École Nationale de Statistique et Analyse de l'Information

Data science, Economic Modeling and Health

Course :Spatial Econometrics

Economic growth and environmental quality: the case of West African countries

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Acronyms and Abbreviations

ECOWAS	Economic Community of West African States
ENSAI	Ecole Nationale de la Statistique et de l'Analyse de l'Information
EKC	Environmental Kuznets Curve
PM2.5	Particulate Matter 2.5
SAR	Spatial Auto Regressive
SARAR	Spatial Auto Regressive with additional Auto Regressive error structure
SEM	Spatial Error Models

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Introduction

With the two oil crises of 1973 and 1979 and the Meadows report (1972) by the Club of Rome's, the issues of natural resource management and environmental preservation began to be integrated by each state in their development process. Indeed, the effects of pollution are numerous, both on health and on the climate. According to the WHO, air pollution is the main environmental risk to health in the world. Thus, exposure to outdoor air pollution leads to the death of approximately 4.2 million people worldwide each year. Since 2013, outdoor air particles are classified as carcinogenic to humans by the International Agency for Research on Cancer (IARC). The toxicity of these particles comes from both their composition and their size. For example, in the long term it is estimated that particulate matter (PM) could result in the development of cancers (lung, bladder), cardiovascular and respiratory diseases, neurodevelopment of children, diabetes. Similarly, CO2 is considered the primary factor in global warming. Indeed, the impact of CO2 and methane on climate change are well known: they absorb solar radiation, reinforcing the greenhouse effect, hence the name greenhouse gases (GHG). For example, a motor car emits carbon dioxide (CO2), lead, benzene, particulates and nitrogen oxides. These products are toxic and harmful to our health, but also to the environment.

Therefore, numerous policies have been put in place at both national and international levels in order to take into account the environmental factor in development guidelines. Today, we talk about green growth or green economy. Since the environment and more generally the environmental quality is classified as a public good, all countries of the world are concerned by these issues. West African countries, which are for the most part considered developing countries, are even more concerned because studies have shown the existence of a relationship between development and environmental pollution. Indeed, one might think that economic growth will necessarily require more energy and materials, which will lead to ever higher levels of environmental degradation. Another view would be that economic growth can improve environmental quality through technological change and economies of scale in reducing pollution, changes in the composition of production, and increasing demand for environmental quality. Therefore, it is important for developing countries, particularly West African countries, to improve this relationship in order to adjust their policies to ensure sustainable development.

In our study, we are interested in studying the relationship between economic development, as measured by night time light, and environmental pollution, as measured by various indicators, in West African countries, taking into account the spatial dimension. The rest of our study will be structured as follows: we will begin by reviewing the existing literature on this subject, and then in Chapter 2 we will present the data and variables used in our study. Chapter 3 presents some spatial descriptive statistics and Chapter 4 the results of our estimations.

Chapter 1

Review of the literature

The literature on the relationship between environmental quality and economic growth has been widely discussed in recent years. The main finding of the studies on the issue is the existence of an inverse U-shaped relationship, commonly referred to as the Environmental Kunzets Curve (EKC) between various pollution indicators and per capita income (Grossman and Krueger 1991, Hettige, Mani and Wheeler 2000, Zaim and Taskin 2000,Zhao et al. 2016, Kharbach and Chfadi 2017...). It states that the level of GDP per capita has a negative effect on environmental quality (measured by pollution levels) at low levels of GDP; but above a certain level, GDP per capita has a positive effect on environmental quality.The EKC has been the dominant approach among economists to modeling ambient pollution concentrations and aggregate emissions since Grossman and Krueger (1991) introduced it. Indeed, Grossman and Krueger (1991, 1995) studied the relationship between per capita income and various environmental indicators. Their study finds no evidence of a steady decline in environmental quality with economic growth. They show that indicators such as sulfur dioxide concentration, suspended particulate matter, biological oxygen, and economic growth show an initial increase, followed by an eventual decline, and exhibit an inverted U-shaped curve.

Conversely, several researchers argue instead that the relationship between pollution and income is monotonic (Stern and Common 2001; Stem 2002; Dasgupta et al. 2002; Azomahou, Laisney, and Van, 2006; Ozturk and Al-Mulali, 2015; ...). Stern and Common (2001) used a larger and more globally representative sample, rather than just sulfur dioxide emissions, and found that per capita sulfur emissions are a monotonic function of per capita income with a global sample and an inverted U-shaped function of income with a sample of high-income countries.

One of the challenges in studying the Kuznets environmental curve is the consideration of spatial relationships between units. Several authors have highlighted the importance to take care of the spatial dimensions in environmental measurements (Bockstael 1996; Goodchild et al. 2000; Anselin 2001). Indeed, several arguments in the literature support the importance of integrating a spatial dimension in the study of the relationship between development and pollution. First, according to Maddison (2005), it does not seem implausible to suggest that observations from geographically adjacent locations may be more closely related than those from geographically distant locations. Indeed, it is legitimate to think that neighboring areas would be more easily affected, either positively or negatively, and would share similar environmental burdens due to the environmental externality or similar production and consumption patterns. Moreover, spillovers induced by technological advancement or policy are more likely to benefit the nearest locations and then spread to adjacent areas (Hao, Liao, Wei, 2015; Hao, Zhang, Zhong, Li, 2015; Hao Liu, 2016).

Furthermore, public authorities in each country constantly evaluate their policies in relation to those of their neighbors in order to reduce the costs of decision-making and to legitimize their actions, especially when there is uncertainty about the effects of these policies. This has been seen in the recent health crisis. This can lead countries to imitate each other's environmental policies, resulting in similar environmental standards. Neighbors Fredriksson and Millimet, (2002) have shown that states in the United States increase their environmental standards in response to improvements in environmental standards by states. Some authors also argue that the shape of the EKC is a consequence of the fact that high-income countries actually export their pollution to lower-income countries (Rothman, 1998; Stern, 2004, 2017). According to Anselin (1988) ignoring spatial dependence leads to a misspecification of the model. He notes that the existence of spatial relationships in the data has important implications for the econometric techniques generally employed, including flawed inference testing procedures and thus could lead to potential bias. Stern and Common (2001) note in their study that when they use a global sample of countries, there is a monotonically increasing relationship between per capita emissions and per capita income. But when the data set is restricted to high-income countries, they obtain an inverse U-shaped relationship. In their study on carbon dioxide emissions.

Chapter 2

Presentation of data & variables

The data used in our study was obtained from GeoQuery. We focus our study on the Economic Community of West African States (ECOWAS) countries in 2013. Our variable of interest are mainly the pollution variables, some region specific informations such as the temperature, the precipitation and the nighttime light (variable that will be refered as night light in the next chapters).

The list of our 8 variables of interest and their signification is displayed in the Table below.

Table 2.1: Variable of interest description and signification

Variables	**Signification**	**Source**
shapeName	Regions names	
shapeGroup	Identifiant of Country	
Population	Population count (UN Adjusted values) from Gridded Population of the World v4	Socioeconomic Data and Applications Center (SEDAC)
Precipitation (*millimeters*)	Average monthly precipitation per year in millimeters. Created using UDel Precipitation dataset (v5.01)	University of Delaware
Temperature (*degrees Celsius*)	Average monthly air temperature per year in degrees Celsius. Created using UDel Air Temperature dataset (v5.01)	University of Delaware
Viirs_Average ($Radiance\ (nW cm^{-2} sr^{-1})$)	Annual VIIRS nighttime lights product Version 2. Average value with background pixels masked	Earth Observation Group - VIIRS Nighttime Light Link
PM2.5AirPollution ($concentration\ (ug/m^3)$)	Particulate matter (PM2.5) estimate, based on prediction model using combination of satellite -based estimate and TM5-FASST simulation	Ambient air pollution exposure estimation for the Global Burden of Disease 2013
OzoneAirPollution ($concentration\ (ug/m^3)$)	Ozone concentration from TM5 FASST simulation. Since the ozone (summer) season varies throughout the globe, it was calculated using a running 3-month average (of daily 1 hour max values)for each grid cell over a full year and the maximumof these values was selected.	Ambient air pollution exposure estimation for the Global Burden of Disease 2013

Other geographic variables (in shapefiles or/and geoJSON form) are used for our spatial analysis. Those variables were given from GeoQuary data request.

15 countries are considered in this study (they represent the 15 countries of ECOWAS in 2013. Morocco joined ECOWAS in 2017).There are 192 different regions (the detailed list is in the appendix B.1)

Table 2.2: Data description

	Overall
	(N=192)
shapeGroup	
BEN (Benin)	13 (6.8%)
BFA (Burkina Faso)	13 (6.8%)
CIV (Ivory Cost)	14 (7.3%)
CPV (Cape Verde)	22 (11.5%)
GHA (Ghana)	16 (8.3%)
GIN (Guinea)	8 (4.2%)
GMB (Gambia)	6 (3.1%)
GNB (Bissao-Guinea)	9 (4.7%)
LBR (Liberia)	15 (7.8%)
MLI (Mali)	9 (4.7%)
NER (Niger)	6 (3.1%)
NGA (Nigeria)	38 (19.8%)
SEN (Senegal)	14 (7.3%)
SLE	4 (2.1%)
TGO (Togo)	5 (2.6%)
Population	
Mean (SD)	1740000 (1960000)
Median [Min, Max]	982000 [5070, 11800000]
Temperature	
Mean (SD)	27.1 (1.64)
Median [Min, Max]	27.2 [21.2, 30.2]
Missing	28 (7.3%)
Precipitation	
Mean (SD)	107 (52.0)
Median [Min, Max]	96.5 [6.31, 260]
Missing	28 (7.3%)
PM2.5AirPollution	
Mean (SD)	30.4 (10.6)
Median [Min, Max]	28.6 [12.2, 107]
OzoneAirPollution	
Mean (SD)	58.1 (10.9)
Median [Min, Max]	56.1 [42.2, 78.8]
Viirs_Average	
Mean (SD)	0.356 (1.24)
Median [Min, Max]	0.0176 [0, 10.6]

Chapter 3

Statistical analysis

3.1 Descriptive Analysis

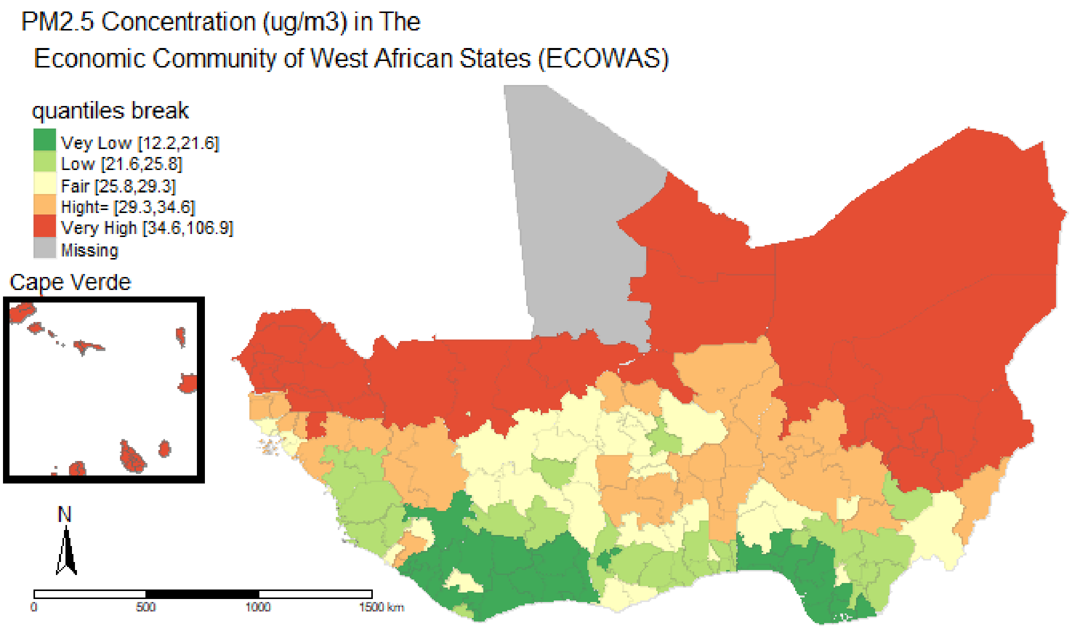


Figure 3.1: PM2.5 Concentration (ug/m3) in The ECOWAS
source:Ambient air pollution exposure estimation for the Global Burden of Disease 2013

The figure 3.1 depicts the PM2.5 concentration in the ECOWAS without any spatial statistic preprocessing. The repartition of PM2.5[1] concentration seem to be polazized in the ECOWAS. The north, maintly composed of country such as Niger, Mali and Senegal have a very high PM2.5 concentration. On the other side, the south with maintly the coastal countries have Low PM2.5 concentration. These observations could be due to many reason :

- Since PM2.5 represent liquid and solid polluant, it can include sand and dust. Knowing that sahara in in the North of ECOWAS, this could explain the high PM2.5 concentration
- Another explaination can be the presence of War and conflict but also uranium mining area in these regions. In 2013, Mali and Niger's north regions were armed conflict grounds.

To refine this descriptive analysis of PM.5, we studied the evolution of PM.5 according to temperature, precipitation, Population and Night light average level. (See the table 3.1 below)

[1]PM 2.5 refers to the size of the pollutant, in micrometers under 2.5 micrometer

Table 3.1: Region's group(based on their PM2.5 concentration (ug/m3) level) with certains caracteristics

	PM2.5 : Vey Low [12.2,21.6] (N=31)	PM2.5 : Low [21.6,25.8] (N=32)	PM2.5 :Fair [25.8,29.3] (N=35)	PM2.5 :Hight ([29.3,34.6] (N=36)	PM2.5 :Very High [34.6,106.9] (N=57)	Overall (N=192)
Temperature (°C)						
Mean (SD)	26.4 (0.659)	27.0 (0.893)	27.5 (0.986)	27.5 (1.29)	27.1 (2.71)	27.1 (1.64)
Median [Min, Max]	26.5 [24.7, 27.4]	27.2 [24.3, 29.0]	27.6 [24.7, 29.2]	27.5 [25.4, 30.1]	28.0 [21.9, 30.2]	27.3 [21.9, 30.2]
Missing	1 (3.2%)	0 (0%)	1 (2.9%)	0 (0%)	12 (21.1%)	14 (7.3%)
Precipitation (in mm)						
Mean (SD)	160 (57.9)	119 (48.2)	111 (44.3)	96.5 (41.5)	54.9 (22.2)	103 (55.1)
Median [Min, Max]	158 [81.6, 260]	102 [45.9, 239]	97.9 [67.7, 235]	84.8 [43.1, 256]	54.8 [6.31, 102]	85.3 [6.31, 260]
Missing	1 (3.2%)	0 (0%)	1 (2.9%)	0 (0%)	12 (21.1%)	14 (7.3%)
Population (in tausend)						
Mean (SD)	2410 (2490)	1970 (1420)	1470 (1470)	1660 (1710)	1470 (2270)	1740 (1960)
Median [Min, Max]	1560 [75.2, 10900]	1400 [56.7, 5290]	961 [61.3, 6970]	954 [28.7, 7680]	305 [5.07, 11800]	982 [5.07, 11800]
Average Night light coverage						
Mean (SD)	0.980 (2.07)	0.213 (0.688)	0.437 (1.66)	0.0963 (0.456)	0.304 (1.01)	0.382 (1.29)
Median [Min, Max]	0.0743 [0.0000292, 10.4]	0.0371 [0, 3.92]	0.0148 [0, 9.69]	0.00819 [0, 2.74]	0.0339 [0.0000502, 5.52]	0.0187 [0, 10.4]

The first interresting observation is the evolution of Temperature. It seems to increase with the PM2.5 concentration. Regions that have very low PM2.5 concentration have an average temperature of 26.4°C in 2013. Regions that have high PM2.5 concentration have an average temperature of 27.5°C in 2013. Second interresting observation is the evolution of Precipitation It decreases with the PM2.5 concentration. Regions that have very low PM2.5 concentration have an average precipitation of 160 mm in 2013. And regions that have very high PM2.5 concentration have an average precipitation of 54.9 in 2013.

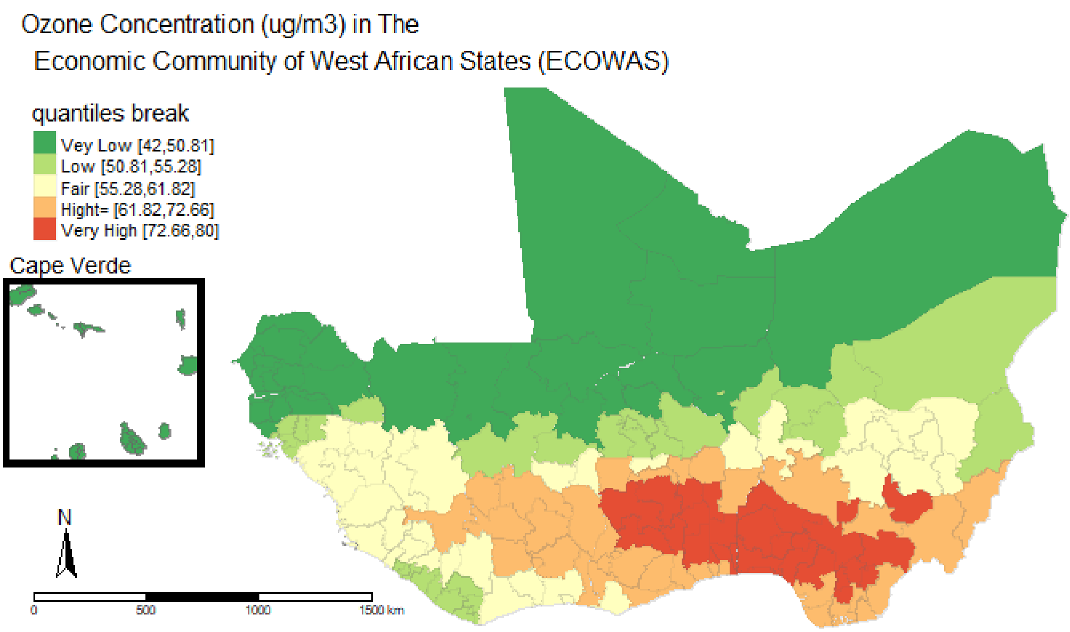


Figure 3.2: OzoneConcentration (ug/m3) in The ECOWAS
source: Ambient air pollution exposure estimation for the Global Burden of Disease 2013

Table 3.2: Region's group(based on their Ozone concentration (ug/m3) level) with certains caracteristics

	Ozone : Vey Low [42,50.81] (N=56)	Ozone :Low [50.81,55.28] (N=34)	Ozone : Fair [55.28,61.82] (N=34)	Ozone :Hight [61.82,72.66] (N=39)	Ozone :Very High [72.66,80] (N=29)	Overall (N=192)
Temperature (°C)						
Mean (SD)	27.0 (2.76)	27.6 (1.40)	26.6 (1.12)	27.1 (0.786)	27.2 (0.513)	27.1 (1.64)
Median [Min, Max]	27.9 [21.9, 30.2]	27.7 [25.3, 30.0]	26.5 [24.3, 28.9]	27.1 [24.7, 28.9]	27.3 [26.0, 28.4]	27.3 [21.9, 30.2]
Missing	12 (21.4%)	1 (2.9%)	0 (0%)	1 (2.6%)	0 (0%)	14 (7.3%)
Precipitation (in mm)						
Mean (SD)	57.8 (25.8)	130 (76.9)	133 (53.3)	110 (41.9)	96.1 (21.7)	103 (55.1)
Median [Min, Max]	54.8 [6.31, 113]	99.4 [23.3, 260]	132 [47.7, 235]	91.0 [45.9, 216]	87.2 [74.6, 159]	85.3 [6.31, 260]
Missing	12 (21.4%)	1 (2.9%)	0 (0%)	1 (2.6%)	0 (0%)	14 (7.3%)
Population (in tausend)						
Mean (SD)	752 (981)	1250 (1560)	2370 (2550)	2230 (1650)	2810 (2440)	1740 (1960)
Median [Min, Max]	268 [5.07, 3970]	319 [28.7, 5380]	1490 [94.6, 11800]	1560 [278, 6420]	2680 [541, 10900]	982 [5.07, 11800]
Average Night light coverage						
Mean (SD)	0.482 (1.61)	0.143 (0.505)	0.189 (0.637)	0.676 (1.87)	0.298 (0.631)	0.382 (1.29)
Median [Min, Max]	0.0287 [0, 9.69]	0.00521 [0, 2.74]	0.00947 [0.000105, 3.29]	0.0593 [0.00215, 10.4]	0.0342 [0.00518, 2.58]	0.0187 [0, 10.4]

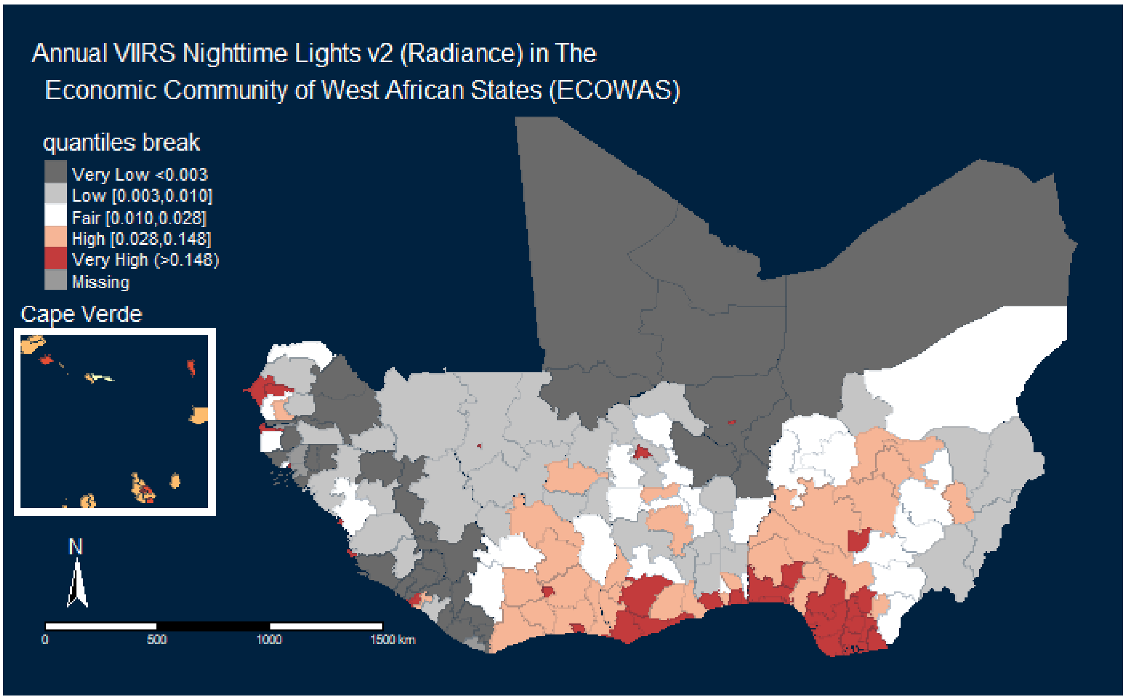
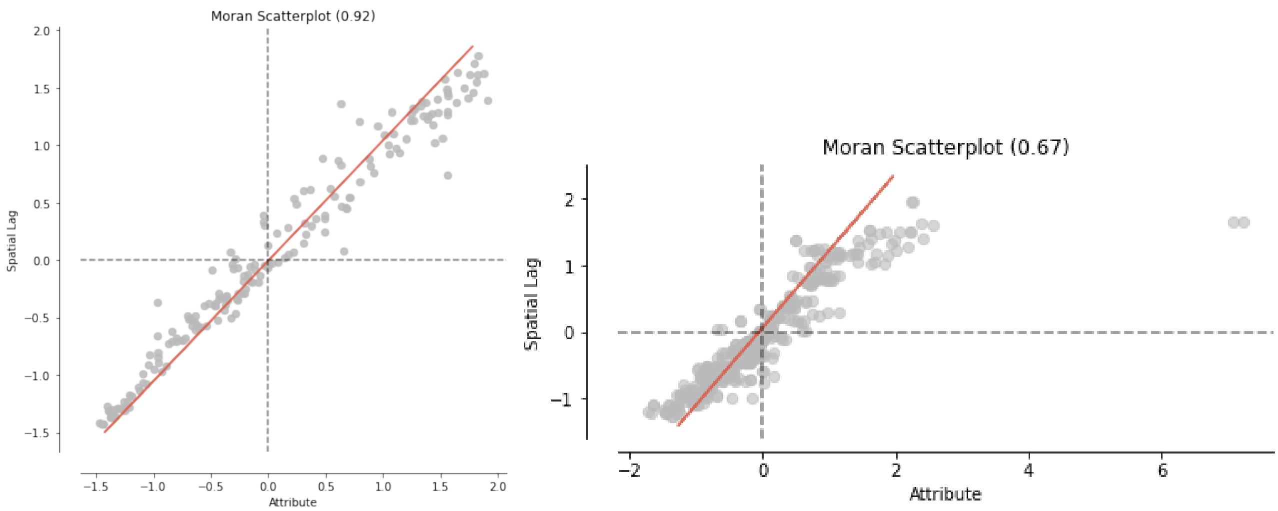


Figure 3.3: Nighttime Lights in The ECOWAS
source: Earth Observation Group - VIIRS Nighttime Lights

3.2 Spatial autocorrelation Analysis : Moran's I (knn weight matrix with 10 neighbors)

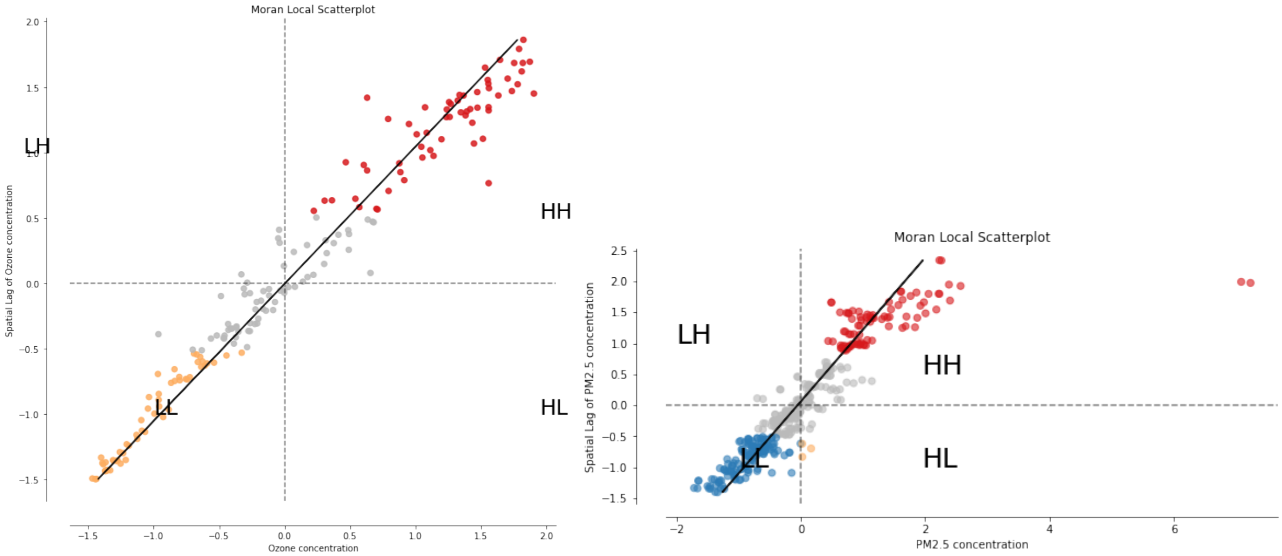
Figure 3.4: Gobal moran's I for Ozone & PM2.5 concentration



The moran's I value the calculated slope of the scatterplot of Ozone concentration and Ozone concentration lag columns (PM2.5 concentration and PM2.5 concentration lag) 3.4 . It does indicate whether or not you have a positive or negative autocorrelation. Values will range from positive one, to negative one.

For Ozone and PM2.5 we have significant positive autocorrelation.That means that values are clustered. Region with the same concentration of PM2.5 and Ozone are concentrated in the same areas. They are not randomly distributed in the map. the are more clustered for Ozone concentration (left figure of figure 3.4).

Figure 3.5: Local moran's I for Ozone & PM2.5 concentration



So far, we have only determined that there is a positive spatial autocorrelation between the average nnight time light in neighborhoods and their locations. But we have not detected where clusters are. Local Indicators of Spatial Association (LISA) is used to do that. LISA classifies areas into four groups: high values near to high values (HH), Low values with nearby low values (LL), Low values with high values in its neighborhood, and vice-versa.

- HH: high concentrations near other high aconcentrations neighbors
- LL: low concentrations geographies near other low concentrations neighbors
- LH (donuts): low concentrations geographies surrounded by high concentrations neighbors
- HL (diamonds): high concentrations geographies surrounded by low arrest neighbors

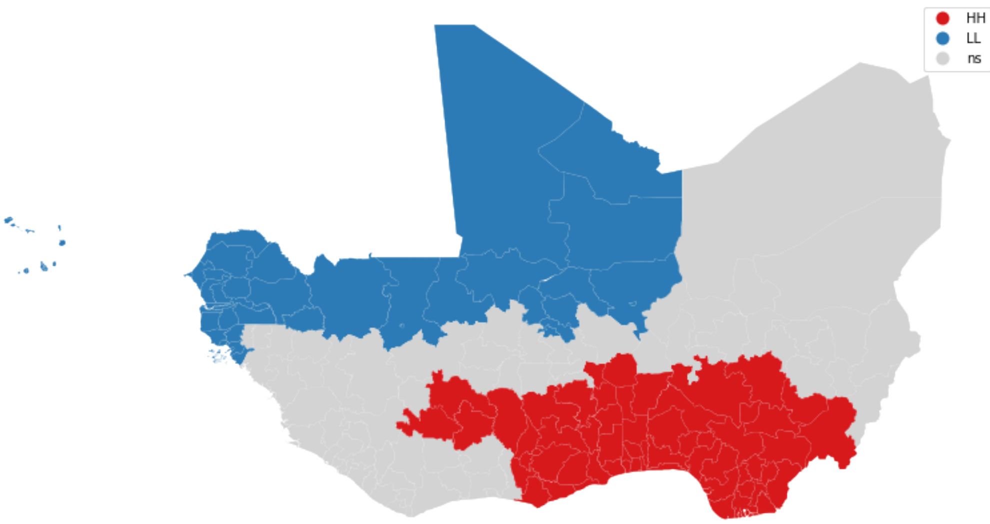


Figure 3.6: Spatial Autocorrelation Map (p value = 0.05) : OzoneConcentration (ug/m3) in The ECOWAS

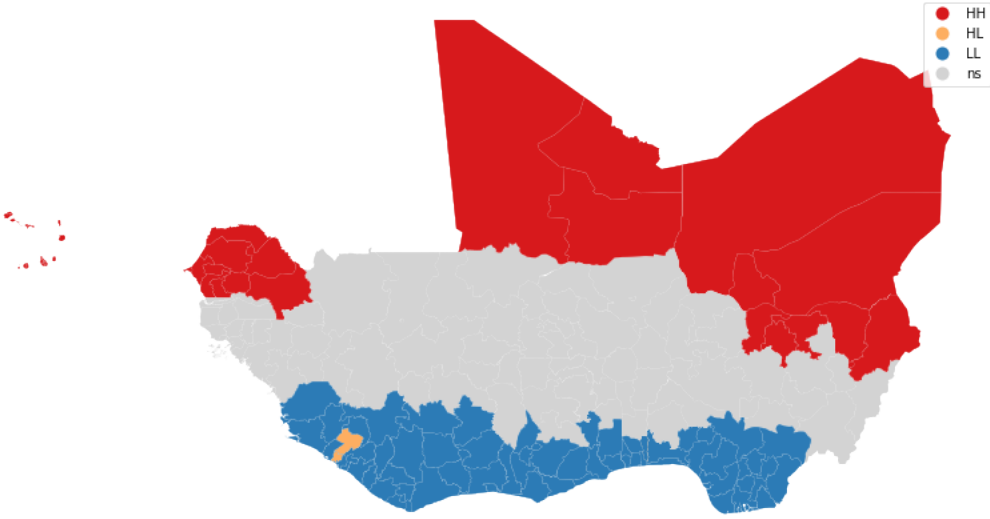


Figure 3.7: Spatial Autocorrelation Map (p value = 0.05) : PM2.5 Concentration (ug/m3) in The ECOWAS

Even if the two variable of pollution are positively correlated (see correlation matrix A.1), the repartition on the map of their cold and hot spot are opposed. For Ozone pollution, hot spots seems to be located in higher-radiance (meaning higher-income) nightlights regions. On the opposite side, hot-spots for PM2.5 concentration seems to be located in lower-radiance nighlights regions. One explaination could be that southern region are coastal regions, meaning there are less likely to be sourrounded by solid pollution such as those emanating from desertic dust, hince there low PM2.5 concentration.

Theses observations are slighly similar to what Xie, et, al.(2019) (9). (Ozone concentration were higher in the west of china, and PM2.5 concentration were higher in the east : there doesn't seem to be a linear pattern between the repartition of Ozone concentration and PM2.5 concentration). They also found that PM2.5 pollution causes much higher health and economic impacts than ozone. In the modeling chapter we will analysis the economic impact of ozone and PM2.5 pollution. The proxy for our economic activity will be the night light. From the global moran's I plots, some outliers stand out. Therefore we will also compare the results for the models with and without logarithm in order to crush as much as possible the dispersion between the values of the different regions.

Chapter 4

Economics modeling : From non spatial Kuznets model to spatial model

In this part, we modeled the links between economic development in the ECOWAS regions and the pollution it suffer from. The aim is to investigate the impact of economic activity on environmental pollution. As we did in the previous chapter, we will consider a region level. analysis[1]. We will use the average nighttime light as a proxy of the GDP for each of our region in the models we will run.

We consider three outcomes variables related to pollution : PM2.5 air pollution, it normalized variant per density and the Ozone pollution. Considering those three will allow us to capture different pattern.

We will present different tests that we compute to choose the appropriate model for our data using different weight matrix and dependant variable. We also present and interpret the result of our models.

4.1 The EKC Model without spatial effect

The methodology

In this part, we briefly present the OLS model we will base our analysis on.
We distinguish two set of model :

- **The model of Kuznets** curve is a particular case of the type 1 model in which we don't add the other dependent variables and only keep the variable of interest and it square (the average nighttime light). It equation can be write as follow:

$$Ln(y_i) = \lambda_0 + \lambda_1(ln(Viirs\_Aver_i))^2 + \lambda_2 ln(Viirs\_Aver_i) + \epsilon_t \tag{4.1}$$

- **The type 1 model** in which we add the log of our variable of interest and it square. The equation can be write as follow:

$$Ln(y_i) = \beta_0 + \beta_1 Ln(Viirs\_Aver_i) + \beta_2(Ln(Viirs\_Aver_i))^2 + \beta_3 Temp_i + \beta_4 Precip_i + \beta_5 PopDensi_i + \epsilon_t \tag{4.2}$$

  To take into account the region for which the value of the pollution or the nighttime light is nil, we add 1 before computing the logarithm in other to correct it value (so as not to have infinite values in the values of logarithm). In fact, the real estimated equation can be written as follow:

$$Ln(y_i{+}1) = \beta_0{+}\beta_1 Ln(Viirs\_Aver_i{+}1){+}\beta_2(Ln(Viirs\_Aver_i{+}1))^2{+}\beta_3 Temp_i{+}\beta_4 Precip_i{+}\beta_5 PopDensi_i{+}\epsilon_t \tag{4.3}$$

- **Type 2 model** in which we don't make any transformation of the data, but we add in the model, the square of our dependent variable. The equation can be write as follow:

$$y_i = \alpha_0 + \alpha_1 Viirs\_Aver_i + \alpha_2 Viirs\_Aver_i^2 + \alpha_3 Temp_i + \alpha_4 Precip_i + \alpha_5 PopDensi_i + \epsilon_t \tag{4.4}$$

In these models, y_i is the outcome variable (the PM 2.5 pollution, the PM 2.5 pollution per density and the Ozone pollution) for the region i, $Viirs\_Avert_t$ is the average nighttime light for the region i, $Temp_t$ is the average temperature for the region i, $Precipt_t$ is the average precipitation for the region i and $PopDensit_t$ is the population density for the region i.

The Kuznet curve

[1] ADM2

The relationship between Average nightlight and PM2.5 pollution present a significant U-shaped pattern as we can see on the Figure below (Figure 4.1, 4.2 & 4.3) . This kind of shape for EKC is not well spread in the literature. The inconclusive results might be a consequence of heterogeneity across and within the income groups (average night light) of different region. Allard et. al. (2018)(1) show evidence for the N-shaped EKC in all income groups, except for the upper-middle-income countries. Heterogeneous characteristics are observed over the N-shaped EKC. Therefore it could be interesting to take into account the third order polynomial equation (i.e. adding $LnViirs\_Aver^3$). What we observed as U shapes could as well be part of the N-shapes curves observed by Allard et al. Also, in their paper, Chang and. al. (2021)(4), highlight the difference of EKC shape according to the level of income of the 284 Chinese regions. In the static and dynamic model (without spatial effect) They observe a U-shape pattern for low-income region.

Table 4.1: EKC

	Dependent variable:		
	LnPM2.5AirPo	LnPM2.5_pe_2	LnOzoneAirPo
	(1)	(2)	(3)
LnViirs_Aver	0.071***	1.420***	0.581***
	(0.008)	(0.065)	(0.040)
$LnViirs\_Aver^2$	0.013***	0.104***	0.056***
	(0.001)	(0.010)	(0.006)
Constant	3.336***	−2.398***	5.278***
	(0.023)	(0.178)	(0.108)
Observations	376	376	376
R^2	0.226	0.625	0.386
Adjusted R^2	0.222	0.623	0.383
Residual Std. Error (df = 373)	0.279	2.185	1.333
F Statistic (df = 2; 373)	54.507***	311.120***	117.288***
Note:			*p<0.1; **p<0.05; ***p<0.01

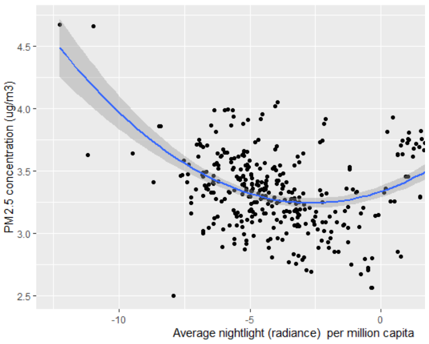


Figure 4.1: *fitting curves of model 4.3, dependent variable : LnPM2.5AirPo*

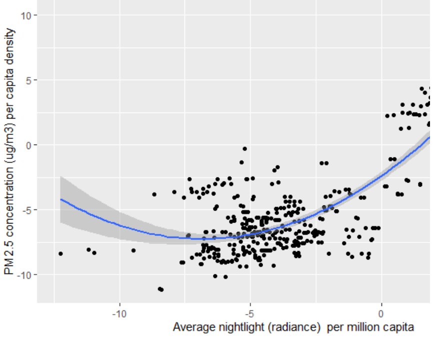


Figure 4.2: *fitting curves of model 4.3, dependent variable : LnPM2.5_pe_2*

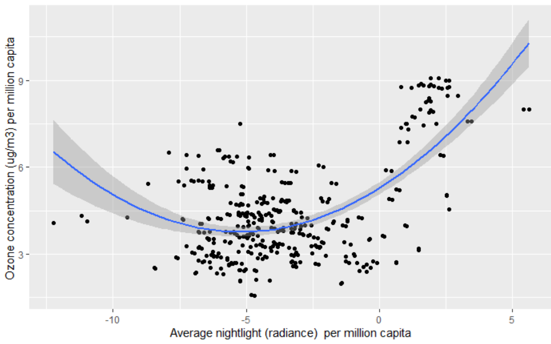


Figure 4.3: *fitting curves of model 4.3, dependent variable : LnOzoneAirPo*

Table 4.2: OLS with the type 1 model

	Dependent variable:		
	LnPM2.5AirPo	LnPM2.5_pe_2	LnOzoneAirPo
	(1)	(2)	(3)
LnViirs_Aver	0.013	1.144***	0.498***
	(0.012)	(0.116)	(0.064)
$LnViirs\_Aver^2$	0.007***	0.090***	0.051***
	(0.001)	(0.013)	(0.007)
Temperatur	−0.030***	−0.526***	−0.250***
	(0.009)	(0.085)	(0.047)
Precipitat	−0.004***	−0.001	0.002
	(0.0003)	(0.002)	(0.001)
PopDensity	0.00003*	−0.0003**	−0.001***
	(0.00002)	(0.0001)	(0.0001)
Constant	4.458***	11.093***	11.739***
	(0.243)	(2.259)	(1.249)
Observations	348	348	348
R^2	0.562	0.558	0.417
Adjusted R^2	0.556	0.551	0.409
Residual Std. Error (df = 342)	0.209	1.940	1.073
F Statistic (df = 5; 342)	87.867***	86.334***	48.957***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.3: OLS with type 2 model

	Dependent variable:		
	PM2.5AirPo	PM2.5_pe_2	OzoneAirPo
	(1)	(2)	(3)
Viirs_Aver	−3.675***	0.559	2.156
	(1.164)	(0.895)	(1.428)
$Viirs\_Aver^2$	0.122	0.023	−0.305*
	(0.145)	(0.112)	(0.178)
Temperatur	−0.468*	−3.476***	0.996***
	(0.278)	(0.214)	(0.341)
Precipitat	−0.130***	−0.063***	0.062***
	(0.009)	(0.007)	(0.011)
PopDensity	0.003**	−0.001	−0.001
	(0.001)	(0.001)	(0.001)
Constant	56.224***	102.453***	25.711***
	(7.853)	(6.036)	(9.632)
Observations	348	348	348
R^2	0.408	0.463	0.109
Adjusted R^2	0.400	0.456	0.096
Residual Std. Error (df = 342)	8.202	6.305	10.061
F Statistic (df = 5; 342)	47.180***	59.071***	8.345***
Note:			*p<0.1; **p<0.05; ***p<0.01

The type 1 model is in fact the same model as the simple OLS EKC model with additional regressors : Temperature, precipitation and population density. For Ln PM25AirPo as dependent variable : the logarithm of Night night average value is not significant anymore. As if it effect was captures with the other variable. For LnPM25_pe_2 as dependent variable : the coefficients for the 2 variables of interest (average night light and it square) doesn't really change from the the simple EKC OLS ones. In fact it is not surprising considering the fact that LnPM25_pe_2 takes into account the density of population.

4.2 The spatial model choice and estimation

4.2.1 The methodology

It is possible that the spatial dimension has been taken into account by some control variables in the OLS regressions we did in the previous part. To confirm this assumption, we start by testing the presence of spatial auto-correlation in the models residuals. This is done afterwards with the Moran test. We will confirm the results but running also the Geary test. If no spatial self-correlation is detected, it means that it has been taken into account by the controls variables. However, if the Moran's test shows that there is a spatial correlation that is significant, the question arises of how to correct for it or to take it into account in our model. To answer the latter question, we will run a several tests to identify the suitable model for our data. These tests are:

- The **SARMA**: The spatial autoregressive moving average test.
- The **LMlag**: the test for a missing spatially lagged dependent variable and it robust variant **RLMlag**;
- The **LMerr**: the test for error dependence and it robust variant **RLMerr**;

The model choice procedure can be summarize in the figure 4.4 bellow.

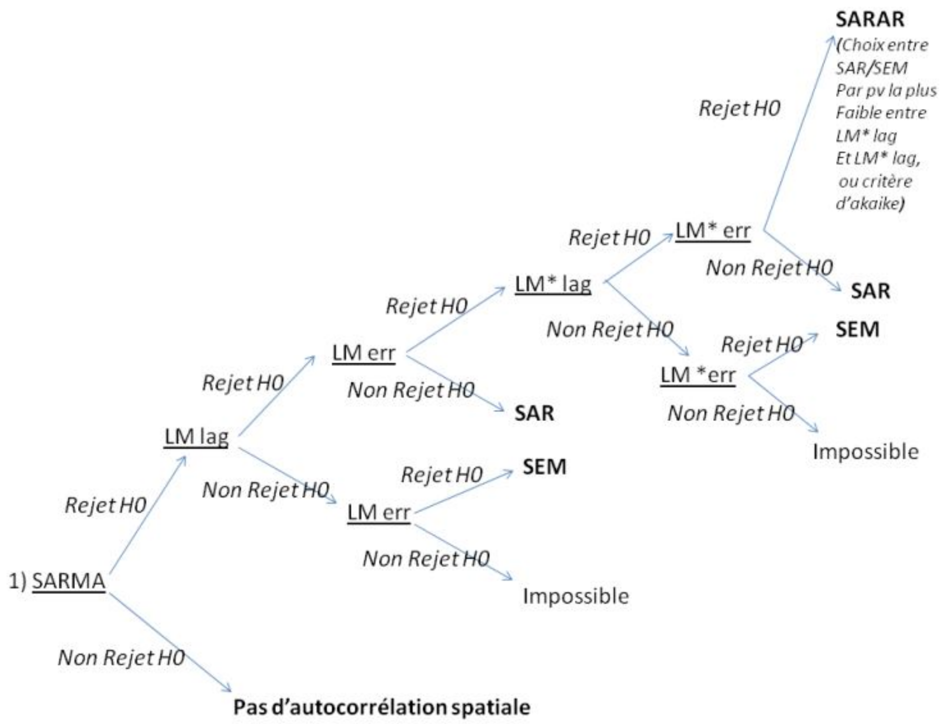


Figure 4.4: Model choice procedure (source course)

To address the robustest of our results, we will compute all these tests for three weight matrix. The aim is to see if for different weight matrix, if the specifications tests will lead to similar or different results.

In this model, we will consider three categories of spatial models :

- the SEM (Spatial Error Model) witch equation can be write as follow:

$$y = X\beta + \epsilon$$

  with $\epsilon = \lambda W\epsilon + \mu$ and $\mu \sim^{idd} N(0, \sigma^2)$. This type of model is appropriate when one suspects the omission of explanatory variables that can follow a spatial auto correlation process.

- the SAR (Spatial Auto Regressive Model) witch can be write as follow:

$$y = \alpha I_N + \rho W y + X\beta + \epsilon$$

  In this model, the observation of y is partly explained by the values taken by y in neighboring regions.

- the SARAR (Spatial Auto Regressive Auto Regressive) model witch can be write as follow:

$$y = \alpha I_N + \rho W_1 y + X\beta + \epsilon$$

  with $\epsilon = \lambda W_2 \epsilon + \mu$ and $\mu \sim^{iid} N(0, \sigma^2)$. The particularity of this model is the use of two weight matrix otherwise the identification will not be possible.

In these model, Wy is an endogenous variable lag by the weight matrix W, ρ is a parameter for the spatial auto regressive relation witch indicate the intensity of the link between the independent variables X and the dependent variable y.

4.2.2 The tests results

The analysis of the residuals in the table C.4 in appendix clearly shows that, for all the weighting matrices, the residuals of the regressions are spatially correlated. In fact, all the p-values are lower that 5%. A similar conclusion is obtained when using the Geary C test which result can be find in the tableC.5 in appendix. In the rest of our study, we will get read of the *Knn3*, *Knn5* and *Knn7* weighted matrix and only consider the *Knn10* because it provide more variability and information regarding the results.

For the specification test, we have close results. In fact, for the variable *PM2.5* for instance in the table C.1 in appendix, we have very low p-value for all the tests and the weight matrix witch drives us to use an **SARAR** model. Even if the p-value of the RLMlag is lower in the type 1 model compare to type 2, the conclusion remain the same for both. The result for the variable *PM2.5 per density* are depicted in table C.2 in appendix. For the type 1 model, all the p-value are lower than 5% what drives us to consider a **SARAR** model, but for the type 2, the p-value are greater than 5% in the *RLMerr* test witch drive us to consider a **SEM** there. In addition, these results are robust to the choice of the weight matrix. Finally for the variable *ozone*, all the p-value are lower than 5% as we can see in the table C.3 in appendix, witch drive us to use a **SARAR** model.

These results are clear, but since the **SARAR** model is unstable and the results are not that significant, we purposely decide to run an **SAR** model for the type 1 models and a **SEM** for the type 2 models (after consultation with the professor). We will interpret the coefficient as if they are from the right model.

4.2.3 Results

In this part, we present the estimation results for each of our outcome of interest. Because of the presence of an auto regressive term in the SAR model, we can't directly interpret the results because it contains two effects that we shall distinguish:

- **Direct effect**: which is the effect of a change in $Virrs\_aver_i$ for the region i on the outcome variable y_i;
- **Indirect effect**: which is the effect of a change in $Virrs\_aver_j$ for the region j in the outcome variable y_i for the region i.

We will then make the distinction between those two models in the **impact part** .

For the PM 2.5 pollution

The table 4.4 present the result of the estimation for the two set of model using the three different weight matrix we discuss before. Globally, we observe that for the two set of models, we have a similar significant coefficient for the same variable. For the type 1 model, the coefficient for average nighttime light is not significant but become significant and negative when we take the squared of the variable. The model show that the average precipitation have a negative and significant effect on the pollution, in other word, the more it rain the lower will be the pollution. The population density have a positive and significant effect on the pollution. The intensity of the effects is almost the same for the three weight matrix.

For the type 2 model, unlike the type 1, the average nighttime light have a negative and significant effect on the pollution but when we take the square variable the effect become insignificant. The precipitation and the density have a same effect as the one in the type 1 model on the pollution.

The knn10 weight matrix have the lower AIC for the two type of model and adjust better to the data.

Table 4.4: Spatial model with PM2.5

	Dependent variable:PM2.5					
	Type 1 model			Type 2 model		
	Queen	Rook	Knn10	Queen	Rook	Knn10
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Viirs_Aver)	0.020	0.023	0.023			
	(0.078)	(0.078)	(0.059)			
$Ln(Viirs\_Aver)^2$	-0.106^{**}	-0.108^{**}	-0.097^{**}			
	(0.048)	(0.048)	(0.039)			
Viirs_Aver				-1.714^{**}	-1.713^{**}	-1.534^{**}
				(0.869)	(0.868)	(0.724)
$Viirs\_Aver^2$				-0.023	-0.024	0.008
				(0.108)	(0.108)	(0.090)
Temperature	-0.006	-0.006	0.011	-0.232	-0.232	0.271
	(0.013)	(0.013)	(0.013)	(0.209)	(0.209)	(0.174)
Precipitation	-0.003^{***}	-0.003^{***}	-0.002^{***}	-0.048^{***}	-0.048^{***}	-0.029^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.009)	(0.009)	(0.007)
PopDensity	0.0001^{***}	0.0001^{***}	0.00004^{***}	0.002^{**}	0.002^{**}	0.001
	(0.00002)	(0.00002)	(0.00002)	(0.001)	(0.001)	(0.001)
Constant	3.804^{***}	3.811^{***}	3.472^{***}	21.878^{***}	21.888^{***}	-0.619
	(0.365)	(0.365)	(0.396)	(6.510)	(6.508)	(4.907)
Observations	356	356	356	356	356	356
Log Likelihood	195.900	196.310	237.190	$-1,163.843$	$-1,163.793$	$-1,110.528$
σ^2	0.016	0.016	0.013	37.363	37.345	26.035
λ	0.828^{***}	0.829^{***}	0.949^{***}	.	.	.
ρ	.	.	.	0.644^{***}	0.644^{***}	0.904^{***}
std-err(λ or ρ)	0.027	0.0273	0.012	0.047	0.047	0.018
Akaike Inf. Crit.	-375.800	-376.620	-458.379	2,343.687	2,343.585	2,237.056
Wald Test (df = 1)	916.616^{***}	922.417^{***}	$6,196.340^{***}$	185.839^{***}	186.156^{***}	$2,311.318^{***}$
LR Test (df = 1)	305.142^{***}	305.961^{***}	387.720^{***}	171.749^{***}	171.851^{***}	278.379^{***}
Note:						*p<0.1; **p<0.05; ***p<0.01

For the PM 2.5 per density

When we normalize the PM 2.5 pollution by the density the results are not better compare to the one we get in the previous part as we can see in the table 4.4. In fact, for the first set of model, the precipitation still have a negative but insignificant effect on the pollution and the population coefficient become negative and significant except when we use the Knn10 matrix weight (it become insignificant). The squared nighttime light has a positive and significant effect on the pollution. For the type 2 model, all the variable are significant and have a negative effect on the normalize pollution except the nighttime light and it squared value. When it is significant, the intensity of the effect is also similar for the other weighted matrix. Globally, the AIC are higher when we use this second dependent variable compare to the result we get with the PM 2.5 pollution. Also, for this variable, the Queen weighted matrix have a lower AIC for the two sets of models.

Table 4.5: Spatial model with PM2.5 per density

	Dependent variable:PM2.5 per density					
		Type 1 model			Type 2 model	
	Queen	Rook	Knn10	Queen	Rook	Knn10
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Viirs_Aver)	−0.001	−0.002	−0.344**			
	(0.145)	(0.144)	(0.146)			
$Ln(Viirs\_Aver)^2$	0.159*	0.159*	0.275***			
	(0.088)	(0.088)	(0.096)			
Viirs_Aver				0.824	0.824	0.379
				(0.755)	(0.755)	(0.792)
$Viirs\_Aver^2$				0.043	0.043	0.067
				(0.094)	(0.094)	(0.099)
Temperature	−0.041	−0.041	−0.045	−1.523***	−1.524***	−1.401***
	(0.026)	(0.026)	(0.031)	(0.244)	(0.244)	(0.261)
Precipitation	−0.0001	−0.0001	0.0003	−0.027***	−0.027***	−0.025***
	(0.001)	(0.001)	(0.001)	(0.006)	(0.006)	(0.007)
PopDensity	−0.0001***	−0.0001***	−0.0001	−0.002**	−0.002**	−0.001
	(0.00003)	(0.00003)	(0.00004)	(0.001)	(0.001)	(0.001)
Constant	1.378*	1.378*	1.357	44.901***	44.933***	41.365***
	(0.747)	(0.747)	(0.885)	(7.020)	(7.019)	(7.533)
Observations	356	356	356	356	356	356
Log Likelihood	−27.473	−27.589	−75.152	−1,111.264	−1,111.291	−1,123.847
σ^2	0.053	0.053	0.078	28.303	28.306	31.211
λ	0.915***	0.915***	0.896***	.	.	.
ρ	.	.	.	0.584***	0.584***	0.564***
std-err(λ or ρ)	0.014	0.014	0.022	0.053	0.053	0.067
Akaike Inf. Crit.	70.946	71.177	166.303	2,238.528	2,238.582	2,263.694
Wald Test (df = 1)	3,912.377***	3,906.604***	1,562.242***	120.601***	120.577***	70.304***
LR Test (df = 1)	341.602***	341.371***	246.245***	85.511***	85.457***	60.344***
Note:						*p<0.1; **p<0.05; ***p<0.01

For the ozone pollution

The result for the ozone pollution are depicted in the table 4.6. All the coefficient estimated using this dependent variable are not significant except for the constant except for the type 2 model with the Knn10 weight matrix. These coefficients are also low and almost nil for most of them. Those "low quality" results may be due to an bias in the model estimation because of the omitted variable or a bad model specification. The type 2 model

Table 4.6: Spatial model for Ozone pollution

	Dependent variable: Ozone Pollution					
	Type 1 model			Type 2 model		
	Queen	Rook	Knn10	Queen	Rook	Knn10
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Viirs_Aver)	−0.018	−0.018	0.003			
	(0.021)	(0.021)	(0.018)			
$Ln(Viirs\_Aver)^2$	0.013	0.012	−0.0004			
	(0.013)	(0.013)	(0.012)			
Viirs_Aver				−0.256	−0.255	−0.260
				(0.297)	(0.296)	(0.300)
$Viirs\_Aver^2$				0.044	0.043	−0.002
				(0.037)	(0.037)	(0.037)
Temperature	0.002	0.002	0.0004	0.011	0.011	−0.127*
	(0.004)	(0.004)	(0.004)	(0.071)	(0.071)	(0.074)
Precipitation	0.0001	0.0001	0.0001	0.002	0.002	0.004*
	(0.0001)	(0.0001)	(0.0001)	(0.002)	(0.002)	(0.002)
PopDensity	−0.00000	−0.00000	−0.00000	−0.0001	−0.0001	0.0001
	(0.00000)	(0.00000)	(0.00000)	(0.0003)	(0.0003)	(0.0003)
Constant	4.007***	4.010***	3.925***	1.824	1.832	3.770*
	(0.119)	(0.119)	(0.180)	(2.027)	(2.016)	(2.137)
Observations	356	356	356	356	356	356
Log Likelihood	648.464	649.497	659.931	−827.209	−825.638	−813.428
σ^2	0.001	0.001	0.001	4.389	4.343	4.443
λ	0.962***	0.962***	0.987***	.	.	.
ρ	.	.	.	0.961***	0.961***	0.986***
std-err(λ or ρ)	0.0068	0.0068	0.0034	0.0071	0.0071	0.0035
Akaike Inf. Crit.	−1,280.928	−1,282.995	−1,303.862	1,670.418	1,667.276	1,642.856
Wald Test (df = 1)	19,677.330***	19,903.960***	83,564.730***	18,035.130***	18,374.910***	78,369.990***
LR Test (df = 1)	1,008.820***	1,010.887***	1,031.754***	994.230***	997.372***	1,021.792***
Note:						*p<0.1; **p<0.05; ***p<0.01

4.2.4 Impact

As we explain above, the results of the SAR model contains two effects: a direct one and an indirect one that we shall take into account when interpreting the results. In the tables 4.7,4.8 and 4.9 we represent those two effects for each of our dependent variable. We recall that the SAR model was computed for the type 2 models. We only report the estimation of the model with the lower AIC regarding the weight matrix for each of our dependent variable for simplicity.

For the PM 2.5 pollution

For this variable we report the result of the SAR model using the Knn10 weight matrix. Only the average precipitation and the nighttime light seems to have a significant effect on the PM 2.5 pollution. The results reported in the table 4.7 show that an increase of one unit in the average nighttime light of one region of our sample induce an decrease of 1.96 in the PM 2.5 pollution for the same region. Also, an increase in the average nighttime light for the neighboring regions of one unit induce an decrease of 14.132 in the PM 2.5 pollution for the current region. The precipitation also induce an decrease in the local region pollution of 0.037 and when the average precipitation increase by one unit for the neighboring region, the impact on the local pollution is almost multiplied by 9 (0.27).

Table 4.7: Impact analysis for the PM2.5 pollution

	PM 2.5		
	Direct	Indirect/spillover effects	Total
Virrs_aver	-1.96	-14.132	-16.092
$Virrs\_aver^2$	0.009	0.069	0.079
Temperature	0.346	2.498	2.845
Precipitation	-0.037	-0.269	-0.306
PopDensity	0.0012	0.0093	0.010

For the PM 2.5 pollution per density

As for the PM 2.5 pollution, we report the estimated impacts in the table 4.8 using the Knn10 weight matrix. In this specification, the average temperature and precipitation are the only variables that have a significant effect. The result shows that an increase of one unit in the average temperature in a given region induce an decrease of 1.641 of the pollution of the same region, and for the neighboring region the effect is 2.023. For the precipitation, the direct and indirect effected are of the same intensity of around 0.03.

Table 4.8: The impact analysis for the PM2.5 per density

	PM 2.5 per density		
	Direct	Indirect/spillover effects	Total
Virrs_aver	0.887	1.094	1.982
$Virrs\_aver^2$	-1.699	-5.352	0.103
Temperature	-1.641	-2.023	-3.665
Precipitation	-0.029	-0.035	-0.064
PopDensity	-0.0016	-0.002	-0.0037

For the Ozone pollution

The impact estimated on the Ozone pollution is depicted in the table 4.9 bellow using the Knn10 matrix. Unlike what we have for the PM 2.5 pollution, the precipitation have a positive effect on the pollution for our region of interest but the temperature sign remain the same. In fact, a one unit increase in the precipitation in a given region will induce an increase of 0.009 unit in the ozone pollution of that same region but for the temperature, a one unit increase will result on an decrease of 0.283. The indirect effect are higher than the direct effect as we can see in this model. In fact, an increase in the neighboring region precipitation will have 300 times more effect on the Ozone pollution than the local increase of the precipitation. For the temperature, the effect is multiplied by 30.

Table 4.9: The impact analysis for the Ozone pollution

	Ozone pollution		
	Direct	Indirect/spillover effects	Total
Virrs_aver	-0.58	-18.035	-18.615
$Virrs\_aver^2$	-0.004	-0.148	-0.15
Temperature	-0.283	-8.821	-9.105
Precipitation	0.009	0.309	0.319
PopDensity	0.0001	0.003	0.003

Conclusion

In this study we use the nighttime light as a proxy for the GDP an address it effect on the pollution for the region of ECOWAS. The relationship between Average nightlight and PM2.5 pollution presented a significant U-shaped. Chang et. al. (2021)(4), highlight the difference of EKC shape according to the level of income. In his non spatial effect model, he observe a U-shape pattern for low-income region. The inconclusive results might be a consequence of heterogeneity. Fixed Effect model could be relevant in this case. Also to study the N shape pattern, it could be interesting to add a $LnViirs\_Aver^3$ regressor.

For the type 1 model, we don't find any significant effect of the nighttime light on the PM2.5, when we add the square of this variable it become significant but the sense of the relation change when we normalize by the density. For the type 2 model, only the average precipitation and temperature seems to have an significant and negative effect on the pollution. Nevertheless, our result show that the precipitation have a positive effect on the ozone pollution.

In the literature, the choice of nightlight as a proxy is not always appropriate. Here we decide to use it as proxy since there is no information of GDP on a regional scale. This choice could bias our interpretation.

We only carried out the cross sectional study. Getting more data from multiple period of time could enable panal data study. This could be a way to put forward more clearly impact of income on pollution. With more time, it could be interesting to gather and work on more variables as regressors. Spend more time one creating a score than would help us to convert nightlight (in Radiance) as GDP (in dollars for example).

Appendix

Appendix A

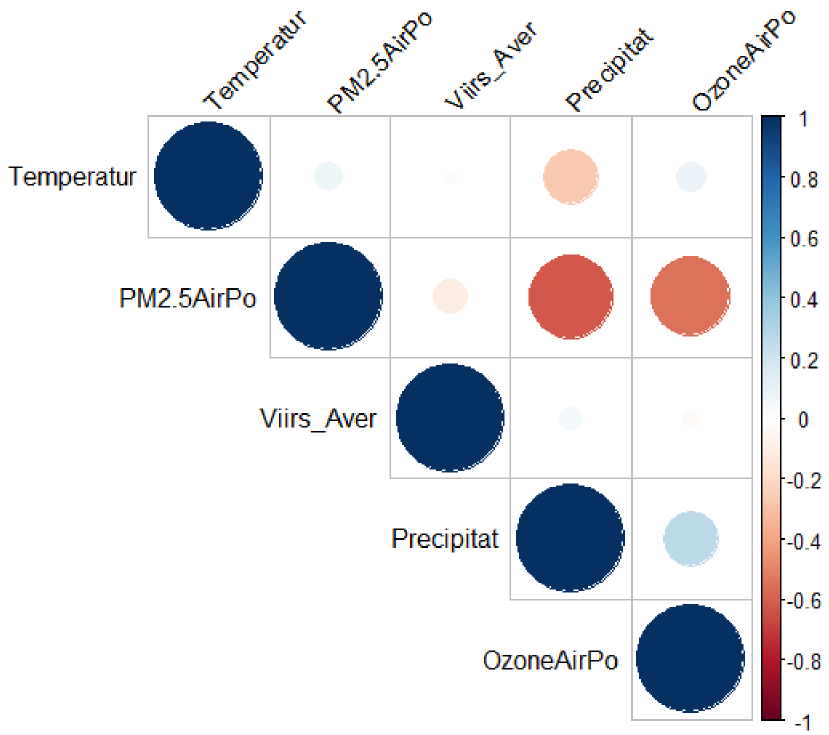


Figure A.1: Correlation matrix for our variable of interest (2013)

Appendix B

Regions of ECOWAS in 2013

Figure B.1: List of the 192 different region of ECOWAS in 2013

shapeName *(Region name from A to C)*
Abia
Adamawa
Ahafo Region
Akwa Ibom
Alibori
Anambra
Ashanti Region
Atakora
Atlantique
BafatÃ¡
Bamako
Bas-Sassandra
Bauchi
Bayelsa
Benue
Biombo
Bissau
Boa Vista
Boke
Bolama
Bomi
Bong
Bono East Region
Bono Region
Borgou
Borno
Boucle du Mouhoun
Brava
Cacheu
Cascades
Central Region
Central River
Centrale Region
Centre
Centre-Est
Centre-Nord
Centre-Ouest
Centre-Sud
Collines
Comoe
Conakry
Cross River

shapeName *(Region name from D to K)*
Dakar
Delta
Denguele
Diourbel
D.A[a] D'Abidjan
D.A De Yamoussoukro
Donga
Dossa
Eastern
Eastern Region
Ebonyi
Edo
Ekiti
Enugu
Est
Faranah
Fatick
Fct
Gabu
Gao
Gbarpolu
Goh-Djiboua
Gombe
Grand Bassa
Grand Cape Mount
Grand Gedeh
Grand Kru
Greater Accra Region
Greater Banjul Area
Hauts-Bassins
Imo
Jigawa
Kaduna
Kaffrine
Kankan
Kano
Kaolack
Kara Region
Katsina
Kayes
Kebbi
Kedougou
Kidal
Kindia
Kogi
Kolda
Kouffo
Koulikouro
Kwara

[a]District Autonome

shapeName *(Region name from L to R)*
Labe
Lacs
Lagos
Lagunes
Littoral
Lofa
Louga
Lower River
Maio
Mamou
Maradi
Margibi
Maritime Region
Maryland
Matam
Mono
Montagnes
Montserrado
Mopti
Mosteiros
Nasarawa
Niamey
Niger
Nimba
Nord
North Bank Division
North East Region
Northern
Northern Region
Nzerekore
Ogun
Oio
Ondo
Osun
Oti Region
Ouémé
Oyo
Paul
Plateau
Plateau Central
Plateaux Region
Porto Novo
Praia
Quinara
Ribeira Brava
Ribeira Grande
R.G[a] de Santiago
River Gee
Rivercess
Rivers

[a]Ribeira Grande

shapeName *(Region name from S to Z)*
São Domingos
São Filipe
São Lourenço dos Órgãos
São Miguel
São Salvador do Mundo
São Vicente
Sahel
Saint Louis
Sal
Santa Catarina
Santa Catarina do Fogo
Santa Cruz
Sassandra-Marahoue
Savanes
Savanes Region
Savannah Region
Sedhiou
Segou
Sikasso
Sinoe
Sokoto
Southern
Sud-Ouest
Tahoua/Agadez
Tambacounda
Taraba
Tarrafal
Tarrafal de São Nicolau
Thies
Tillaberi
Tombali
Tombouctou
Upper East Region
Upper River
Upper West Region
Valle Du Bandama
Volta Region
Western Area
Western Division
Western North Region
Western Region
Woroba
Yobe
Zamfara
Zanzan
Ziguinchor
Zinder/Diffa
Zou

Appendix C

Specification test output

Table C.1: Specification test for the PM2.5

	Dependent variable : PM2.5					
	Type 1 model			Type 2 model		
	Queen	Rook	Knn10	Queen	Rook	Knn10
LMerr	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***
LMlag	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***
RLMerr	2.964e-14***	3.375e-14***	<2.2e-16***	7.588e-10***	7.936e-10***	<2.2e-16***
RLMlag	2.891e-05***	2.802e-05***	1.106e-07***	0.02195*	0.02226*	0.01183*
SARMA	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***

Table C.2: Specification test for the PM2.5 per density

	Dependent variable : PM2.5 per density					
	Type 1 model			Type 2 model		
	Queen	Rook	Knn10	Queen	Rook	Knn10
LMerr	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***
LMlag	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***
RLMerr	2.717e-5***	2.597e-05***	5.081e-07***	0.1463	0.1489	0.05578 .
RLMlag	<2.2e-16***	<2.2e-16***	<2.2e-16***	8.461e-10***	9.209e-10	0.01183*
SARMA	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***

Table C.3: Specification test for the Ozone pollution

	Dependent variable : Ozone					
	Type 1 model			Type 2 model		
	Queen	Rook	Knn10	Queen	Rook	Knn10
LMerr	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***
LMlag	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***
RLMerr	0.0005839***	0.0005839***	1.315e-13***	0.042199*	0.0412721*	1.268e-08***
RLMlag	0.0003661***	0.0003661***	0.006752**	0.000227***	0.0002456***	0.002284**
SARMA	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***	<2.2e-16***

Table C.4: Moran's test p-values on the residuals of the regressions

	Dependent variable		
	PM 2.5	PM2.5 per density	Ozone
Queen	<2.2e-16***	<2.2e-16***	<2.2e-16***
Rook	<2.2e-16***	<2.2e-16***	<2.2e-16***
Knn3	<2.2e-16***	<2.2e-16***	<2.2e-16***
Knn5	<2.2e-16***	<2.2e-16***	<2.2e-16***
Knn7	<2.2e-16***	<2.2e-16***	<2.2e-16***
Knn10	<2.2e-16***	<2.2e-16***	<2.2e-16***

Table C.5: Geary C test p-values on the residuals of the regressions

	Dependent variable		
	PM 2.5	PM2.5 per density	Ozone
Queen	<2.2e-16***	1.668e-15***	<2.2e-16***
Rook	<2.2e-16***	<2.2e-16***	<2.2e-16***
Knn3	<2.2e-16***	<2.2e-16***	<2.2e-16***
Knn5	<2.2e-16***	<2.2e-16***	<2.2e-16***
Knn7	<2.2e-16***	<2.2e-16***	<2.2e-16***
Knn10	<2.2e-16***	<2.2e-16***	<2.2e-16***

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