Housing market impacts of air pollution

Do objective or subjective measures of air quality matter?

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Motivation

- Agglomeration economies presents important positive externalities (Glaeser, 1998; Duranton and Puga, 2004):
  - Reduction of transportation costs
  - Higher flow of information
  - Greater specialization and division of labor

- Diseconomies of agglomeration are the opposite (Da Schio et al., 2019):
  - Overcrowding
  - Congestion
  - Ecosystem degradation $\Longrightarrow$ air pollution

- Air pollution has important negative effects on several socioeconomic variables:
  - Health (Cohen et al., 2017; Wei et al., 2022)
  - Education (Sunyer et al., 2015; Zhang et al., 2018)
  - Labor (Poudyal et al., 2013; He et al., 2019)
  - Housing market (Wang and Lee, 2022; Wang et al., 2022)

- Analyzing the effect of air pollution on the housing market is important for several reasons (Wang et al., 2022):
  - Property values: air pollution can negatively impact the desirability of neighborhoods
  - Health impacts: poor air quality is linked to various health issues, which can affect residents' quality of life
  - Urban planning: city planners and policymakers can use this analysis to promote sustainable urban development
  - Community awareness: highlighting the impact of air pollution on housing can raise public awareness

Overall, understanding how air pollution affects the housing market is crucial for economic stability, public health, and effective urban planning

Motivation

- Research on the effects of air pollution on the housing market is based on the theory of the Hedonic Price Method of Rosen (1974). However, empirical research has focused attention on objective measures of pollution, while subjective indicators based on people's perceptions have received less attention

- Three relevant aspects justify the inclusion of subjective variables to estimate the impact of air quality on real estate markets:
    - Objective and subjective air quality measures are not strictly related (Berezansky et al., 2010)
    - Neighborhood halo effect (Brody et al., 2004) $\Longrightarrow$ people tend to overestimate ambient conditions by place attachment affecting the housing market
    - The importance of subjective variables in assessing the impact of public policies on well-being (Kahneman et al., 1997)

Contribution

- This paper contributes to the literature on the effects of environmental amenities on the housing market, including subjective and objective metrics of air quality
- We offer new empirical evidence on the effects of subjective metrics of air quality on housing market, understanding how perception about the enviroment differ from objective measures and the different effects that may exist on housing market
- Using data at the intra-urban level in Medellín (Colombia) on a sample of dwellings, we identified the effect of objective and subjective metrics of air pollution on housing market through spatial hedonic models correcting different possible causes of endogeneity

Relevant literature

There are few papers in the literature that estimate spatial hedonic models that incorporate both objective and subjective indicators of air quality

- Chasco and Le Gallo (2013, 2015)
    - Madrid (Spain)
    - Objective indicator: several types of air pollutants $(SO_2, NO_x, NO_2, CO, PM)$
    - Subjective indicator: population's perception of pollution
    - Spatial quantile and multilevel models
    - Housing prices are better explained by subjective evaluation factors than by objective measurements
- Montero et al. (2018)
    - Madrid (Spain)
    - Only included subjective indicator: population's perception of pollution
    - Spatial parametric and semiparametric models
    - Strong negative impacts of subjective evaluation of air pollution on housing market

This paper aims to offer new evidence on the effects of environmental amenities on the housing market, including subjective and objective metrics of air quality in a spatial hedonic model in the context of a developing-country city

Data and descriptive evidence

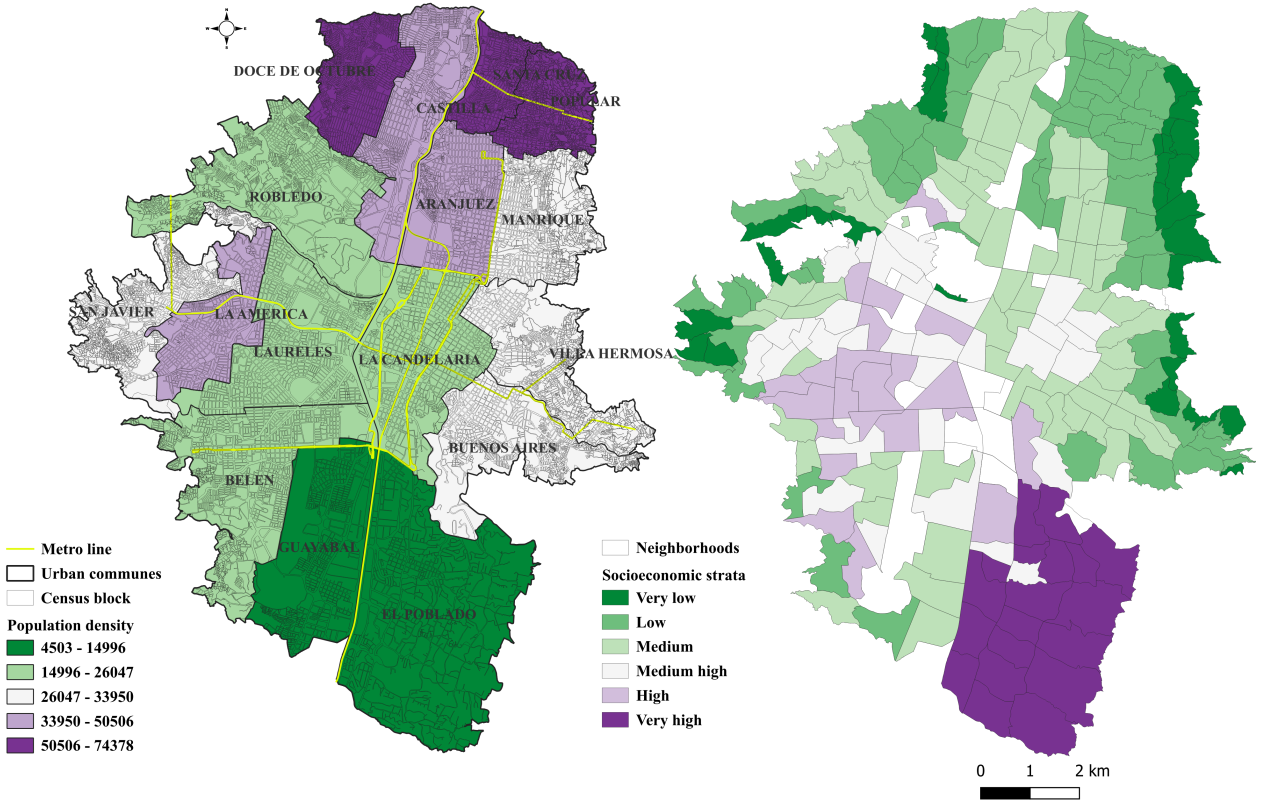
Study area: Medellín (Colombia)

- Population: 2.5 millions (Colombia: 49 millions; Bogotá: 7 millions)
- Area: 380 km2 (Colombia: 1,141,748 km2)
- Density: 6640/km2 (Bogotá: 4531/km2)
- Administrative division: 16 communes and 243 neighborhoods

Figure 1. Study area: Medellín

A. Population density

B. Distribution of income categories

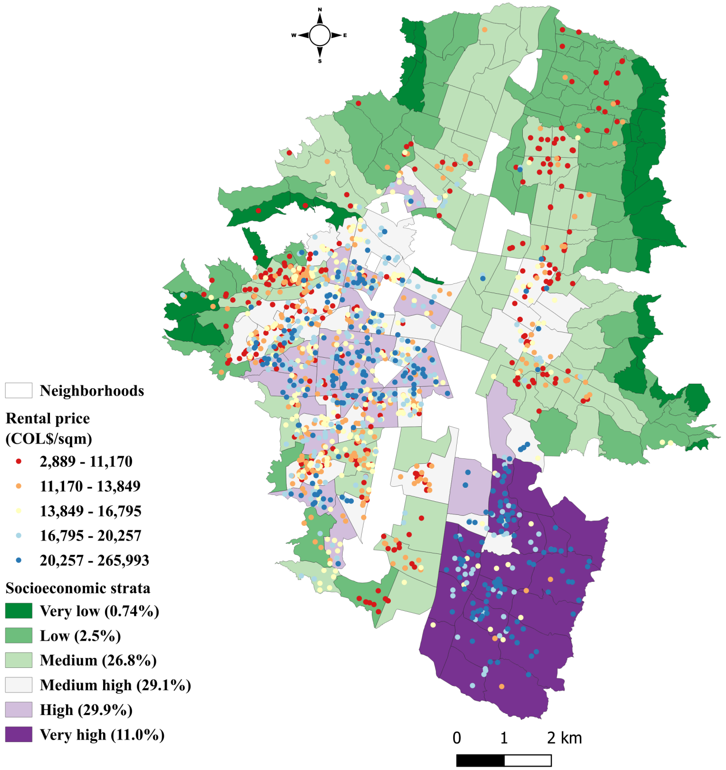


Data and descriptive evidence

Housing market

- The data used in this paper came from the Medellín Real Estate Observatory (OIME, *Observatorio Inmobiliario de Medellín*) in 2018
- The database contains information on the rental price, area in square meters, number of rooms, number of bathrooms, number of garages, quality of floors, and location of dwellings (coordinates XY)
- The sample includes a total of 1,745 dwellings, which are distributed in 146 neighborhoods (60% of the urban area of Medellín)

Figure 2. Spatial distribution of dwellings, rental prices and income categories



Data and descriptive evidence

Objective measure of air quality

- PM2.5: particulate matter with a diameter of 2.5 microns (μm)
- The information comes from SIATA (*Sistema de Alerta Temprana de Medellín y el Valle de Aburrá*) $\Longrightarrow$ 10 monitoring stations
- The average of the daily maximum for the worst quarter in 2017 (Anselin and Lozano-Gracia, 2008)
- Ordinary Krigin interpolation (Anselin and Le Gallo, 2007)

Subjective measure of air quality

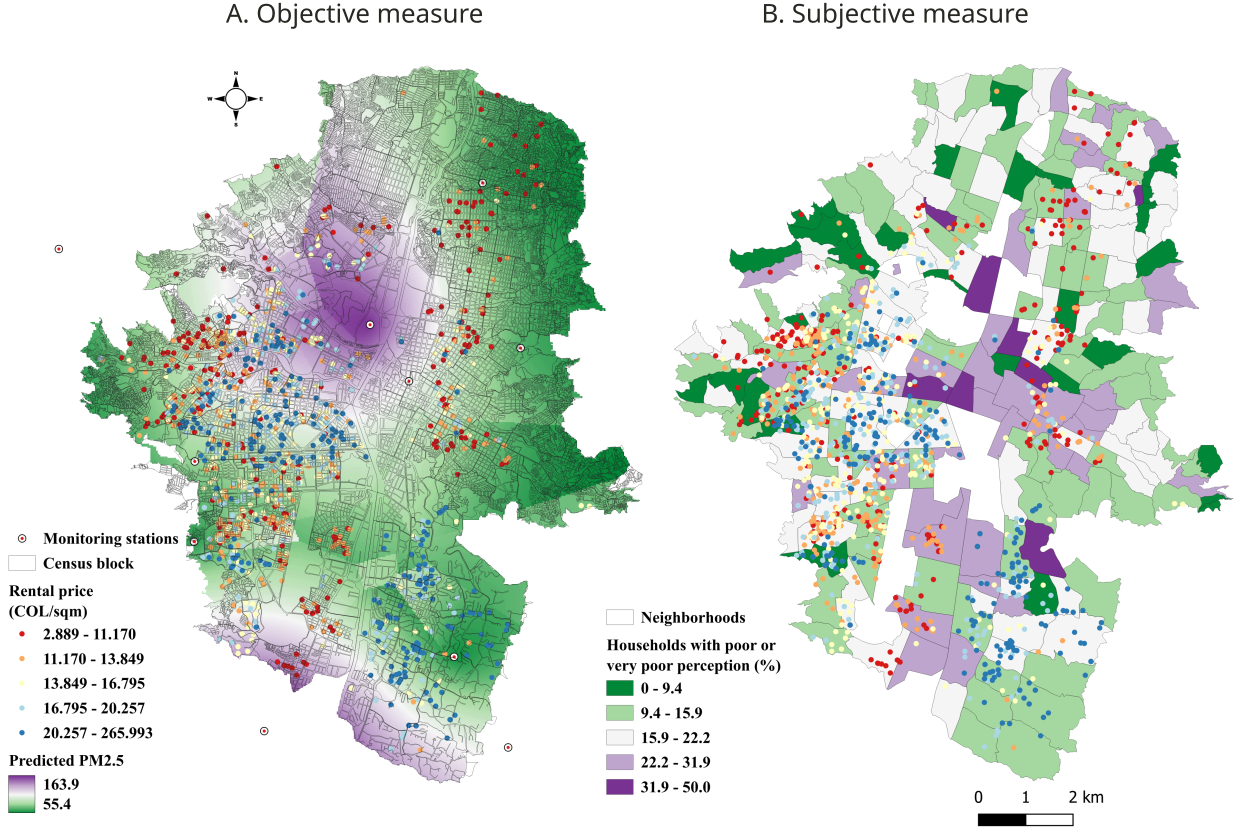
- Proportion of households in the neighborhood that consider air quality to be poor or very poor (Chasco and Le Gallo, 2013, 2015)
- The data used came from the Quality of Life Survey for Medellín in 2017 (ECV, *Encuesta de Calidad de Vida*). The sample includes a total of 42,806 individuals (12,205 households)

Air Pollution Index (API)

- API captures the interaction between the objective and subjective air quality variables
- Simple average between the objective and subjective air quality indicators (previously, the variables were scaled between 0 and 1)

Data and descriptive evidence

Figure 3. Measures of air quality and housing rental prices



The spatial distribution of air pollution shows that:

- $\Uparrow$ objective measure $\Longrightarrow$ northwest of the city
- $\Uparrow$ subjective measure $\Longrightarrow$ center of the city
- spatial differences between objective and subjective measures $\Longrightarrow corr(\text{PM2.5}, \text{perceived}) = 0.06,\ \text{Pvalor} = 0.02$

The spatial relationship between air pollution and housing rental prices shows that areas with high rental housing values (*El Poblado* and *Laureles*) present low levels of air pollution (both, PM2.5 and perceived)

Data and descriptive evidence

Table 1. Descriptive statistics

N = 1,745 dwellings

Variable	Mean	SD	P25	Median	P75	Min	Max
Rental price (COL$)	1,570,059	1,092,262	900,000	1,250,000	1,800,000	220,000	10,000,000
Rental price (COL$/sqm)	16,683	11,356	11,765	15,200	19,157	2,889	265,993
Air quality measures							
Objective measure (PM2.5, µm/cm)	96.93	19.27	82.19	92.93	107.46	60.82	148.53
Subjective measure (% households)	34.36	8.77	28.75	33.33	39.58	12.06	79.31
Control variables							
Structural characteristics of dwellings							
Area (m2)	98.77	55.89	64.00	85.00	118.00	12.00	439.00
# Bedrooms	2.80	0.91	2	3	3	1	9
# Bathrooms	2.09	0.83	2	2	2	1	6
Floor quality: good	0.23	0.42	0	0	0	0	1
Floor quality: medium	0.65	0.47	0	1	1	0	1
Floor quality: bad	0.12	0.31	0	0	0	0	1
Amenities at the census block level							
Distance to the nearest metro station (mts)	12.29	7.45	6.70	10.74	16.68	0.42	39.02
Tertiary education (%)	52.63	14.78	43.80	54.90	63.90	0	84.40
Homicide rate (per 10,000 people)	0.05	0.53	0	0	0	0	10.39
Unemployment rate (%)	6.38	4.47	3.22	5.41	8.58	0	47.44
Instrument variable							
Wind direction (degrees)	145.91	11.24	140.93	149.35	154.57	118.01	159.26

Notes: Floor quality: good: porcelain or marble; medium: ceramics or granite; bad: tile or cement.

Econometric model

The hedonic price model to be estimated is as follows:

$$log(Rental\ price_i) = \alpha + \beta AP_i + \mathbf{S}_i'\boldsymbol{\omega}_1 + \mathbf{N}_j'\boldsymbol{\omega}_2 + u_i$$

$Rental\ price_i$: housing rental price of dwelling i
AP_i: air pollution measure in dwelling i: objective measure, subjetive measure or API
$\mathbf{S}_i$: a matrix of structural characteristics of each dwelling i
$\mathbf{N}_j$: a matrix of amenities in each census block j
$\boldsymbol{\omega}_1, \boldsymbol{\omega}_2$: vectors of coeffecients to estimate
u_i: error term

Our coefficient of interest to estimate is β, which represent the effect of air pollution on the housing market

Econometric model

To account for spatial dependence in the hedonic price model, we estimate three types of spatial models:

Spatial Lag Model (SLM)

$$log(Rental\ price_i) = \alpha + \beta AP_i + \mathbf{S}_i'\boldsymbol{\omega}_1 + \mathbf{N}_j'\boldsymbol{\omega}_2 + \gamma W log(Rental\ price_i) + u_i$$

Spatial Error Model (SEM)

$$log(Rental\ price_i) = \alpha + \beta AP_i + \mathbf{S}_i'\boldsymbol{\omega}_1 + \mathbf{N}_j'\boldsymbol{\omega}_2 + u_i$$

$$u_i = \rho W u_i + \epsilon_i$$

Spatial Autoregressive Combined Model (SAC)

$$log(Rental\ price_i) = \alpha + \beta AP_i + \mathbf{S}_i'\boldsymbol{\omega}_1 + \mathbf{N}_j'\boldsymbol{\omega}_2 + \gamma W log(Rental\ price_i) + u_i$$

$$u_i = \rho W u_i + \epsilon_i$$

Where W is a matrix $(i \text{ x } i)$ of spatial connectivity among dwellings, which is measured as six nearest neighbors (NN=6)

Econometric model

Estimating the proposed hedonic model may face two problems related to endogeneity due to (Anselin, 1988; Anselin and Lozano-Gracia, 2009):

- measurement errors in contamination levels by the interpolation and subjective responses
- the inclusion of spatially lagged dependent variable $(W log(Rental\ price_i))$

To deal with these endogeneity problems, we use an Instrumental Variable (IV) approach (Chay and Greenstone, 2005; Bayer et al, 2006; Lee, 2006):

- we use the wind direction as an instrument for the measures of air pollution $\Longrightarrow$ air pollutions is affected by meteorological factors and wind can be helpful in dispersing pollutants (Deryugina et al., 2019; Bondy et al., 2020; Carneiro et al., 2021; Jon et al., 2023) ⏭
- endogeneity problem associated with the inclusion of a spatial lag in the models is corrected including spatial lags of a superior order of control variables (Kelejian and Robinson, 1993; Kelejian and Prucha, 1998; Fingleton and Le Gallo, 2008). $\Longrightarrow$ spatial lags of order 2 (López et al., 2020)

We use spatial two-stage least squares (S2SLS) to estimate the models and use a robust heteroskedastic estimator to correct standard errors

Results

Table 2. Estimates of hedonic price model

$Y = log(Rental\ price)$

	Model 1					Model 2					Model 3				
	No spatial models		Spatial models (IV)			No spatial models		Spatial models (IV)			No spatial models		Spatial models (IV)		
	OLS	IV	SAR	SEM	SAC	OLS	IV	SAR	SEM	SAC	OLS	IV	SAR	SEM	SAC
Objective measure	-0.055*	-0.674***	-0.220***	-0.218*	-0.226***										
	(0.0334)	(0.0678)	(0.0589)	(0.1245)	(0.0650)										
Subjective measure						0.160***	1.925***	-0.357***	0.342	-0.383**					
						(0.0484)	(0.3273)	(0.1375)	(0.3432)	(0.1485)					
API											-0.028	-1.485***	-0.604***	-0.318	-0.629***
											(0.0550)	(0.2285)	(0.1269)	(0.2802)	(0.1361)
$Wlog(Rental\ price)$			0.377***		0.383***			0.395***		0.401***			0.393***		0.400***
			(0.0278)		(0.0291)			(0.0296)		(0.0310)			(0.0282)		(0.0233)
ρ				0.534***	0.107*				0.521***	0.125*				0.541***	0.187***
				(0.0301)	(0.0557)				(0.0336)	(0.0681)				(0.0311)	(0.0597)
N	1745	1745	1745	1745	1745	1745	1745	1745	1745	1745	1745	1745	1745	1745	1745
LM tests of spatial dependence															
LM_{SLM}	266.8***					257.0***					268.3***				
Robust LM_{SLM}	126.3***					119.8***					125.6***				
LM_{SEM}	181.1***					178.9***					185.0***				
Robust LM_{SEM}	40.7***					41.7***					42.3***				
LM_{SAC}	307.5***					298.7***					310.7***				
Diagnostic tests of the instrumental variable (wind direction)															
Weak instruments		124.1***					69.7***					157.4***			
F-stat first stage		414.1***					21.4***					169.4***			

Notes: All models include the set of control variables mentioned in Table 1. Robust heteroskedastic standard errors in parenthesis. Spatial models are estimated by spatial two-stage least squares (S2SLS). We instrument air pollution measures using wind direction. The inclusion of spatial lag in the models is instrument using lag of order 2 of control variables. In the spatial models we use a W matrix measuring the spatial connectivity as six nearest neighbors (NN=6) among dwellings. *p<0.1; **p<0.05; ***p<0.01.

- In general, the results show that air pollution present a negative and significant effect on housing rental price
- When spatial dependence is consider in different structures, subjective air pollution measure shows a larger negative effect on housing market compared to the effect of objective metric, and the magnitude of the effect is amplified with the interaction of the subjective and objective variables

Results

Table 3. Direct and indirect spillovers effects

	SAR			SAC		
	DE	IE	TE	DE	IE	TE
Objective measure	-0.225***	-0.128***	-0.354***	-0.227***	-0.026***	-0.254***
	(0.0011)	(0.0004)	(0.0016)	(0.0014)	(0.0001)	(0.0015)
Subjective measure	-0.366***	-0.224***	-0.590***	-0.384***	-0.054***	-0.439***
	(0.0007)	(0.0003)	(0.0010)	(0.0008)	(0.0001)	(0.0009)
API	-0.620***	-0.376***	-0.997***	-0.632***	-0.142***	-0.775***
	(0.0013)	(0.0005)	(0.0018)	(0.0014)	(0.0002)	(0.0017)

Notes: DE: direct effects; IE: Indirect effects; TE: Total effects. Standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

- The estimated direct effects of air pollution on housing market confirm our previous findings that housing rental prices are more affected by subjective evaluation factors than by objective measurements
- The indirect effect (or spillover effect) of air pollution on housing rental prices is also negative and statistically significant, indicating that the rental price of one dwelling is affected by the level of air pollution of neighboring dwellings
- These results confirm that housing decisions are subject to perceptions of place and it is important to consider the spillover effects of air pollution on housing market

Conclusions

- In this study we analyze the effects of environment amenities on the housing market, evaluating the importance of perception of air quality on housing rental price in the context of a developing-country city, Medellín (Colombia)

- From a point of view of the spatial distribution of objective and subjective metrics of air pollution and their relationship with housing market, we found:
  - Spatial differences between objective and subjective measures
  - Areas with high rental housing values present low levels of air pollution (both, objective and perceived air quality)

- The estimates of the spatial hedonic price models showed that housing rental prices are more affected by subjective evaluation factors than by objective metrics

- Additionally, there are spatial spillover effects of air pollution on housing rental prices $\Longrightarrow$ This suggests that air pollution present important negative effects on housing market, so that a city policy is needed in Medellín to reduce air pollution and its effects

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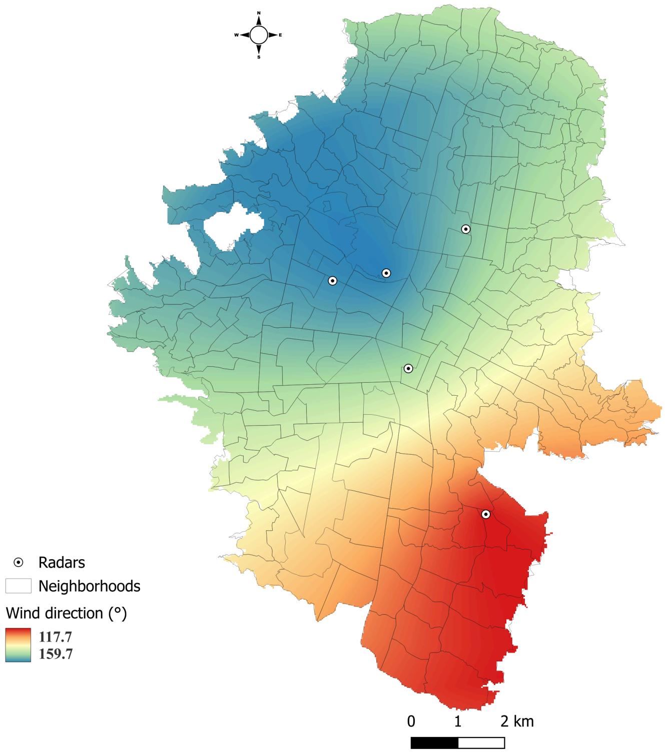
Slides in html

Slides in PDF

Instrument construction: wind direction

- Data: SIATA, five meteorological stations in Medellín
- Annual average of wind direction in 2017
- Ordinary Krigin interpolation to obtain a continuous map of wind direction throughout the city

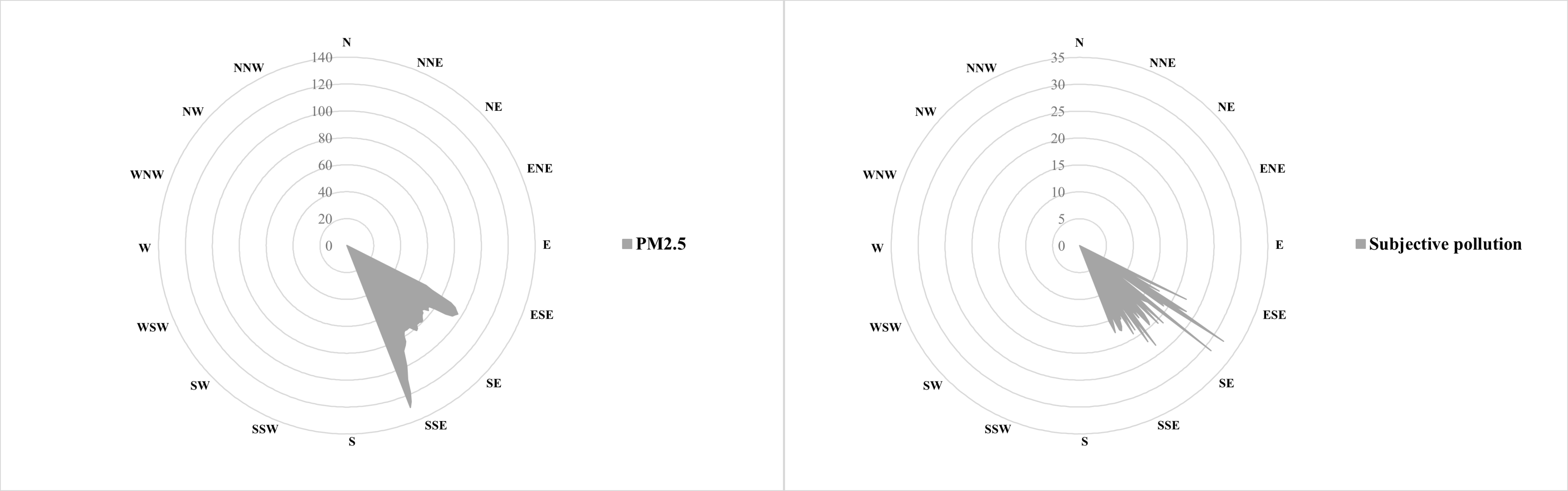
Figure 4. Wind direction



- Wind direction is reported as the direction the wind is coming from and it is measured in degrees
- In our case, wind direction in Medellín is between 118° and 160°, which indicates that winds are coming from the Southeast

Instrument construction: wind direction

Figure 5. Wind rose driagrams between wind direction and objective and subjective measures of air quality



The idea is that whether the wind is parallel or perpendicular to the road (in upwind or downwind direction) could influence air quality (Zhou and Levy, 2007)