{z(s_i, t)\beta} \times \exp^{\xi(s_i, t)} \times \exp^{\varepsilon(s_i, t)} \] (20)

**Findings**

Locations increase the expected apartment prices up to 82.21%, as well as decrease the expected apartment prices to 55.06%.
Findings

- Several housing structural attributes and accessibility attributes affect apartment prices.
Findings

- Several housing structural attributes and accessibility attributes affect apartment prices.
- It is clear that space and time significantly affect Corsican apartment prices. In particular, locations highly affect apartment prices.
Findings

- Several housing structural attributes and accessibility attributes affect apartment prices.
- It is clear that space and time significantly affect Corsican apartment prices. In particular, locations highly affect apartment prices.
- We can not neglect dependence in space and over time. Hence, fixed effects models are not alternatives to mixed effects models.
Conclusion

- Rather than ad hoc models, hierarchical spatiotemporal models and the INLA-SPDE approach work as a general framework dealing with housing transaction data.
Conclusion

- Rather than ad hoc models, hierarchical spatiotemporal models and the INLA-SPDE approach work as a general framework dealing with housing transaction data.
- It is necessary to incorporate time and space in models when we handle housing transaction data.
Rather than ad hoc models, hierarchical spatiotemporal models and the INLA-SPDE approach work as a general framework dealing with housing transaction data.

It is necessary to incorporate time and space in models when we handle housing transaction data.

The way to gauge time and space effects is also important. Categorical variables in fixed models do not take spatial effects fully into account.
Future studies

- Priors?
Thanks for your attention.