

# Intro to Spatial Analytics and Remote Sensing applications for urban and spatial economics

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# Part 1: Intro to Spatial Analytics

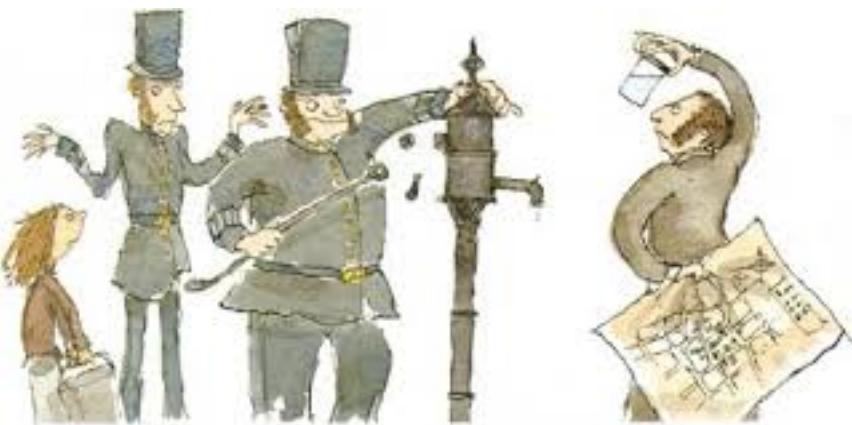
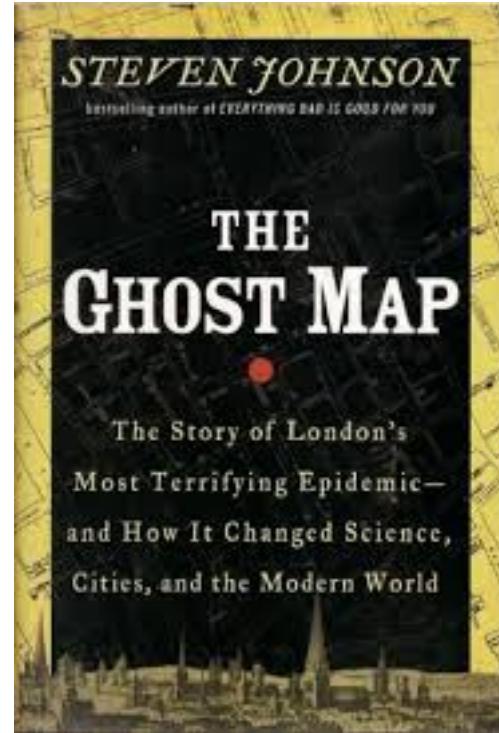
# Who is John Snow?



*John Snow*



# Who is John Snow?



# First Law of Geography

"everything is  
related to  
everything else,  
but near things  
are more related  
than distant  
things."

Waldo Tobbler

# Motivation

- Substantive
  - From Adam Smith invisible hand to social networks
    - Individual vs. socio-spatial interaction
    - Peer effects, contagion, imitation, trends
  - Spatial externalities
    - Costs/Benefits from activities that impact in a different location
    - Spatial spillovers:
      - Good: neighbor playing the piano
      - Bad: neighbor with COVID-19 and not quarantining
    - Spatial multipliers
      - Investment in a park → housing prices
  - Spatial Mismatch/Disparities
  - Spatial Context

# Motivation

- Practical
  - Data: geo-located observations
    - Private sources
    - Public sources
    - Self reported vs. Web scraped
  - Spatial mismatch between data and social processes
    - Labor markets vs. Cities and Counties → Labor Market areas
    - Epidemic spread vs. Data collection in hospitals
  - Neighborhood Effects
  - Spatial interpolation
  - Change of support problem
    - Data at different spatial levels that don't overlap
      - Ej: Parents' income aggregated at the school level used to predict municipalities' income level

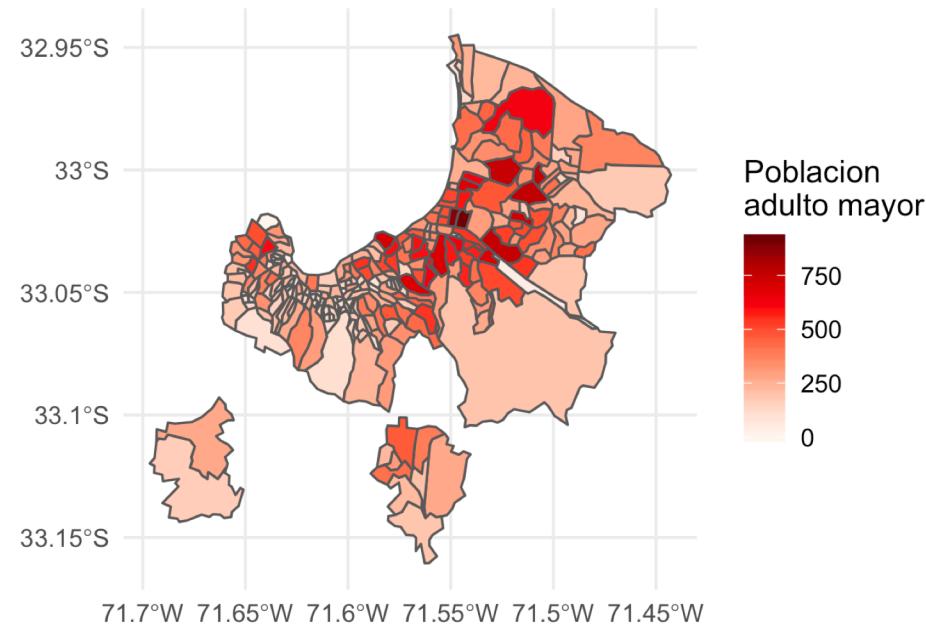
# What is Spatial Analytics?

- More than just mapping
  - Added value in the explanation
  - Combination of methods, theory, data manipulation
  - Knowledge discovery
  - “from data, to information, to knowledge, to wisdom”
  - Correlation is not causation, and this applies also to spatial analysis.

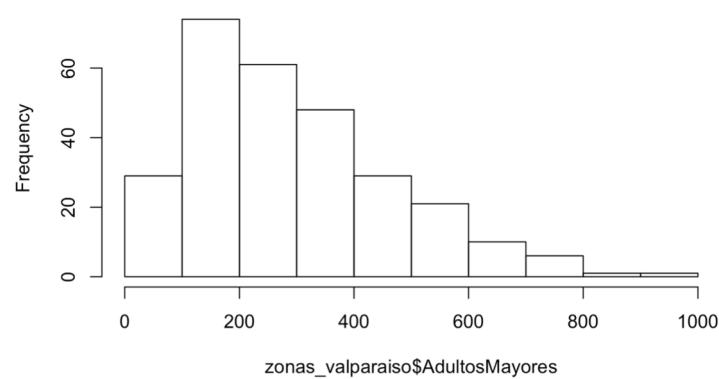
# Questions of Spatial Analytics

- Where do things happen
  - Patterns, clusters, hot spots, disparities,..
- Why do things happen
  - Location decisions
- How, things that happen, affect other things (spillovers) and how context affect what happens (interaction)
- Where should things be happening/be located
  - Optimization

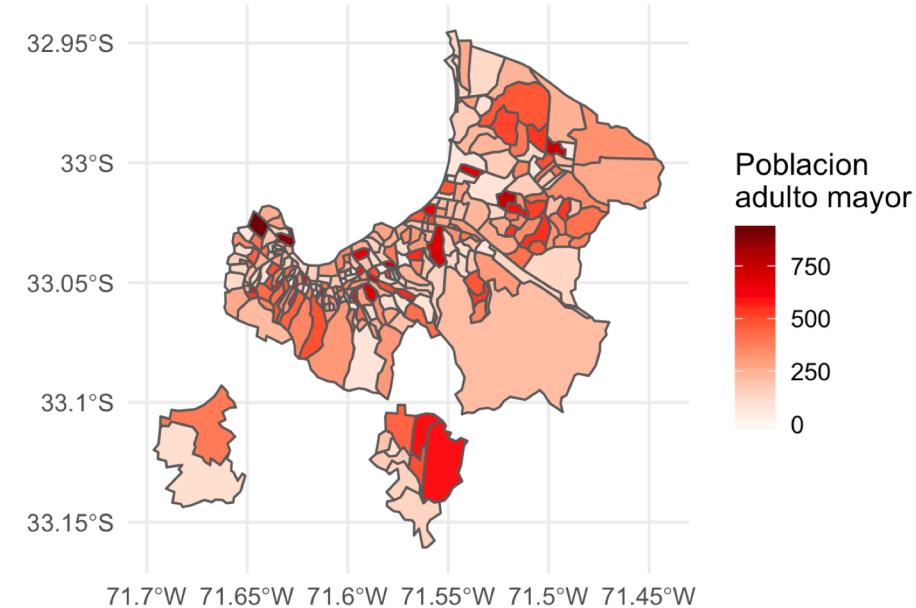
Poblacion de 65 años y más  
Valparaíso y Viña del Mar



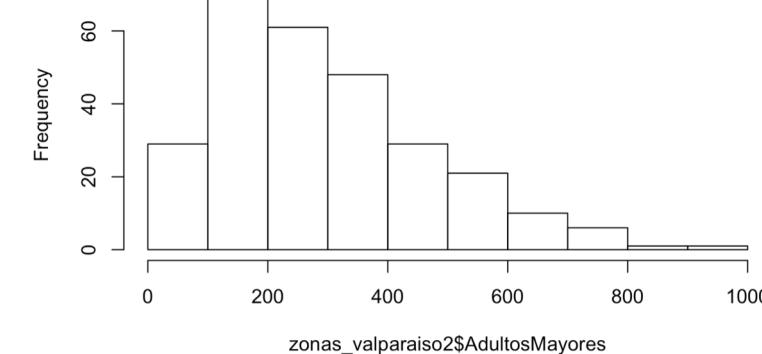
Histograma Adultos Mayores Viña-Valpo



Poblacion de 65 años y más  
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Histograma Adultos Mayores Viña-Valpo



# Part 2: Applications

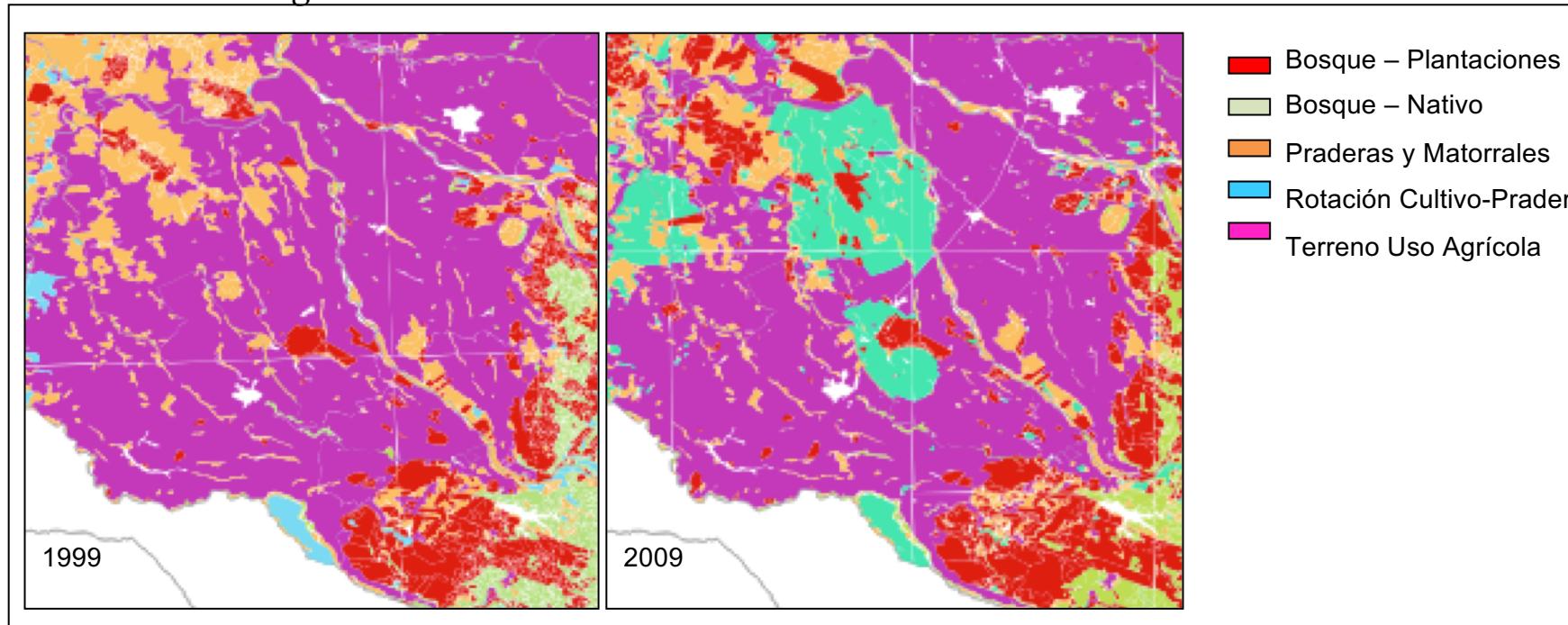
# Outline

1. Economic impacts of land use changes and forestry expansion
2. Using ML for predicting forest fires from forest plantations
3. Satellite imagery for estimating the impact of green areas in housing prices
4. Effects of school distances on Educational Outcomes
5. Other
  1. Bonus – Patrones espaciales de la Ley de Protección del Empleo (Boletín CEPR)
  2. ML on predicting Deforestation patterns (Ivan Flores)

# 1

# Spatial patterns of forestry expansión matter

Figura 2. Ejemplo del cambio de uso de suelo potencialmente causado por la expansión Forestal en la Región del Maule 1999-2009



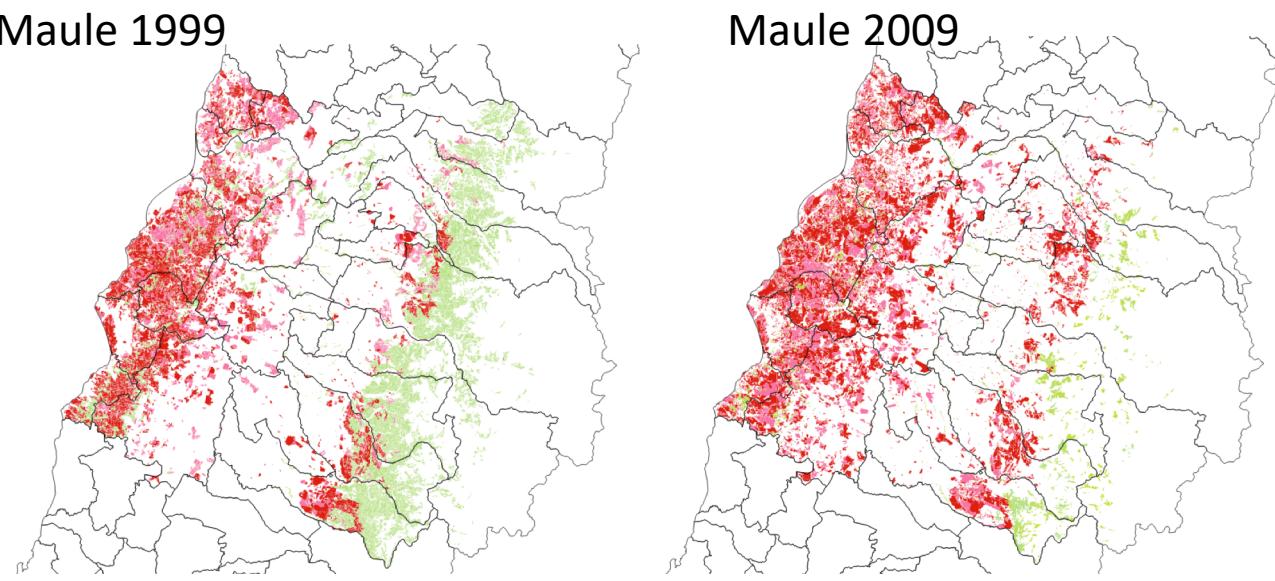
Fuente: Elaboración propia con datos del Sistema de Información Territorial (SIT) CONAF

Nota: Zoom de la Figura 1. Como se aprecia, en 2009 el área de plantación de bosques (en rojo) que tiene a su alrededor áreas de Rotación Cultivo-Pradera (en cian), es nueva. Estas dos áreas en 1999 estaban clasificadas como Praderas y Matorrales y Terreno de Uso Agrícola respectivamente. La otras dos áreas que pasaron de Terrenos Agrícolas a Rotación Cultivo-Pradera en el panel del 2009, también contienen asentamientos de plantaciones de bosques. Estos cambios pudieron deberse a la escasez de agua producto de la instalación de plantaciones de bosques de especies exóticas de alto consumo de agua.

Forestry expansion has occurred at the expense of agriculture and pasture land-uses

Percentage	(1)	(2)	(3)	(4)
	Agriculture	Pasture	Wetland	Native forest
Forestry	-0.388 (0.034)***	-0.609 (0.036)***	0.000 (0.004)	0.003 (0.014)
Year	-0.024 (0.271)	-0.231 (0.289)	-0.041 (0.029)	-0.138 (0.111)
Constant	29.362 (0.660)***	35.804 (0.702)***	0.854 (0.070)***	21.824 (0.269)***
Observations	232	232	232	232

\*\*\* p<0.001; \*\* p<0.005; \*p<0.010



Forestry expansion reduces:

- employment, particularly in non-forestry agricultural activities,
- reduces labor earnings and the probability of finding formal jobs

<i>Urbano y Rural</i>		(1)
	In_income	
forestry_sd	-0.213*** (0.076)	
Mean(y)	12.395	
N	25657	

<i>Urbano</i>		(2)
	In_income	
forestry_sd	-0.340*** (0.085)	
Mean(y)	12.080	
N	9395	

<i>Rural</i>		(2)
	In_income	
forestry_sd	-0.145** (0.072)	
Mean(y)	12.578	
N	16262	

Standard errors in parentheses  
= \* p<0.1, \*\* p<0.05, \*\*\* p<0.01"

# 2

# Predicciones de incendios forestales

Variable dependiente:

- Incendios forestales (dicotómica)

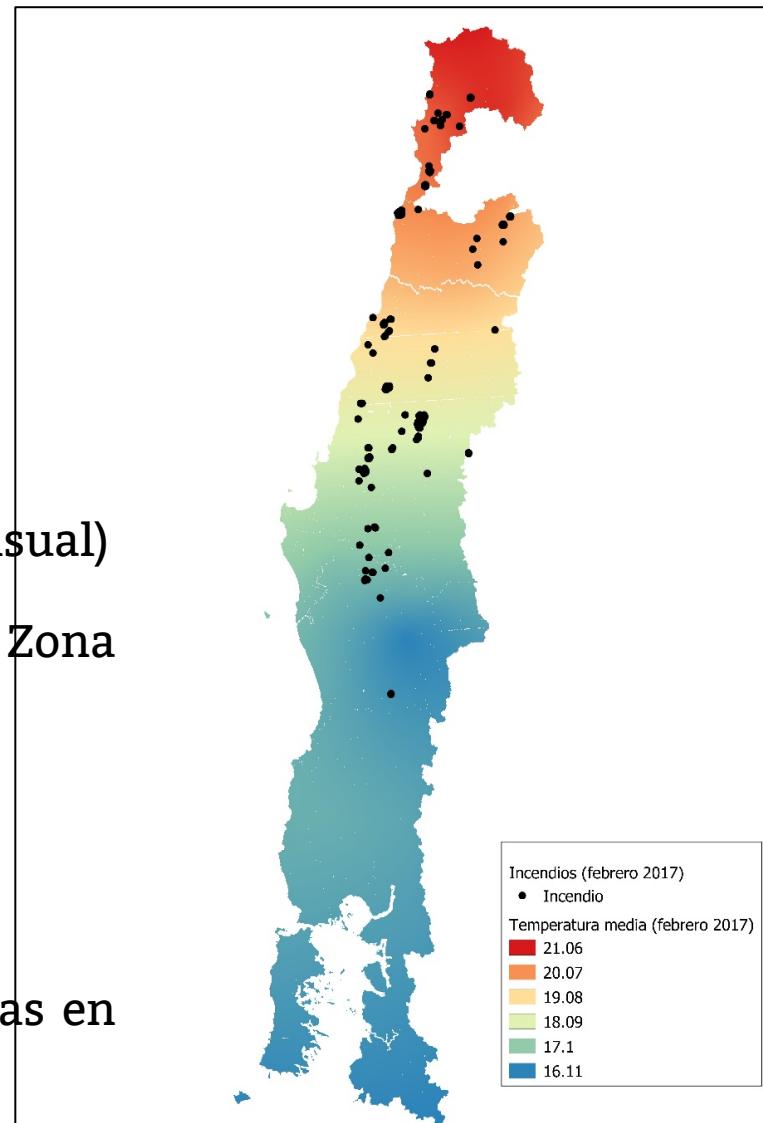
Variables independientes:

- Meteorológicas (precipitaciones mensuales y temperatura media mensual)
- Geográficas (Altitud, Pendiente, Rugosidad, TRI)
- Uso de suelos (Áreas protegidas, Áreas forestales, Bosque nativo, Zona agrícola, Pasturage, Humedales)
- Dummys de mes (mes\_1, mes\_2, mes\_3)

Random forest:

- Número de árboles a estimar: 100
- Training set: muestra aleatoria del 70% de observaciones
- Testing set: muestra aleatoria del 30% de observaciones (no incluidas en training set)

Temperatura media e incendios en febrero de 2017



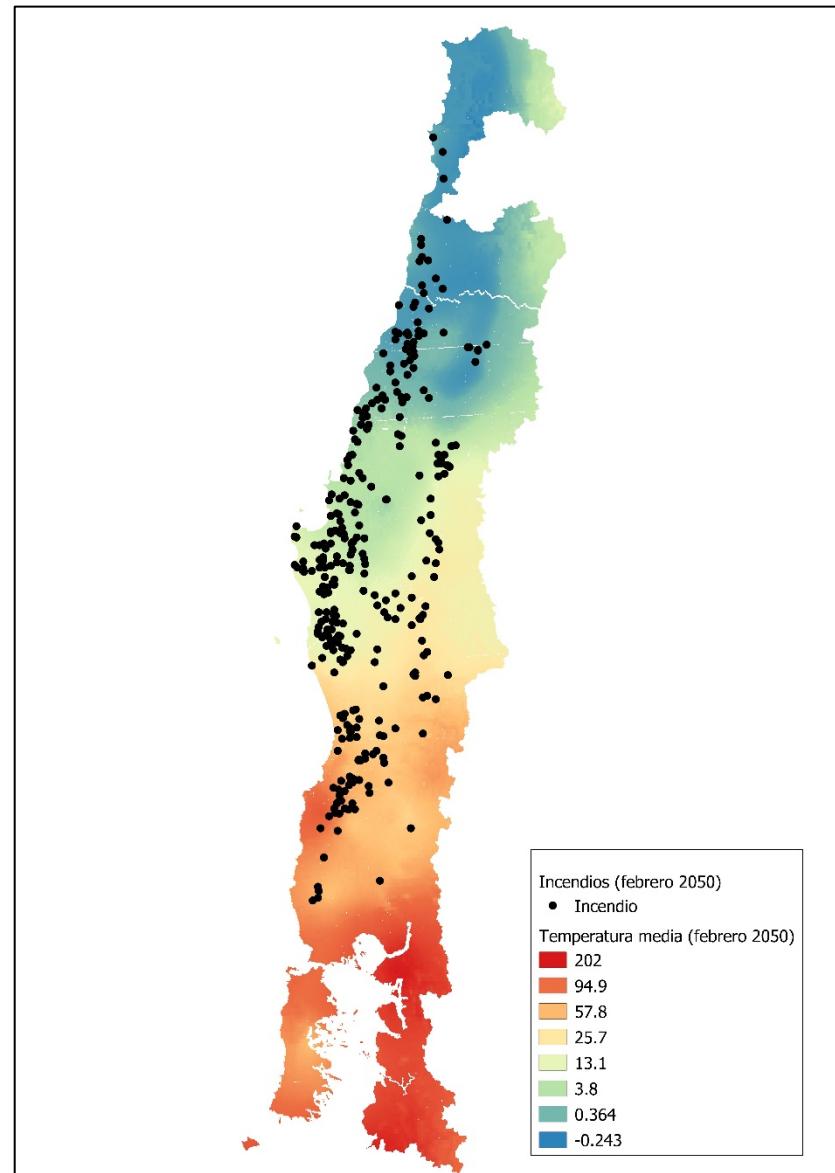
# Incendios forestales y cambio climático (preliminar)

Para predecir la ocurrencia de incendios en zonas forestales en 2050 en un contexto de cambio climático, se realizó lo siguiente:

- Se descargaron y procesaron los datos históricos de clima de 1970-2000 de WorldClim
- Se hizo match con la base de escenarios climáticos y se calcularon las variaciones en temperatura y precipitaciones para el escenario más drástico (rcp85):  $\text{var\_temp\_rcp85} = (\text{temp\_rcp85}/\text{temp\_1970\_2000})$ .
- Posteriormente se agregaron las variaciones a la base con datos de estaciones meteorológicas y se calculan las posibles temperaturas de chile en 2050 ( $\text{temp\_2017} * \text{var\_temp\_rcp85}$ ).

Con esta base (y agregándole variables geográficas y de uso de suelo) se prueba el modelo previamente estimado.

Incendios 2050 y Forestales



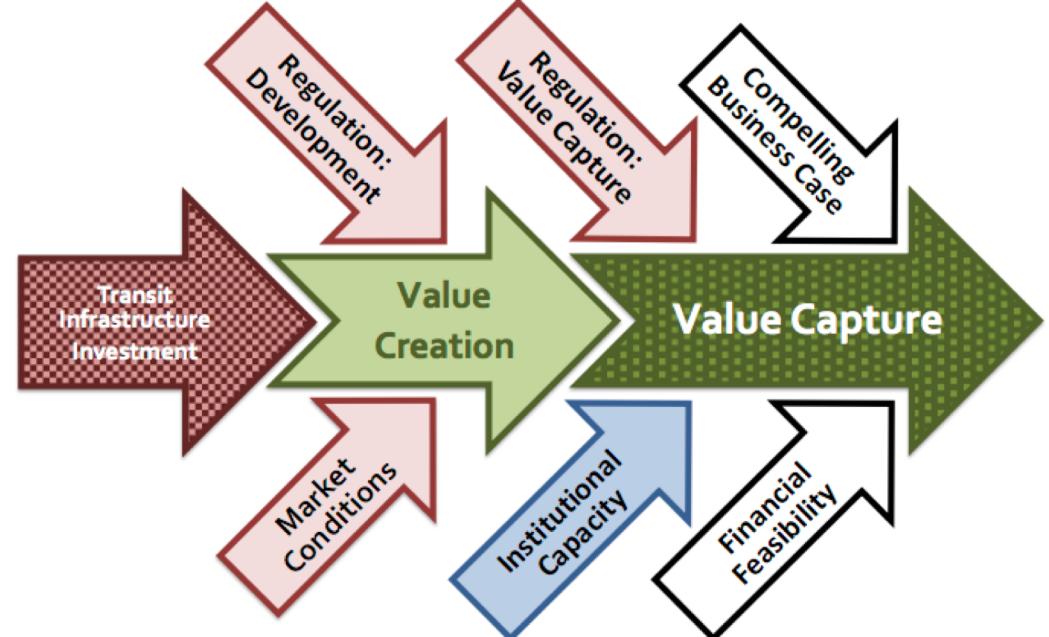
# 3

## Main Question

How much should we ‘capture’ in property taxes from public investment in green areas?

## Main Goal

Revealing how much people is willing to pay can help in creating a plan and advocating for urban renewal



- Non Parametric
  - Locally Weighted Regression (LWR)

$$\sum_{i=1}^n (y_i - \alpha - \beta'(x_i - x))^2 K(\psi_i)$$

$$Z_i = \begin{pmatrix} 1 \\ x_i \end{pmatrix} \quad \theta = \begin{pmatrix} \alpha \\ \beta \end{pmatrix}$$

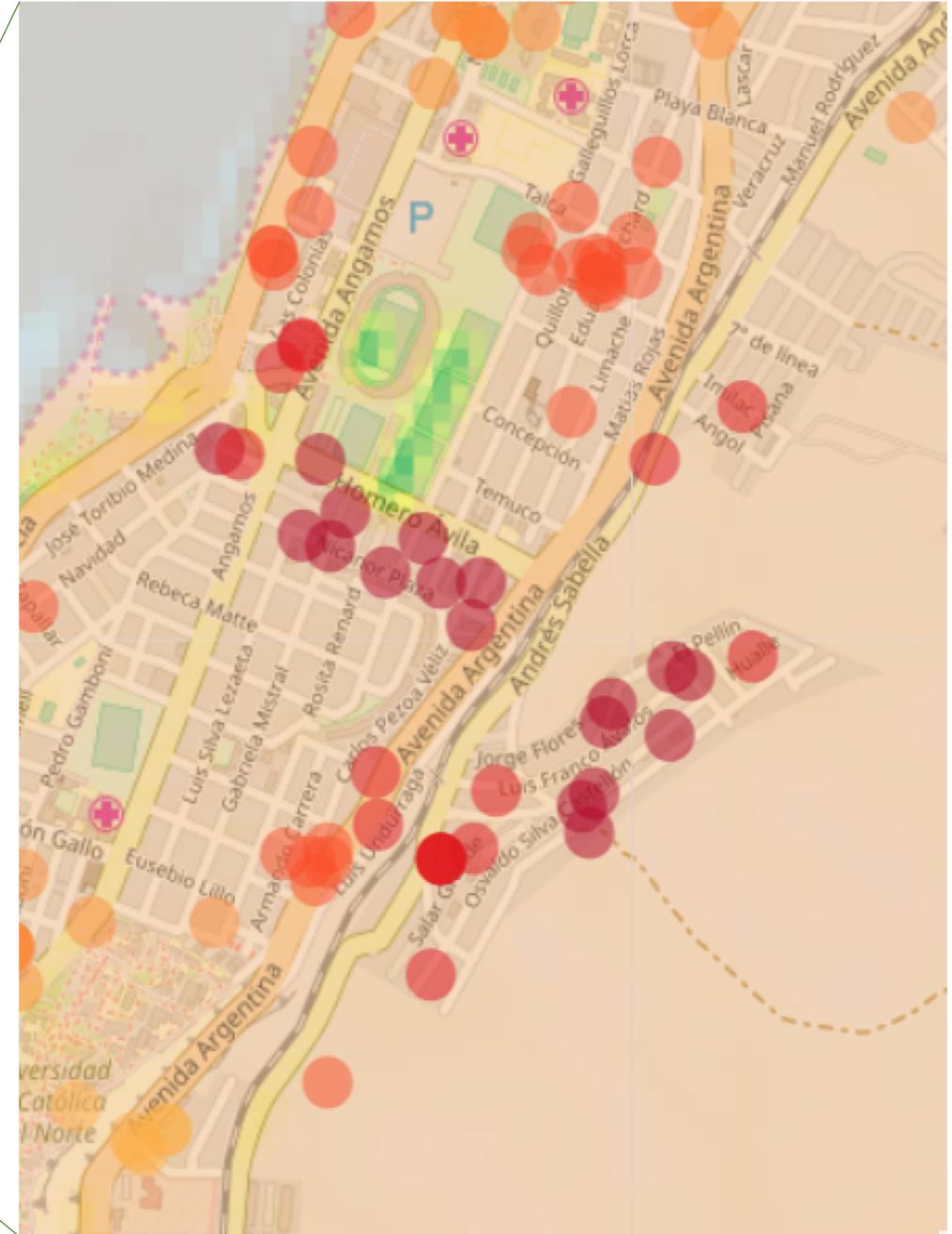
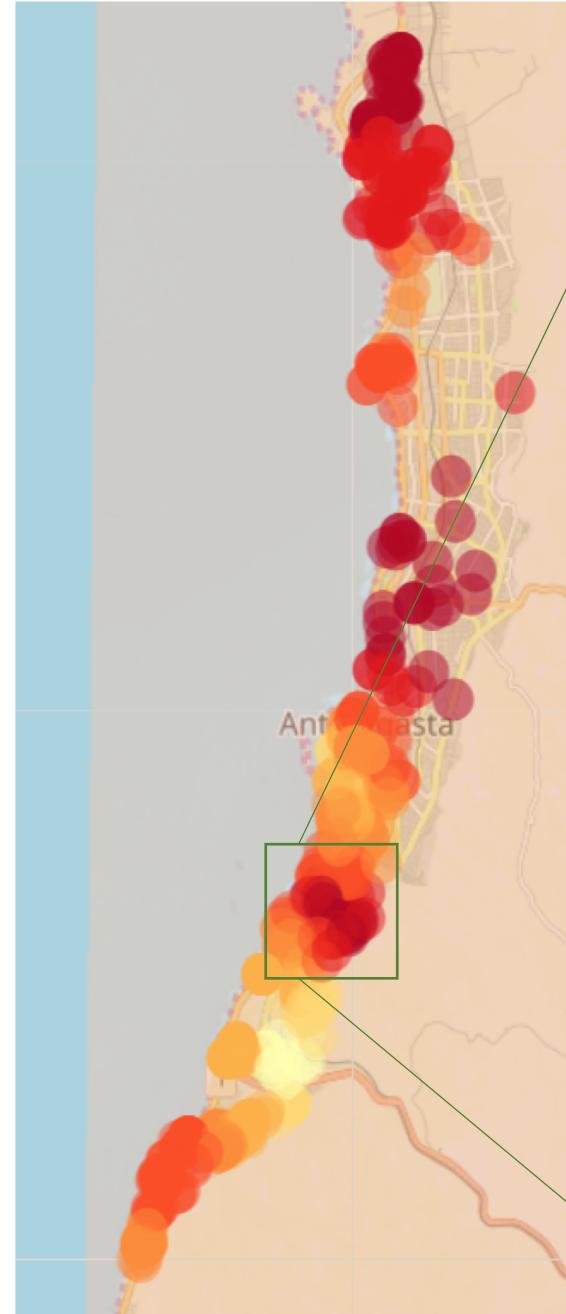
$$\hat{\theta}(x) = (\sum_{i=1}^n K(\psi_i) Z_i Z_i')^{-1} \sum_{i=1}^n K(\psi_i) Z_i' y_i$$

A regression of  $w_y$  on  $w_z$ , where

$$w_i = K \left( \frac{x_i - x}{h} \right)^{1/2}$$

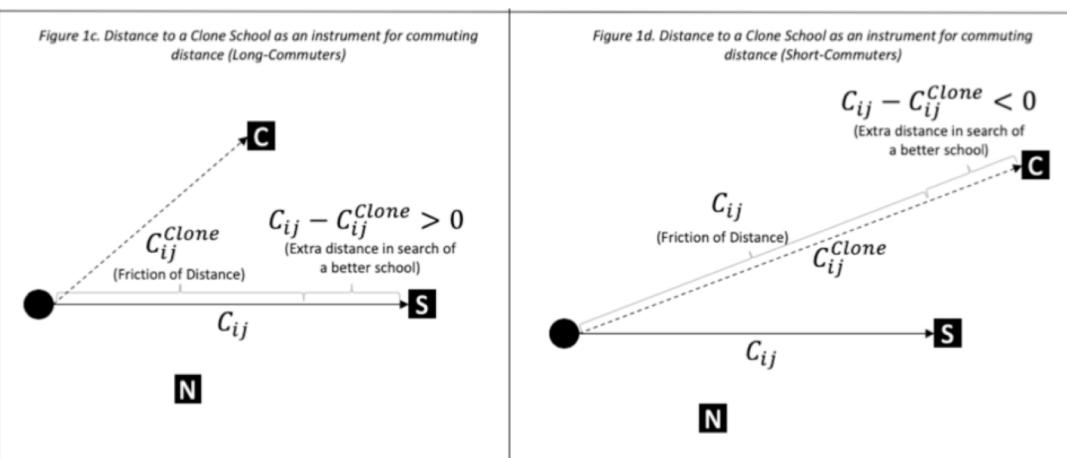
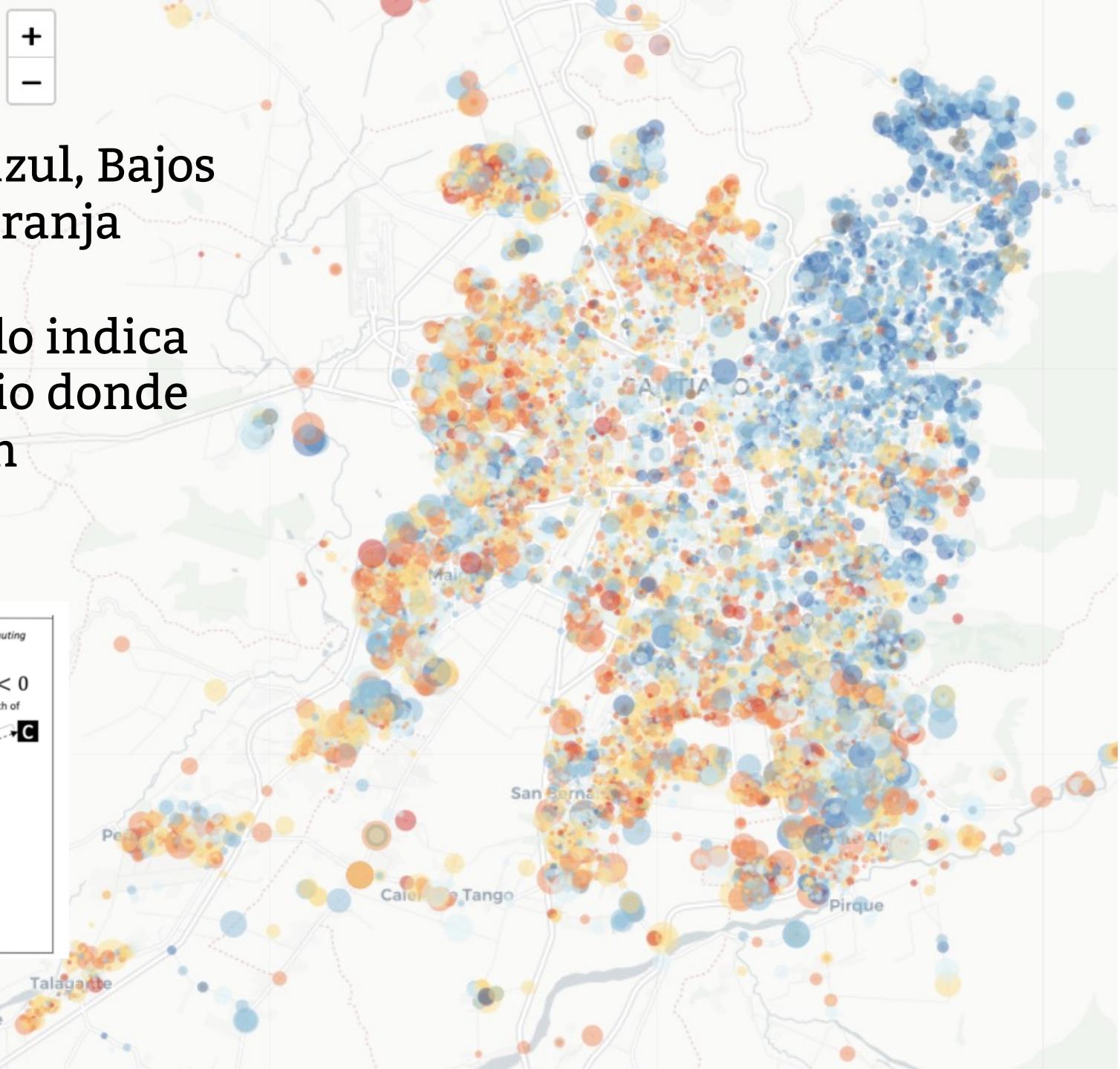
Each point is a housing unit colored by the willingness to pay for closeness to green areas

More red colors indicate higher willingness to pay



# 4

## PSU 2010 Altos puntajes en azul, Bajos puntajes en naranja



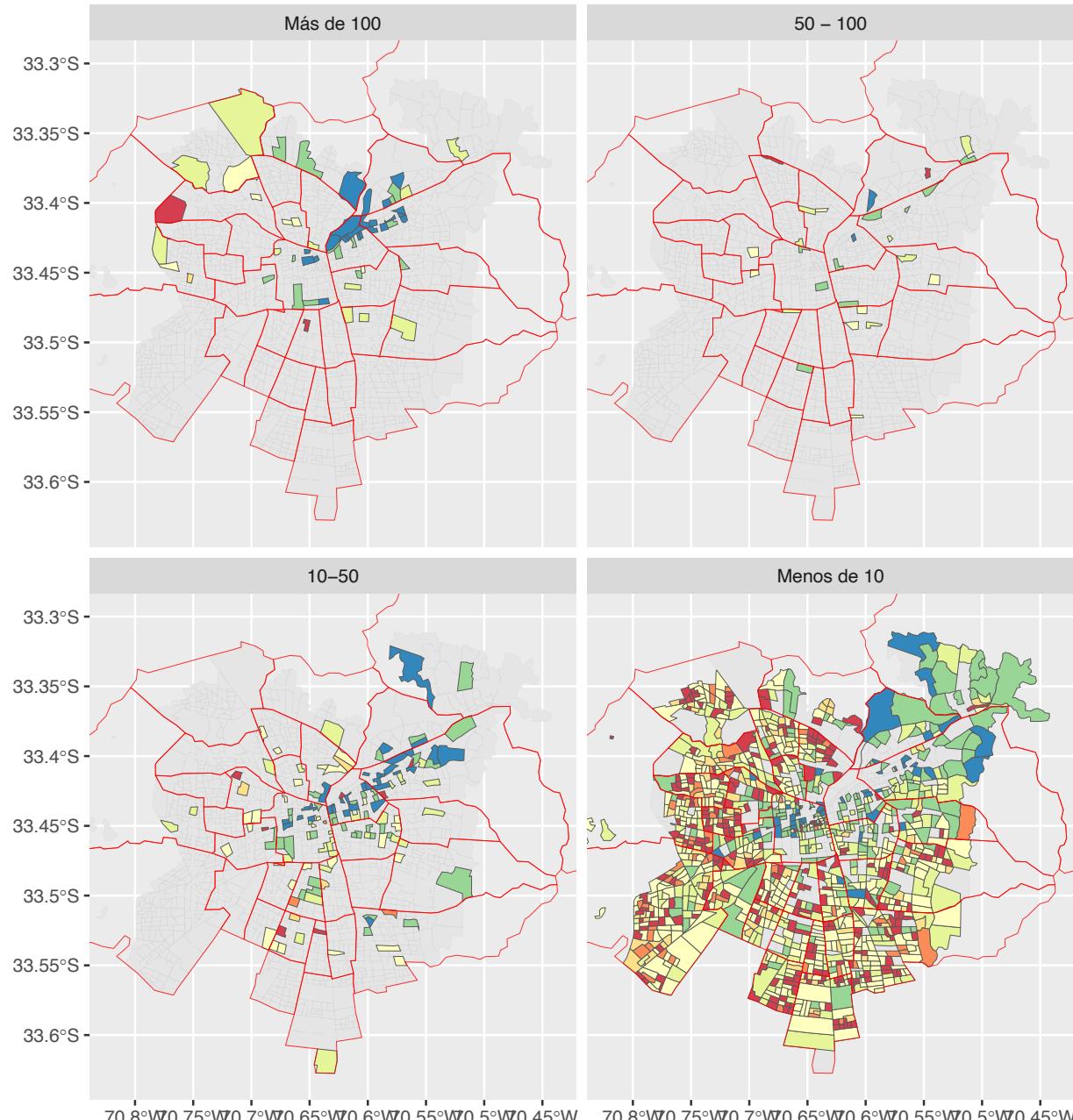
## Bonus

La mayoría de las personas cubiertas por la LPE están en áreas que hasta el 6/07 tenían baja movilidad y que son de mayores ingresos.

Potencial pérdida de empleo en las áreas de residencia de mayor poder adquisitivo

Desafíos importantes de movilidad y organización de la reapertura

Movilidad y Ley de Protección del Empleo (LPE)  
Segmentación de zonas censales por número de trabajadores adscritos a la LPE



4



# Testing the accuracy of machine learning methods to predict deforestation spatial patterns using Monte Carlo simulations

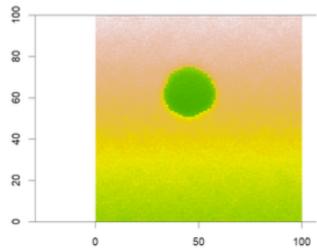
Ivan Flores

Department of Agricultural and Consumer Economics  
University of Illinois at Urbana-Champaign

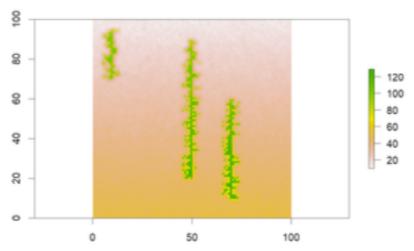
June 07, 2020

## Methods & Data

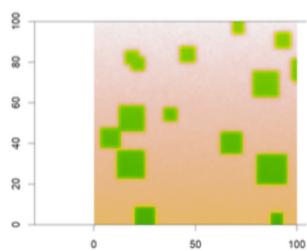
- Variation in lags (0, 0.5, 0.9) and  $W$  definition (Queen, Rook)
- Simulated data



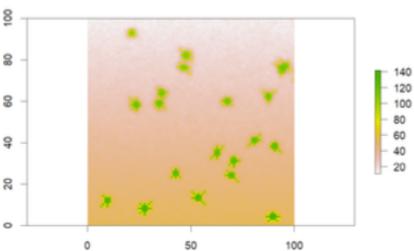
(a) Radial



(b) Fish-bone



(c) Geometric



(d) Diffuse

Ivan Flores ( UIUC )

ML deforestation prediction

06/07/20

## Spatial patterns of human activities

### • Fish-bone

- Perpendicular smaller roads spawn from a main road simulating the structure of a fish spine
- Related to new colonizations and planned movements as well as early stages of illegal activities such as logging and mining (Solinge, 2014)



(a) 2000



(b) 2010



(c) 2019

Figure 3: BR-163, State of Pará, Brazil

# Practical example

Fork: <https://github.com/estebanlp/Intro2SpatialAnalytics.git>