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**Abstract**

We study the spatial distribution of air pollutants in Honshu and Kyushu, before and after the Fukushima incident in 2011. For this, we use satellite data at the municipal level of fine particulate matter and ozone concentrations, along with population density, accessibility to cities, and night lights. We rely on dependence analysis and an algorithm to endogenously partition and classify municipalities into different clusters, based on their geographic and similar attributes, for the period under study. From the spatial analysis we are able to observe the specific locations of the hot spots (high-value clusters) and cold spots (low-value clusters). These clusters reveal high positive correlations between air pollution and economic activity, throughout the years that we study. Furthermore, the regionalization analysis we perform partitions Honshu and Kyushu into different geographical regions that are intertemporally robust, allowing us to detect locations where targeting policies can improve the air quality of the population.

*Keywords:* Air pollution, Japan, Regionalization, Spatial analysis.

## 1 Introduction

Events such as the 2011 Fukushima nuclear incident are very rare and can cause severe environmental and health effects on the population. Additionally, these incidents may generate disruptions in the production of goods and the economy in general. In the case of Japan, the Fukushima accident altered the energy production structure due to the shutdown of the nuclear power plants. This gave rise to increased levels of air pollution due to the shift into relying on more fossil fuels, such as coal and liquefied natural gas, to satisfy the general energy demands of the population and industry. This rise in air pollution though, was not evenly distributed, affecting more certain regions than others. Because of this, it is important for policy makers to have at their disposal information regarding which areas/regions are more affected, so that they can improve the quality of life of the respective populations.

We utilize satellite data of particulate matter ($PM_{2.5}$), ozone concentrations, population density, night lights, and accessibility to cities from the *AidData* geoquery database (Goodman et al., 2019). We analyze $PM_{2.5}$ and ozone concentrations since these air pollutants are more easily identifiable. We do not need to detect where they originated (as in the case of greenhouse gas emissions), only where they concentrate, facilitating their study. Relying on principal component analysis (PCA), spatial dependence analysis, and a regionalization algorithm, we find and analyze clusters of municipalities in the islands of Honshu and Kyushu, Japan, that present similar levels of economic activity and air pollution levels. We do this for the period before and after the 2011 Fukushima incident. Specifically, we analyze the years 2010, 2011, and 2012. Through PCA, we reduce the variables into two components. Component one (PC1), is comprised of variables associated to economic activity (population density, night lights and accessibility to cities), and $PM_{2.5}$. Component two (PC2) is mostly comprised of ozone concentrations. We focus on Honshu and Kyushu because these are the most populated islands in Japan.

We then proceed to use the spatial dependence method proposed by Anselin (1995). This allows us to find regional hot spots (i.e. high-value clusters), cold spots (i.e. low-value clusters), and spatial outliers. Finally, we employ a regionalization method by Duque et al. (2012), to endogenously derive the regional boundaries from the pollution levels and economic activity of the municipalities that make up the islands under study.

In this work, we find positive and statistically significant levels of spatial dependence for PC1 and PC2, in different municipalities of Honshu and Kyushu for every year under study. The PC1 data reveals clusters that have higher levels of economic activity and $PM_{2.5}$ in the metropolitan areas of Tokyo, Nagoya and Osaka in Honshu. We observe other clusters with similar attributes also present in the center to south of Kyushu. Meanwhile, the PC2 data shows large clusters with low levels of pollution to the center and the south of Honshu (these may have been slightly influenced due to variations in energy production after the 2011 incident). In the case of Kyushu, we can see some clusters with low levels of pollution to the northwest, and some clusters of high pollution levels to the south of Kyushu, partially coinciding with the ones found in PC1.

The regionalization analysis, based on the PC1 and PC2 data, allows us to partition Honshu and Kyushu into different analytical regions (which range from 6 to 9, depending on the island) considering similar constraints. These new regions possess borders that differ from those of the traditional administrative regions of Japan. It is thus important to develop policies to improve air quality, coordinating throughout the different municipalities in these new regions.

This article contributes in three ways. First, by restricting the detection of clusters to locational similarity among regions, for different years. Second, by endogenously obtaining the results, for different years as well as for the period under study as a whole. In this way, it is not necessary to a priori define the number of clusters.[1] By doing so, we distinguish ourselves from studies such as Austin et al. (2012) and Cheng et al. (2013), which rely on exogenously given clustering methods, requiring to specify the number of clusters a priori. Finally, we complement spatial dependence analysis and regionalization methods, for the various years under study. From the combination of both tools, we detect endogenous and spatially contiguous clusters that are robust.[2] To the best of our knowledge, this hasn't been done in the context of air pollution before and after the 2011 Fukushima incident. The information obtained from these clusters will allow local and national governments in the creation and improvement of policies addressing the quality of life of their citizens, by picking out the regions that need more immediate attention.

The consequences of air pollution on human health are large. The effects can go from minor

[1]Some of the methods where clusters need to be previously defined include hierarchical clustering, DBSCAN, and K-means.

[2]Methodologically, Mendez and Gonzales (2021) is the nearest to our work, although in the context of human capital.

upper respiratory irritation to lung cancer, all the way to chronic bronchitis, and asthmatic attacks (Bernstein et al., 2004; Kampa and Castanas, 2008). Lanzi et al. (2018) evaluates what the costs of outdoor air pollution are and finds that, if nothing is done, these will reach up to 1% of global GDP by 2060. Dechezleprêtre et al. (2019) estimates that a rise of 1 $\mu g/m^3$ in $PM_{2.5}$ concentrations in a given year, can impact real GDP by 0.8%.

Various studies analyze the impacts of air quality on the Japanese population. Katanoda et al. (2011) investigate the repercussions that sulfur dioxide, nitrogen dioxide, and $PM_{2.5}$ have on individuals from three different prefectures. The authors note pronounced increases in lung cancer and respiratory diseases as a result of long-term exposure to air pollutants. From a nationwide population-based longitudinal survey Yorifuji et al. (2015) observe that during pregnancy, exposure to air pollution raises the chances of babies being born with low weight.

There have also been many studies employing spatial data to analyze air pollution in Japan. Using contour maps Kume et al. (2007) specify the distribution of the variation of air pollutants, on a monthly basis, for the years 2001 to 2002 for Shizuoka. Araki et al. (2015) rely on regression-kriging to analyze air pollutants, from 2009 to 2010 and observe that this methodology predicts with high accuracy and spatial resolution the spatial distribution of air pollutants in this country. A study by Shimadera et al. (2009) shows that transboundary air pollutants originating in neighboring Asian countries has a significant effect on ionic concentrations in fog in the Kinki region.

After the 2011 Fukushima Daiichi nuclear reactor incident, there have been many works investigating the consequences it generated. Tsuruta et al. (2014) study 40 sites of air quality monitoring stations in eastern Japan, hours after the Fukushima accident. They show how polluted air masses were moved to Fukushima prefecture as well as the Tokyo Metropolitan Area. Kharecha and Sato (2019) evaluate the effects that the 2011 Fukushima accident had on the energy production in Japan and in Germany, and note that there was an initial rise in $CO_2$ emissions, followed by a decline due to renewable energy production accompanied by lower energy use. Nevertheless, the authors explain that both countries could have prevented air-induced deaths by reducing fossil fuel power output instead of the nuclear one. Neidell et al. (2021) explore the unintended impacts on health from stopping nuclear power after the Fukushima incident. They find that an increase in electricity prices from this translated into a decrease in energy consumption, which caused an increase in mortality during cold periods of time. The authors mention the importance of discussing the health benefits of using nuclear power, particularly for lower-income households, due to the lower costs of energy production.

In the field of regional science, it is common to use various techniques of spatial clustering in order to summarize information, determine the number of clusters to work with, and to define the regions to target and analyze (Duque et al., 2011). One such method is that of regionalization, also known as regional clustering (Maravalle and Simeone, 1995) and clustering under connectivity constraints (Hansen et al., 2003). This methodology serves as a way to homogenize regions through the aggregation of different geographical areas into one.

The rest of this work is as organized follows. In the next section we talk about the data used and lay out the descriptive statistics of the variables we study. In section 3 we present the results. In section 4 we discuss the complementarity of these methods along with some policy implications. Section 5 concludes.

# 2 The Data

## 2.1 Description of the Database

In this work we rely on data on air pollution from the *AidData* geoquery database (Goodman et al., 2019). Specifucally, we use the following five variables:

- **Particulate matter ($PM_{2.5}$) concentration:** This measure provides information on the micrograms (one-millionth of a gram) of gaseous pollutants per cubic meter ($\mu g/m^3$) of ambient air, for the years 2010-2012. The particles estimated can be of various chemicals. The original source of the data comes from the *Ambient air pollution exposure estimation for the Global Burden of Disease 2013* (Brauer et al., 2016).

- **Ozone concentration:** This measure deals with the quantity of ozone molecules accumulated in the air in the years from 2010, 2011, and 2012. Being exposed to this gas for long periods of time may cause asthma and other respiratory problems. The original source is the *Ambient air pollution exposure estimation for the Global Burden of Disease 2013* (Brauer et al., 2016).

- **Population density:** This variable gives an approximation of the number of people per square kilometer in 2010. The source of this data comes from *CIESIN* (Columbia University, 2018).

- **Night lights:** This indicator shows the lights originating in cities, towns, and other places with persistent lighting, including gas flares, measured in digital numbers (DNs) for the years 2010, 2011, and 2012. We utilize this variable as an approximation of the economic activity that occurs in a given region. The source for this data comes from the *NOAA National Geophysical Data Center* (Lights, 2017).

- **Accessibility to cities:** This indicator explains the approximate time, in minutes, from a given point to the nearest city in 2015. The source for this is *The Malaria Atlas Project* (Weiss et al., 2018).

These indicators are useful to our work because:

1. They are associated to the Sustainable Development Goals (SDGs) of the United Nations. Concretely, particulate matter and ozone concentrations refer to SDG3. Night lights is related to SDG7 since it alludes to providing access to “affordable, reliable, sustainable and modern energy for all” and SDG8 by allowing “sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all”. Regarding population density and accessibility to cities, they relate to SDG11 by making “cities and human settlements inclusive, safe, resilient and sustainable”.

2. They allow us to show, without overlapping, the ideas and definitions we want to analyze in this writing.

## 2.2 Descriptive Statistics and Maps

In Table 1 we can observe a summary of the variables we discussed before, for the case of the island of Honshu for the years 2010, 2011, and 2012. Throughout these years we can see that the average $PM_{2.5}$ concentration slightly decreases. In contrast, Ozone concentration moderately increased throughout the period under study. Table 2 shows the same summary of variables, but for the case of Kyushu. It is worth noting that even though Kyushu presents a smaller mean population density than Honshu, it has a higher concentration of $PM_{2.5}$ and very similar levels of ozone concentration. Pollution incoming from other neighboring countries may be one of the reasons for this (Yim et al., 2019). Yoshino et al. (2016) explain that the city of Fukuoka in Kyushu, suffers from trans-boundary air pollution both during the winter-spring season as well as in summer. This significantly affects the quality of air.

Night lights are very important as an indicator due to their strong correlation with economic activity. We rely on these in order to examine economic activity for various cities and regions. Areas that have more economic activity, such as urban areas, display brighter lights than those with less activity (say, rural areas). Accessibility to cities measures the amount of time that it takes to the nearest urban center, from any given point in the map. This data allows us to appreciate how travel time varies from different urban centers. These tend to possess more resources and infrastructure than rural areas.

Figures 1 and 2 give us a glimpse at the spatial distribution of $PM_{2.5}$ concentrations for Kyushu and Honshu, for the years 2010 and 2012 (before and after the 2011 event). We can see that for 2010, most of the concentrations in Honshu are located in the Kantou region, as well as in parts of the Chuubu and Kansai regions. In the case of Kyushu, the Fukuoka and Kumamoto areas present higher levels of concentrations. Furthermore, we can see the evolution of pollution in the year 2012: Fukushima, Niigata, and Gunma have increases in concentrations of $PM_{2.5}$. Meanwhile, in Kyushu, Oita prefecture also sees a rise in concentrations or $PM_{2.5}$. It is apparent that municipalities in these regions with high values of pollution tend to cluster with other municipalities that also have high values, and vice-versa. However, we also notice that these clusters are not contiguous. Additionally, the number of clusters shown is exogeneous, thus having to decide it a priori. Because of this, we will proceed later to show results from endogenous clusters that are also contiguous.

Table 1: Descriptive statistics for Honshu

(a) 2010

| Statistic | Mean | St. Dev. | Min | Q1 | Median | Q3 | Max | Obs. |
|---|---|---|---|---|---|---|---|---|
| **Particulate Matter Concentration** ($\mu g/m^3$ $PM_{2.5}$, 2010) | 14.69 | 3.74 | 0 | 11.98 | 13.86 | 17.50 | 24.16 | 1173 |
| **Ozone concentration** ($\mu g/m^3$, 2010) | 60.05 | 3.87 | 0 | 59.80 | 60.72 | 61.18 | 62.79 | 1173 |
| **Population density** (number of people, 2010) | 1418.75 | 3067.86 | 2.59 | 96.95 | 305.91 | 1142.43 | 43303.93 | 1173 |
| **Night lights** (DNs, 2010) | 18.64 | 11.09 | 0 | 8.73 | 16.06 | 30.37 | 35 | 1173 |
| **Accessibility to cities** (distance in minutes, 2015) | 15.15 | 16.53 | 0 | 1.61 | 9.96 | 23.83 | 86.99 | 1173 |

(b) 2011

| Statistic | Mean | St. Dev. | Min | Q1 | Median | Q3 | Max | Obs. |
|---|---|---|---|---|---|---|---|---|
| **Particulate Matter Concentration** ($\mu g/m^3$ $PM_{2.5}$, 2011) | 14.47 | 3.60 | 0 | 11.90 | 13.89 | 16.95 | 22.82 | 1173 |
| **Ozone concentration** ($\mu g/m^3$, 2011) | 60.26 | 3.94 | 0 | 59.89 | 60.93 | 61.59 | 63.14 | 1173 |
| **Population density** (number of people, 2010) | 1418.75 | 3067.86 | 2.59 | 96.95 | 305.91 | 1142.43 | 43303.93 | 1173 |
| **Night lights** (DNs, 2011) | 22.77 | 15.95 | 0.06 | 8.72 | 17.94 | 38.54 | 49 | 1173 |
| **Accessibility to cities** (distance in minutes, 2015) | 15.15 | 16.53 | 0 | 1.61 | 9.96 | 23.83 | 86.99 | 1173 |

(c) 2012

| Statistic | Mean | St. Dev. | Min | Q1 | Median | Q3 | Max | Obs. |
|---|---|---|---|---|---|---|---|---|
| **Particulate Matter Concentration** ($\mu g/m^3$ $PM_{2.5}$, 2012) | 14.33 | 3.61 | 0 | 11.78 | 13.95 | 16.45 | 23.35 | 1173 |
| **Ozone concentration** ($\mu g/m^3$, 2012) | 60.47 | 4.01 | 0 | 59.96 | 61.01 | 62 | 63.51 | 1173 |
| **Population density** (number of people, 2010) | 1418.75 | 3067.86 | 2.59 | 96.95 | 305.91 | 1142.43 | 43303.93 | 1173 |
| **Night lights** (DNs, 2012) | 20.28 | 13.69 | 0 | 8.05 | 16.77 | 34.35 | 42 | 1173 |
| **Accessibility to cities** (distance in minutes, 2015) | 15.15 | 16.53 | 0 | 1.61 | 9.96 | 23.83 | 86.99 | 1173 |

Table 2: Descriptive statistics for Kyushu

(a) 2010

| Statistic | Mean | St. Dev. | Min | Q1 | Median | Q3 | Max | Obs. |
|---|---|---|---|---|---|---|---|---|
| **Particulate Matter Concentration** ($\mu g/m^3$ $PM_{2.5}$, 2010) | 16.65 | 2.29 | 12.98 | 14.86 | 15.94 | 18.11 | 23.54 | 205 |
| **Ozone concentration** ($\mu g/m^3$, 2010) | 59.38 | 0.64 | 57.71 | 59.11 | 59.21 | 59.91 | 61.88 | 205 |
| **Population density** (number of people, 2010) | 530.63 | 794.99 | 6.58 | 113.47 | 530.63 | 647.82 | 6704.06 | 205 |
| **Night lights** (DNs, 2010) | 14.90 | 9.38 | 0.09 | 7.38 | 12.82 | 22.05 | 34.83 | 205 |
| **Accessibility to cities** (distance in minutes, 2015) | 15.25 | 12.73 | 0 | 4.17 | 11.90 | 23.55 | 51.88 | 205 |

(b) 2011

| Statistic | Mean | St. Dev. | Min | Q1 | Median | Q3 | Max | Obs. |
|---|---|---|---|---|---|---|---|---|
| **Particulate Matter Concentration** ($\mu g/m^3$ $PM_{2.5}$, 2011) | 16.87 | 2.17 | 13.10 | 15.13 | 16.35 | 18.42 | 23.23 | 205 |
| **Ozone concentration** ($\mu g/m^3$, 2011) | 59.56 | 0.61 | 57.81 | 59.34 | 59.41 | 59.63 | 62.02 | 205 |
| **Population density** (number of people, 2010) | 530.63 | 794.99 | 6.58 | 113.47 | 530.63 | 647.82 | 6704.06 | 205 |
| **Night lights** (DNs, 2011) | 17.57 | 12.66 | 0.13 | 7.22 | 13.81 | 26.81 | 47.34 | 205 |
| **Accessibility to cities** (distance in minutes, 2015) | 15.25 | 12.73 | 0 | 4.17 | 11.90 | 23.55 | 51.88 | 205 |

(c) 2012

| Statistic | Mean | St. Dev. | Min | Q1 | Median | Q3 | Max | Obs. |
|---|---|---|---|---|---|---|---|---|
| **Particulate Matter Concentration** ($\mu g/m^3$ $PM_{2.5}$, 2012) | 17.16 | 2.46 | 11.98 | 15.05 | 17.01 | 18.88 | 25.69 | 205 |
| **Ozone concentration** ($\mu g/m^3$, 2012) | 59.74 | 0.59 | 57.91 | 59.52 | 59.63 | 59.81 | 62.18 | 205 |
| **Population density** (number of people, 2010) | 530.63 | 794.99 | 6.58 | 113.47 | 530.63 | 647.82 | 6704.06 | 205 |
| **Night lights** (DNs, 2012) | 15.45 | 11.02 | 0 | 6.22 | 12.30 | 22.86 | 41.74 | 205 |
| **Accessibility to cities** (distance in minutes, 2015) | 15.25 | 12.73 | 0 | 4.17 | 11.90 | 23.55 | 51.88 | 205 |

# 3 Results

## 3.1 Principal Component Analysis

Tables 3 and 4 provide a summary of the results from the principal component analysis. These tables show the results for each of the years under study and are comprised of three parts. First comes the proportion of total variance, derived from the principal components. We refer to the first component as PC1 and the second component as PC2. These explain the variance for Honshu and Kyushu, for each year. In the case of Honshu, PC1 explains 59, 58, and 57 percent for each year respectively, while PC2 does so for 21 percent in each separate year. For Kyushu, PC1 is 61, 59, and 55 percent and PC2 is 19, 20, and 22 percent respectively. When we consider these cumulatively, the two components represent more than 75 percent of the total variance, a large proportion.

The second part describes the squared correlations of the components with the original variables. This tells us the size of the correlations, allowing us to analyze the components in function of the original variables. As an illustration, the variables that mainly constitute PC1 for Honshu and Kyushu are particulate matter, population density, night lights, and accessibility to cities. In PC2, ozone concentration is the most representative variable. In order to determine the number of components we will use, we rely on the so called "Kaiser criterion" (Kaiser, 1960). According to this criterion, we should only make use of those eigenvalues whose values exceed one (shown in the third part of the table). In our case, this means using the first two components, explaining a percentage higher than 75 percent of total variance for each island.

By reducing the dimensionality of the variables into PC1 and PC2, in order to summarize a large proportion of the variance, we can now study their spatial distribution. We then continue by studying the spatial dependence and the patterns of regionalization for the two components. By doing so, we can detect clusters that are spatially contiguous and face similar characteristics or attributes.

Table 3: Principal Component Analysis (Honshu)

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Total variance and cumulative proportion.** | | | | | | | | | | | | | | | |
| | **2010** | | | | | **2011** | | | | | **2012** | | | | |
| | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** |
| Proportion of variance | 0.59 | 0.21 | 0.13 | 0.05 | 0.02 | 0.58 | 0.21 | 0.13 | 0.05 | 0.03 | 0.57 | 0.21 | 0.13 | 0.06 | 0.03 |
| Cumulative proportion | 0.59 | 0.80 | 0.93 | 0.98 | 1.00 | 0.58 | 0.79 | 0.92 | 0.97 | 1.00 | 0.57 | 0.78 | 0.91 | 0.97 | 1.00 |
| **Squared correlations between the components and the variables.** | | | | | | | | | | | | | | | |
| | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** |
| Particulate matter (PM2.5) concentration | **0.83** | 0.04 | 0.00 | 0.08 | 0.04 | **0.82** | 0.05 | 0.00 | 0.08 | 0.05 | **0.76** | 0.06 | 0.01 | 0.15 | 0.02 |
| Ozone concentration | 0.09 | **0.88** | 0.01 | 0.02 | 0.01 | 0.12 | **0.84** | 0.01 | 0.02 | 0.01 | 0.16 | **0.79** | 0.00 | 0.04 | 0.01 |
| Population density | 0.47 | 0.08 | 0.42 | 0.03 | 0.00 | 0.49 | 0.09 | 0.38 | 0.04 | 0.00 | 0.49 | 0.09 | 0.38 | 0.04 | 0.00 |
| Night lights | 0.85 | 0.03 | 0.02 | 0.03 | 0.06 | 0.84 | 0.05 | 0.02 | 0.03 | 0.07 | 0.81 | 0.06 | 0.02 | 0.01 | 0.10 |
| Accessibility to cities | 0.68 | 0.02 | 0.19 | 0.10 | 0.01 | 0.66 | 0.02 | 0.23 | 0.09 | 0.01 | 0.65 | 0.04 | 0.23 | 0.05 | 0.03 |
| **Criterion to choose the number of components.** | | | | | | | | | | | | | | | |
| | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** |
| Eigenvalues | 2.93 | 1.05 | 0.65 | 0.25 | 0.12 | 2.92 | 1.05 | 0.63 | 0.26 | 0.14 | 2.87 | 1.03 | 0.64 | 0.28 | 0.17 |
| Kaiser Criterion | 2 | | | | | 2 | | | | | 2 | | | | |

Table 4: Principal Component Analysis (Kyushu)

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Total variance and cumulative proportion.** | | | | | | | | | | | | | | | |
| | **2010** | | | | | **2011** | | | | | **2012** | | | | |
| | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** |
| Proportion of variance | 0.61 | 0.19 | 0.11 | 0.06 | 0.02 | 0.59 | 0.20 | 0.11 | 0.08 | 0.02 | 0.55 | 0.22 | 0.13 | 0.09 | 0.02 |
| Cumulative proportion | 0.60 | 0.80 | 0.91 | 0.98 | 1.00 | 0.59 | 0.79 | 0.90 | 0.98 | 1.00 | 0.55 | 0.76 | 0.89 | 0.98 | 1.00 |
| **Squared correlations between the components and the variables.** | | | | | | | | | | | | | | | |
| | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** |
| Particulate matter (PM2.5) concentration | **0.70** | 0.00 | 0.17 | 0.12 | 0.01 | **0.62** | 0.02 | 0.25 | 0.10 | 0.01 | **0.42** | 0.17 | 0.39 | 0.02 | 0.00 |
| Ozone concentration | 0.10 | **0.86** | 0.03 | 0.00 | 0.00 | 0.07 | **0.85** | 0.06 | 0.00 | 0.00 | 0.11 | **0.71** | 0.17 | 0.01 | 0.00 |
| Population density | 0.56 | 0.08 | 0.34 | 0.02 | 0.01 | 0.58 | 0.10 | 0.25 | 0.05 | 0.01 | 0.59 | 0.14 | 0.05 | 0.20 | 0.01 |
| Night lights | 0.91 | 0.02 | 0.00 | 0.00 | 0.07 | 0.90 | 0.03 | 0.00 | 0.00 | 0.07 | 0.87 | 0.05 | 0.00 | 0.00 | 0.08 |
| Accessibility to cities | 0.78 | 0.00 | 0.02 | 0.18 | 0.02 | 0.76 | 0.00 | 0.00 | 0.22 | 0.01 | 0.75 | 0.00 | 0.01 | 0.21 | 0.03 |
| **Criterion to choose the number of components.** | | | | | | | | | | | | | | | |
| | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** |
| Eigenvalues | 3.04 | 0.96 | 0.56 | 0.32 | 0.12 | 2.95 | 1.00 | 0.57 | 0.37 | 0.11 | 2.73 | 1.08 | 0.63 | 0.44 | 0.12 |
| Kaiser Criterion | 2 | | | | | 2 | | | | | 2 | | | | |

## 3.2 Spatial Dependence

In Figures 3 and 4 as well as in Figures 5 and 6, we observe the graphs of the Local Moran scatter plot for autocorrelation for Honshu and Kyushu, respectively. The X axis in these graphs presents the values of PC1 and PC2, respectively. The Y axis displays the weighted mean of the neighbors (that is to say, the spatial lag). The regression line in these graphs highlights the degree of spatial dependence. The Moran scatter plot is made of four quadrants: Top-right, top-left, bottom-right, and bottom-left. The top-right and bottom-left ones depict the spatial clusters. These emphasize municipalities and their neighbors having similar high/low values, respectively, in PC1 and PC2. In the top-left and bottom-right parts of the graphs we observe the spatial outliers and their geographical positions. These outliers depict municipalities with high values in PC1 and PC2, surrounded by neighbors whose values are low or vice-versa. The highlighted dots in Figures 3a-3c and 4a-4c, for Honshu, as well as in Figures 5a-5c and 6a-6c, for Kyushu, refer to the observations that are statistically significant ($p$-value of 0.01). By doing so, we reduce any chances related to the multiple comparison problem. According to Anselin (1995), this is a problem that may arise when performing any analysis of local indicators of spatial association (LISA).

Figures 7 (for Honshu) and 8 (for Kyushu) lay out the spatial distribution of municipalities that are statistically significant. If we consider the four quadrants in the Moran scatter plots, the municipalities under study are grouped into hot spots (high-high) clusters and cold spots (low-low) clusters, for PC1 and PC2 respectively. The remnants are spatial outliers.

In Figures 3-8 we can see the presence of positive and statistically significant spatial dependence. Interestingly, in both Honshu and Kyushu the level of $PM_{2.5}$ concentration, night lights, population density, and accessibility to cities (captured here by PC1) that the municipalities have, is very similar to that of its adjacent neighbors.

This relationship is captured by the global Moran's I. In Honshu, this coefficient's values for PC1 are 0.871, 0.873, and 0.868 for each of the respective years under study. For Kyushu, the values are 0.801, 0.796, and 0.783, respectively. For both Honshu and Kyushu these are very high values, implying that there is a very high spatial dependence. For Honshu, in Figure 7a we see clusters of hot spots in the Tokyo, Nagoya, and Osaka areas (which are made of 183, 177, and 177 municipalities for 2010, 2011, and 2012, respectively). These are comprised of high mean levels of $PM_{2.5}$ concentrations (20.52 $\mu g/m^3$ for 2010, 20.10 $\mu g/m^3$ for 2011, and 19.76 $\mu g/m^3$ for 2012),[3] population density (5913.28 people per square km), night lights (33.99 DNs, 46.44 DNs, and 40.35 DNs, for each year), and accessibility to cities (0.36 minutes).[4] The cold spots are made of 159, 155, and 145 municipalities, for the years analyzed, with a considerable accumulation of these in the Tohoku region. These present lower levels of $PM_{2.5}$ concentration (10.73 $\mu g/m^3$, 10.52 $\mu g/m^3$, and 10.32 $\mu g/m^3$, respectively), population density (80.06 people per square km), night lights (6.31 DNs, 6.60 DNs, and 6.18 DNs for its respective year), and a higher distance to nearby cities (42.28 minutes). For Kyushu, we see in Figure 8a that the hot spots are positioned more to the center and south. Meanwhile, the cold spots are focused to the northwest (these include cities with larger populations such as Fukuoka, Kitakyushu, and Kumamoto, amongst others).

Figures 4 and 7b exhibit Honshu's spatial dependence for PC2. We find that, even though there is a positive and statistically significant spatial dependence for the period under study, it is lower than PC1's (this is captured through the slope of Moran's I being flatter than before). In this case, the values for this dependency are 0.215, 0.233, and 0.254, respectively. PC2's hot spots for Honshu are very few and are located in parts of the Tokyo, Kansai, and Chugoku regions (they comprise only 6 municipalities for all years under study). Instead, the cold spots are considerably large. They consist of parts of the Tokyo, Chuubu, and Kansai areas. For Kyushu (as was the case for Honshu), the main variable of interest in PC2 is concentrations of ozone. Only 15 municipalities in Kyushu act as hot spots. These municipalities possess higher levels of ozone concentrations (61.68 $\mu g/m^3$ for 2010, 61.21 $\mu g/m^3$ for 2011, and 61.19 $\mu g/m^3$ for 2012).

The Moran scatter plot serves as a way to help recognizing bi-dimensional clusters. The first dimension refers to the values of the principal components (in our case, economic activity and air pollution) while the second dimension alludes to the spatial contiguity (i.e., the geographic proximity) of the municipalities. Would there be a way to consider and classify the areas in grey in the maps, (Figures 7 and 8), which are not statistically significant? To answer this, in the next section we make use of the Max-p clustering algorithm developed by Duque et al. (2012)

## 3.3 Regionalization through the Max-p algorithm

In Figure 9, we can see the different regions into which Japan divides. These regions are categorized into administrations based on natural and historical reasons. If we go to lower levels, Japan can be categorized into 47 prefectures or even into municipalities. At the same time, various administrative regions usually vary in their economic activities and in the geographical scope in which these are realized. Due to this, by taking into account spatial autocorrelations,

[3] The numbers in parenthesis explain the mean value for the municipalities that are part of the hot spots. These values are in their original scale, just as in Tables 1 and 2.

[4] The lower the value of this variable, the better the accessibility.

we protect ourselves from overestimating the effects that urban agglomeration may play (Otsuka, 2021).

By relying on the Max-p algorithm, it is possible to group different regions into analytical ones, based on their economic activities and/or pollution levels. In contrast to the standard regional divisions, which only give information on locational similarity, by partitioning Honshu and Kyushu into analytical regions we can attain additional information regarding their locational and attribute similarity. In Figure 9 we see that the municipalities present only a similar location (locational similarity), but they do not necessarily share similarity of attributes (i.e. level of pollution or economic activity). The analytical regions we observe in Figures 10-13 present clusters of spatially contiguous municipalities having: a) similar levels of pollution and/or economic activity, and b) spatial heterogeneity in each administrative region, up to a certain degree. For example, we detect this in the Kantou region in Figure 9. When examining the economic activity and pollution levels, we find five different clusters within its administrative boundaries (Figures 10 and 11).

Two things are worth highlighting from the regionalization process. The first is that the air and ozone pollution levels (expressed through PC1 and PC2, respectively) spread throughout multiple administrative regions. This means that it is imperative for all the affected regions to coordinate so that the situation improves. The second thing to bear in mind is that a number of regions are spatially more uneven and heterogeneous than others. As an example, for PC1, Kantou has five clusters while Touhoku has only two.

It is important to consider that pollution levels before and after the Fukushima event altered how analytical regions should potentially be considered. For this, we obtain these regions separately for each year under study and also for the whole period. In Figures 10-13, we can see that it would appear the Fukushima event had a stronger effect on Honshu, when considering PC1, than on Kyushu. From 2011, the region colored in red greatly increased and absorbed many municipalities initially belonging to the light green region. The pollution levels changed after 2010, and thus many municipalities should then be included in a region with similar attributes. When regionalizing for the whole period, we see that the analytical regions remain largely stable and have a structure similar to that of 2011 and 2012. This allows policymakers to consider a random shock that alters energy usage, such as the Fukushima incident in 2011, when designing policies to reduce pollution levels and improve the inhabitants' quality of life.

From these results, we note that the pollution levels do not attain the environmental quality standards that the Ministry of the Environment set.[5] These annual quality standards call for concentrations of $PM_{2.5}$ to be less than or equal to 15.0 $\mu g/m^3$. From Table 5, we see that in Honshu and Kyushu, the number of municipalities that exceed this level is high before and after 2011. In the past few years, the number of air quality monitoring stations has grown significantly (from slightly fewer than 100 in 2010 to approximately 1875 stations in 2018). This allows for more precise monitoring of air pollution and its sources. Because of this, there have been advancements in the reduction of $PM_{2.5}$ concentrations, although Ozone concentrations have continued increasing in recent times (Ito et al., 2021). From this, we know that additional efforts must be made to improve air quality.

Through a deeper understanding of how multiple variables interact spatially, we can better communicate how to deal with these issues to policymakers and interested parties. By better grasping how pollution is spatially distributed throughout the various regions, policymakers may develop and target different policies more effectively.

[5] https://www.env.go.jp/en/air/aq/aq.html

Table 5: Municipalities with high pollution

| | 2010 | |
|---|---|---|
| **Island** | **Number of municipalities** | **% of total** |
| Honshu | 465 | 39.6 |
| Kyushu | 144 | 70.2 |

| | 2012 | |
|---|---|---|
| **Island** | **Number of municipalities** | **% of total** |
| Honshu | 431 | 36.7 |
| Kyushu | 156 | 76.1 |

# 4 Discussion and policy implications

The two previous subsections manifest that both the Local Moran and the Max-p clustering method work as complementary analyses. The Local Moran analysis detects clusters of hots spot and cold spots, while the Max-p algorithm groups the remaining municipalities into clusters with similar attributes. The usage of these techniques does not necessarily translate into a one to one superposition of clusters. However, such an analysis helps with the detection of robust spatial clusters that merit further study. These clusters may provide important information at the local/regional and national level to policymakers for the planning and elaboration of policies that target areas where improving air pollution is more pressing.

We need to take into consideration two things when comparing the resulting spatial clusters. First, the Local Moran method evaluates only observations from the high-high and low-low quadrants of the graph, while the Max-p algorithm relies on all of them. Second, usually the size of the clusters derived from the Max-p algorithm tends to be larger than those from the Local Moran ones. This is because the Local Moran method analyzes spatial contiguity through first order neighbors (i.e. those who are more proximate or direct neighbors). Alternately, the Max-p algorithm considers also those of higher order (i.e. neighbors or neighbors, and so on). Because of this, we see that these methodologies complement each other very well. By relying on both of these methodologies, we can appreciate different things through the respective information they provide.

The use of a spatial approach allows us to observe the changes in $PM_{2.5}$ and ozone concentrations before and after the 2011 incident in Fukushima. This event generated the need to rely on alternative energy production sources, such as thermal power, which is highly polluting, to satisfy the energy demands of homes and industries. This likely increased the concentrations of pollutants in different parts of Honshu and Kyushu that previously had safer air pollution levels. Also, although air pollution is of more significance at the local and regional level, many pollutants and small particles such as $PM_{2.5}$ can be carried across large distances by wind, affecting other regions. Because of this, it is fundamental for policymakers to develop policies where different municipalities and regions can coordinate with each other to find solutions that tackle these issues effectively. A regionalization analysis, as we have shown in this study, can contribute to doing this by pinpointing clusters of regions where this coordination is likely to have positive outcomes. In our analysis, the number of clusters remained constant throughout the period under study, although the size of some of these changed. Performing a regionalization for the whole period, thus, shows us how the regions should instead be considered.

According to Kaneyasu et al. (2020), many of the sources of $PM_{2.5}$ in Japan come from the combustion of coal and oil by factories, transportation, and heating. Moreover, there is transboundary air pollution from other Asian countries (Yim et al., 2019). Some policies and regulations that may contribute in changing these pollution patterns include: Enhancing and re-enforcing the monitoring system for data collecting to study and implement measures for $PM_{2.5}$. Also, implementing taxes and subsidies to promote larger shares of cars sold that meet more stringent environmental standards by 2030. Finally, international cooperation by means of joint research and efforts in cutting $PM_{2.5}$ concentrations can have a strong impact in decreasing air pollution levels.

# 5 Conclusion

In this work, we find clusters of municipalities in Honshu and Kyushu with similar pollution levels and of economic activity. To analyze this, we make use of principal component analysis and techniques from spatial data analysis. We then evaluate differences, at the regional level, of $PM_{2.5}$ concentration, ozone concentration, population density, night lights, and accessibility to cities. From the PCA, we reduce all these variables into PC1 and PC2. PC1 mostly depicts the municipal variation in $PM_{2.5}$ as well as population density, night lights and accessibility to cities. PC2 mostly represents the municipal variation in the pollution through ozone concentration. We then pinpoint at clusters of municipalities that have spatial contiguity and that share similar levels of economic activity and air pollution.

We find that there is a positive and statistically significant level of spatial dependence throughout the regions. The economic activity and levels of air pollution, expressed through PC1 and PC2, that the average municipality has is highly similar to that of other municipalities with which it shares geographic borders. As an example, the PC1 clusters of hot spots for the metropolitan areas of Tokyo, Nagoya, and Osaka, are interesting. These clusters present high levels of particulate matter concentration, population density, and night lights.

Using a regionalization algorithm by Duque et al. (2012), we produce outcomes that are largely consistent with those we obtained from the spatial dependence analysis. This algorithm partitions Honshu and Kyushu into different regions, based on the results derived from the PC1 and PC2 variables. The regions obtained by the algorithm differ from those of the historical administrative regions. This suggests that pollution and economic activities extend throughout administrative borders. By generating these new boundaries, different municipalities can coordinate in producing, designing, and implementing policies to improve air pollution levels.

Additionally, we explore the changes in $PM_{2.5}$ and ozone concentrations for the immediate years before and after the 2011 incident in Fukushima. These pollution levels affected the way analytical regions are evaluated, so we obtain these for each year under study and also for the whole period. When doing so, we appreciate that the analytical regions remain mostly stable throughout the period under study.

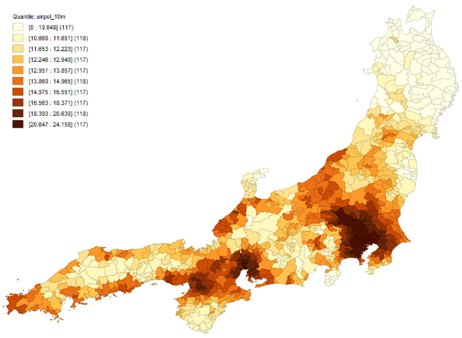
In Kyushu the share of renewable energy generation is usually high and the electricity market price often tends to zero. Understanding the effect that the diffusion of renewable energy has on the concentrations of $PM_{2.5}$ and ozone would be important to improve people's quality of life. Additionally, Exploring the correlation between economic activity and the seasonal variation of pollutants in Kyushu and Honshu, in order to understand "imported" air pollution (i.e., air pollution incoming from other countries) could be an interesting avenue of research. We leave both of these questions for future studies.

# 6 Appendix

## 6.1 Figures

Figure 1: **$PM_{2.5}$ pollution in Honshu**

(a) 2010



(b) 2012

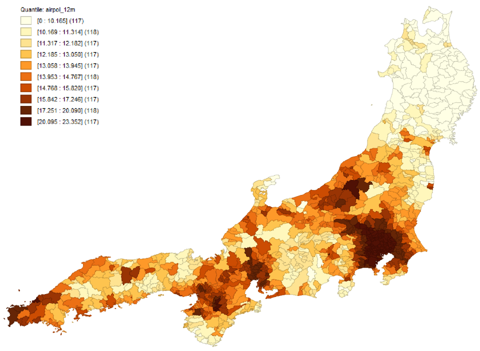
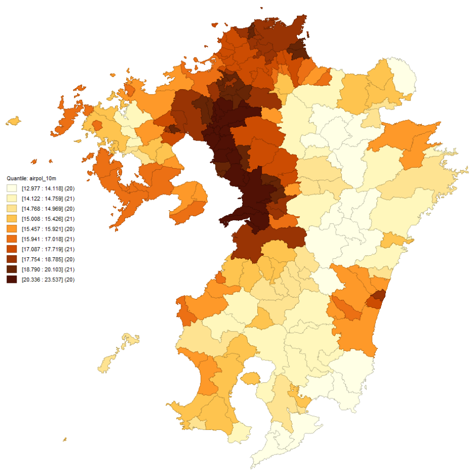


Figure 2: **$PM_{2.5}$ pollution in Kyushu**

(a) 2010



(b) 2012

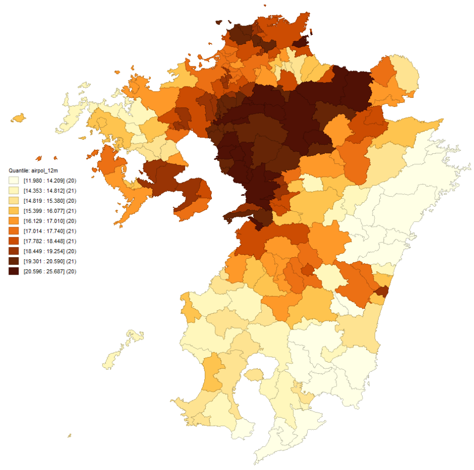
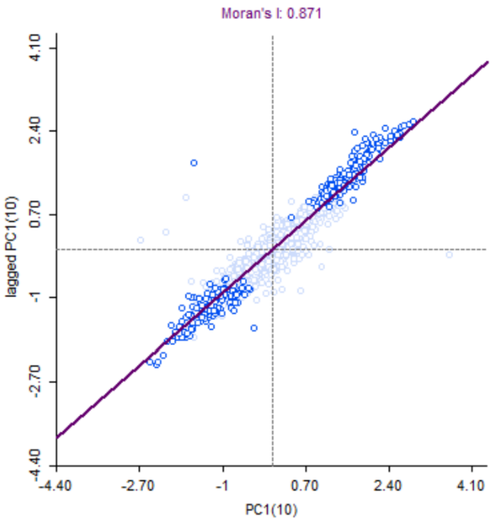
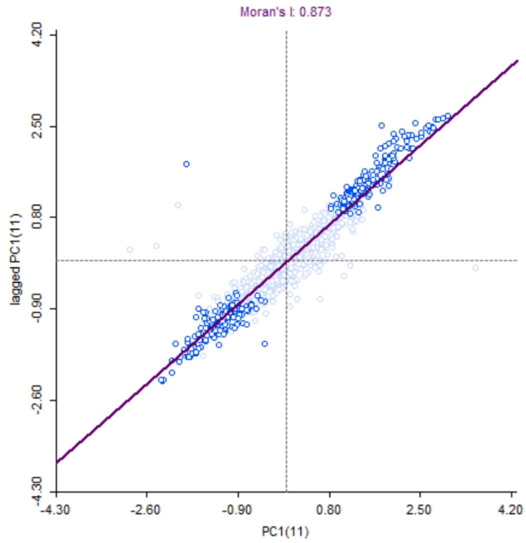


Figure 3: **Spatial Autocorrelation Honshu 2010-2012 (PC1).**

(a) 2010




(b) 2011




(c) 2012

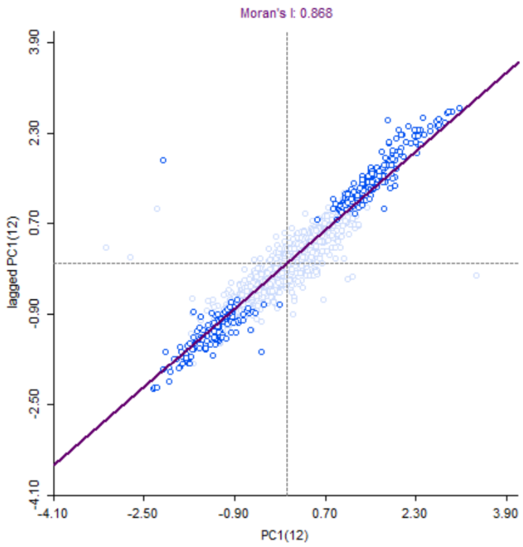
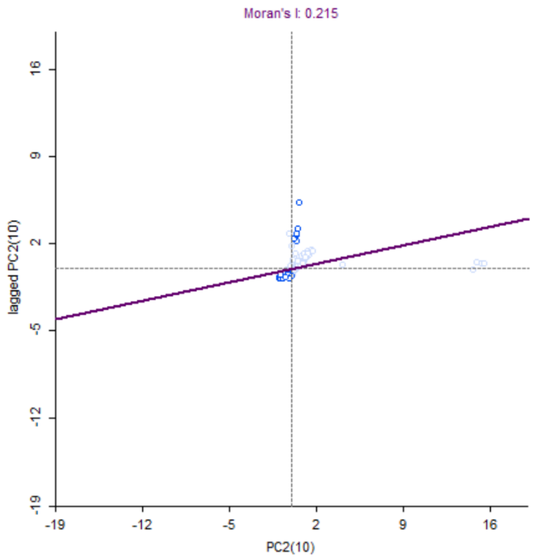
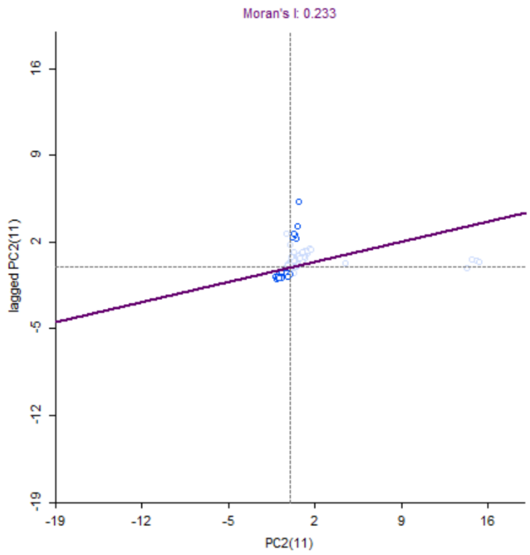


Figure 4: **Spatial Autocorrelation Honshu 2010-2012 (PC2).**

(a) 2010




(b) 2011




(c) 2012

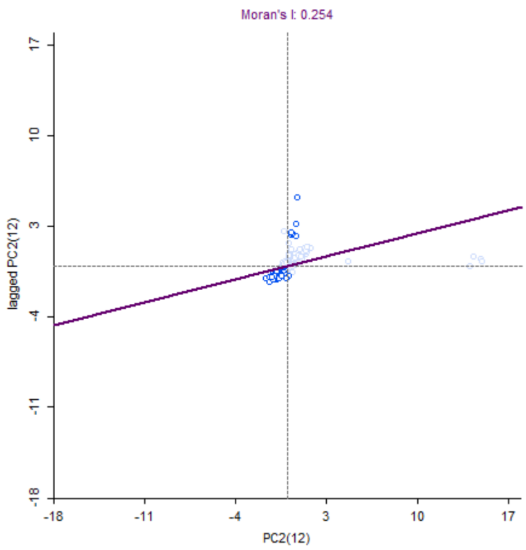
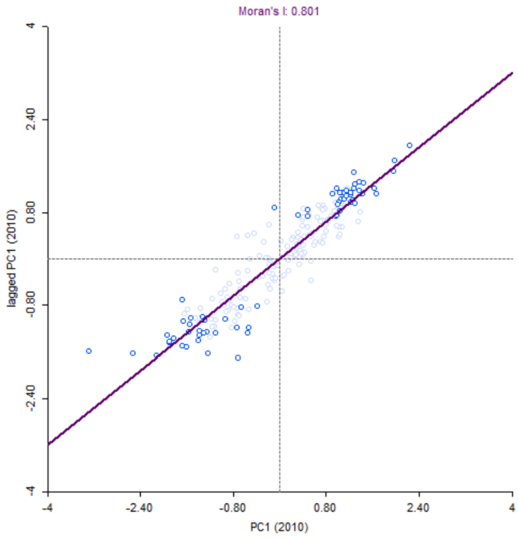
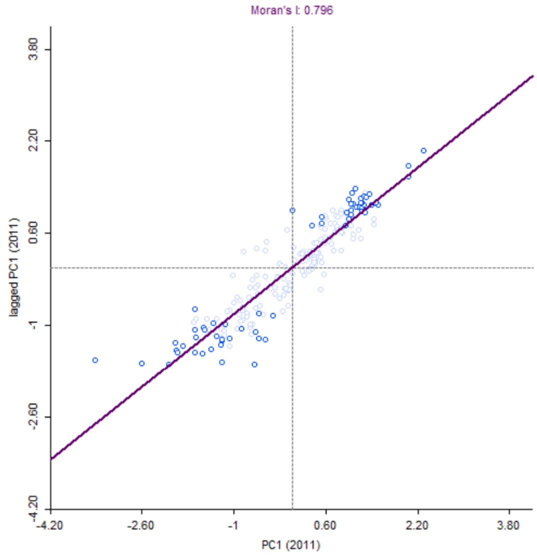


Figure 5: **Spatial Autocorrelation Kyushu 2010-2012 (PC1).**

(a) 2010




(b) 2011




(c) 2012

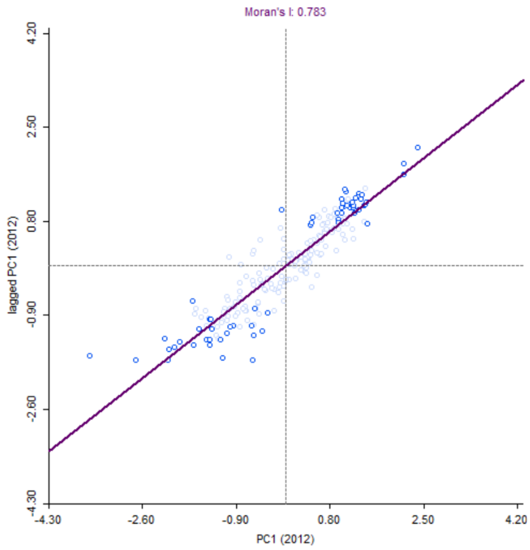
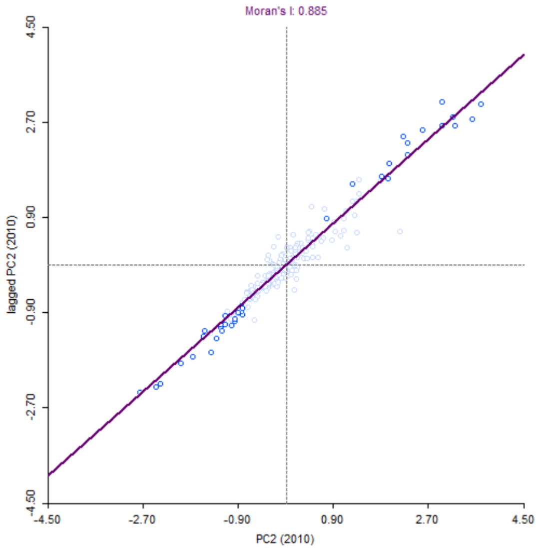
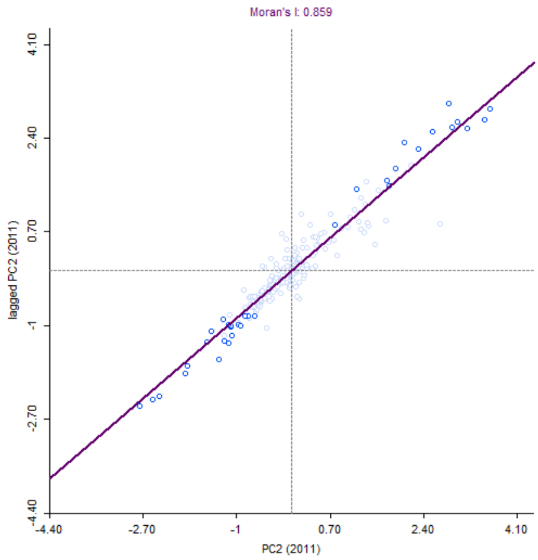


Figure 6: **Spatial Autocorrelation Kyushu 2010-2012 (PC2).**

(a) 2010




(b) 2011




(c) 2012

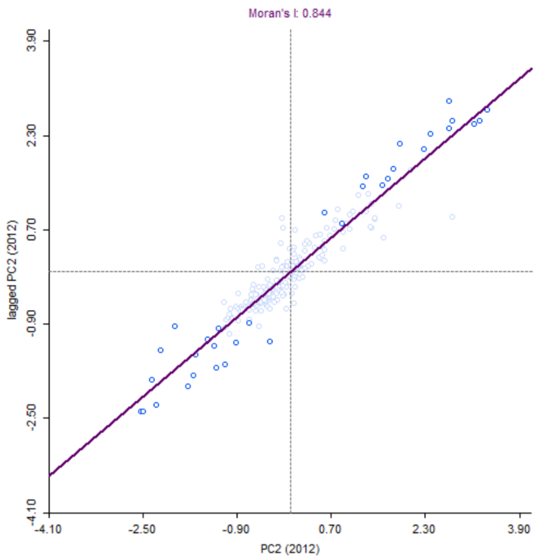
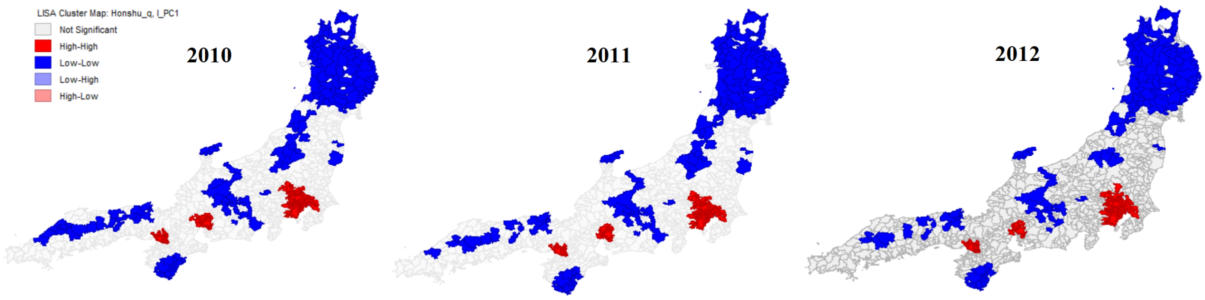


Figure 7: **Hot spots and Cold spots (Honshu).**

(a) PC1




(b) PC2

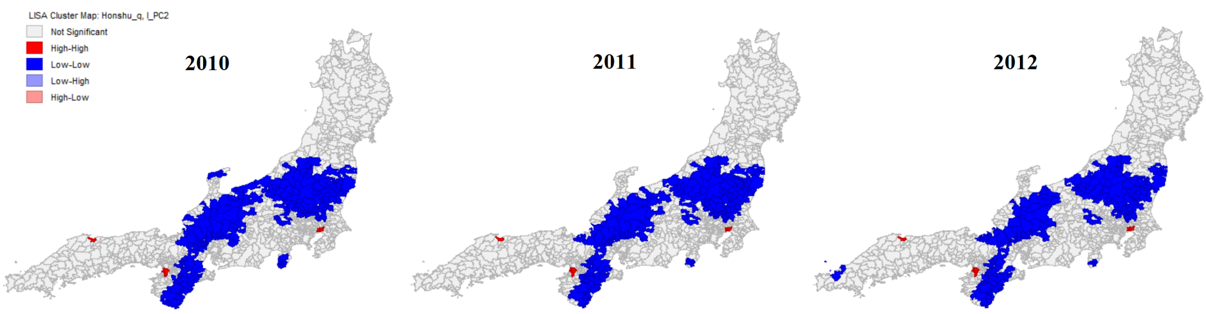
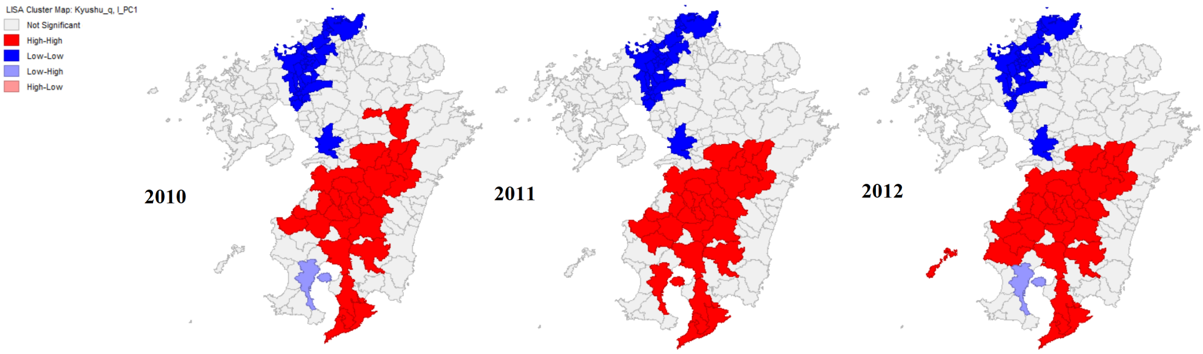


Figure 8: **Hot spots and Cold spots (Kyushu).**

(a) PC1




(b) PC2

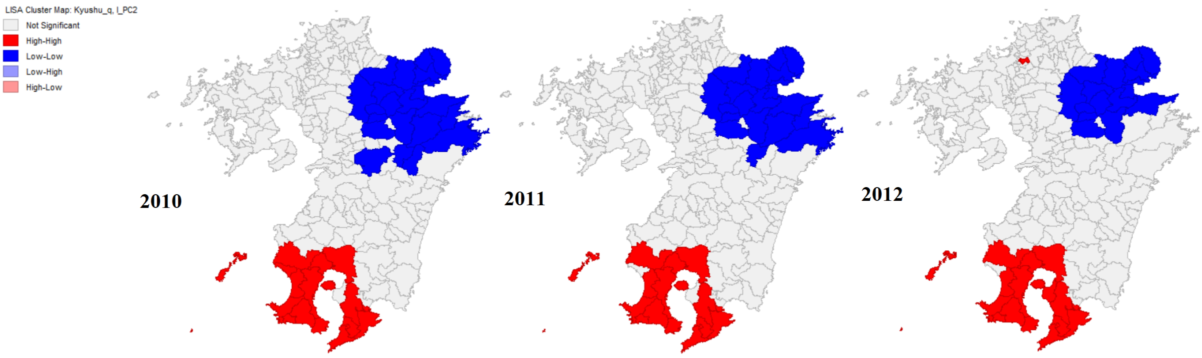



Figure 9: **Administrative regions.**

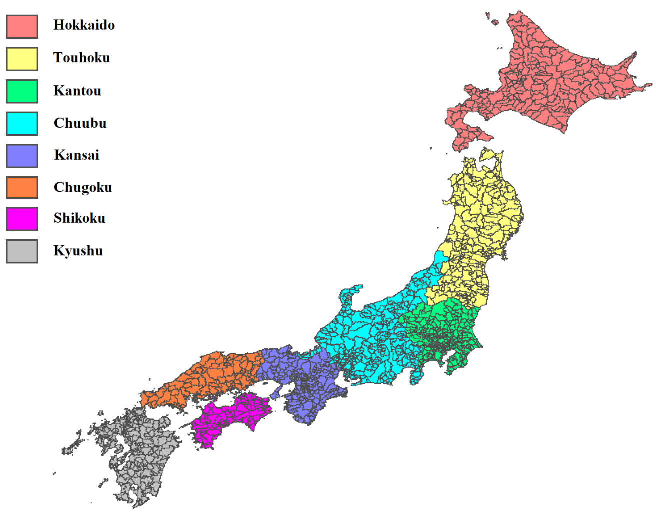
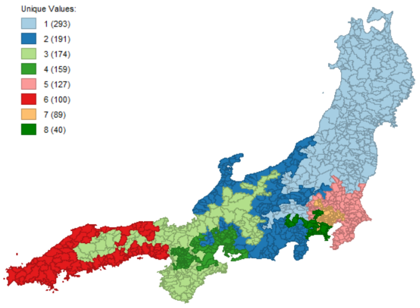
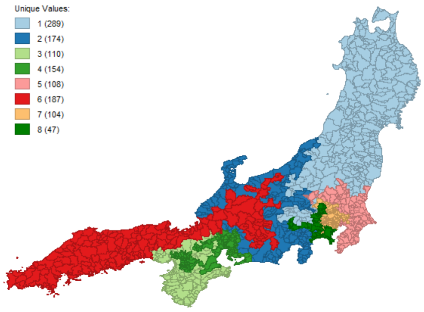


Figure 10: **Regionalization: Analytical regions for Honshu (PC1).**

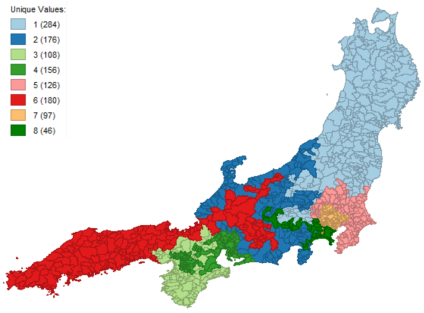
(a) 2010




(b) 2011




(c) 2012




(d) 2010-2012

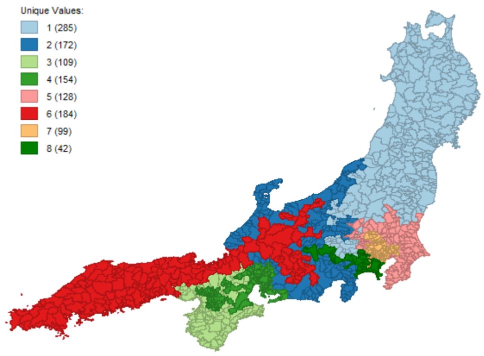
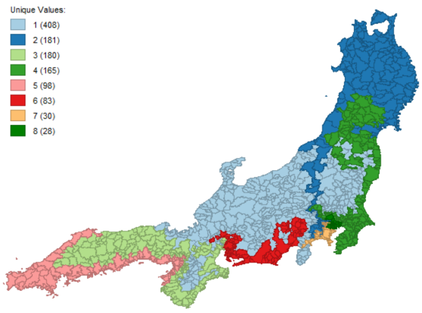
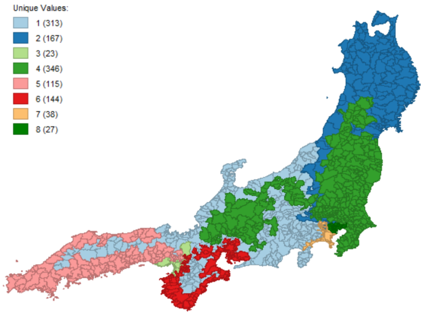



Figure 11: **Regionalization: Analytical regions for Honshu (PC2).**

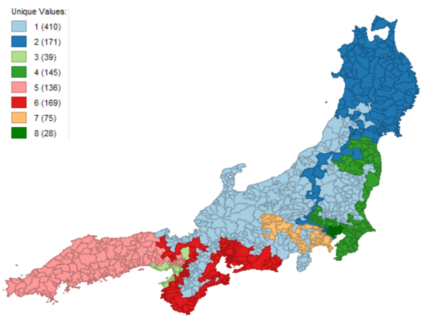
(a) 2010




(b) 2011




(c) 2012




(d) 2010-2012

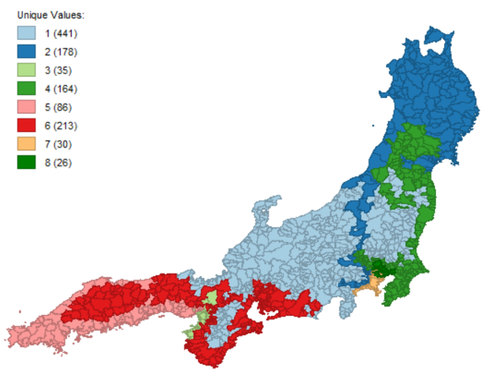
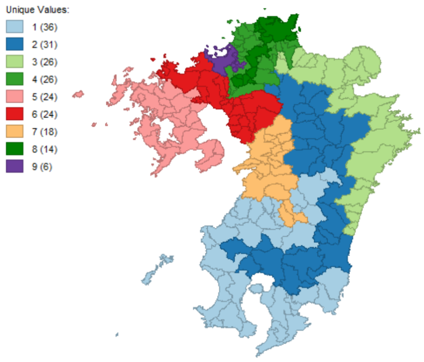
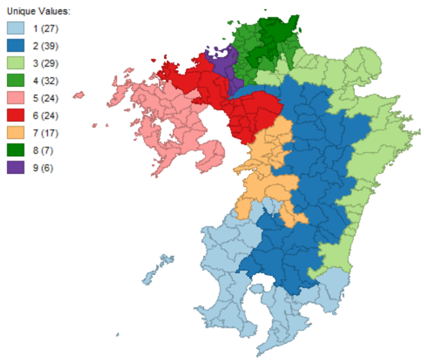


Figure 12: **Regionalization: Analytical regions for Kyushu (PC1).**

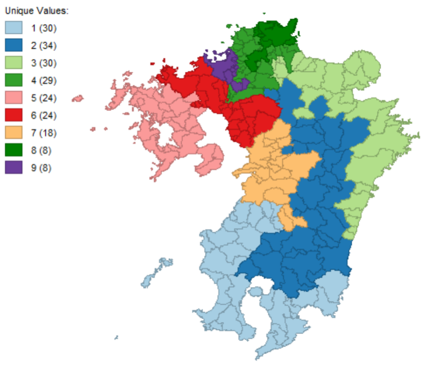
(a) 2010




(b) 2011




(c) 2012




(d) 2010-2012

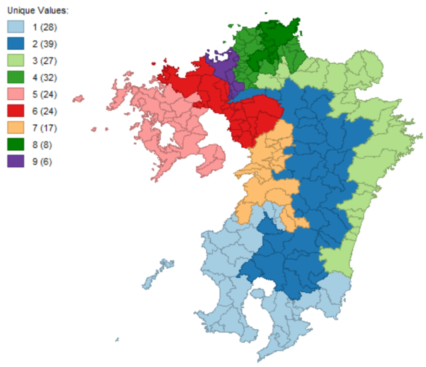
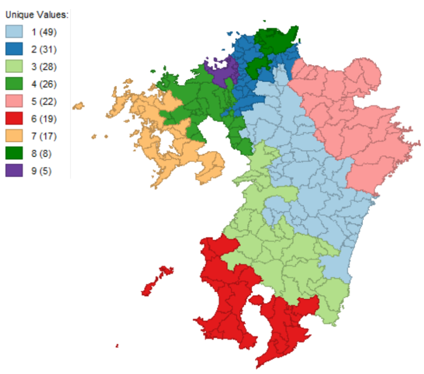
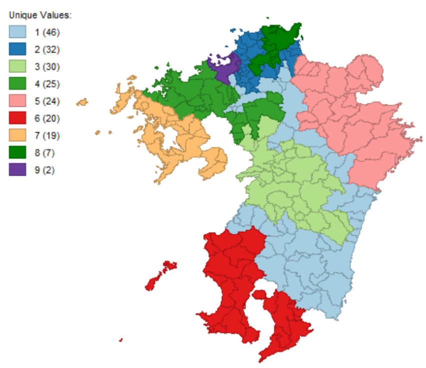


Figure 13: **Regionalization: Analytical regions for Kyushu (PC2).**

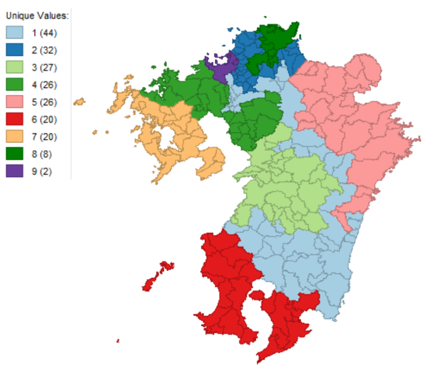
(a) 2010



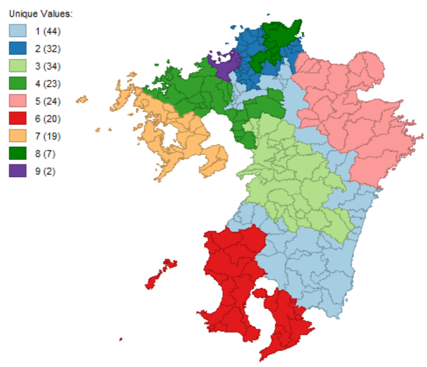

(b) 2011




(c) 2012




(d) 2010-2012



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