PREDICTING GROSS METROPOLITAN PRODUCT WORLDWIDE USING STATISTICAL LEARNING MODELS, SOCIO-ECONOMIC, AND SATELLITE IMAGERY DATA

by

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DEDICATION

In dedication to my sister, Rezvan, who taught me my first words, inspired every accomplishment, and has been a true mentor all my life. With special thanks to my parents, Pari and Majid, who have provided me with unending love, encouragement, and support.

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Abstract

Gross metropolitan product (GMP) is one the most critical indicators for determining a metropolitan area's economic performance. While GMP data currently exists for major cities in the US and OECD countries, the rest of the world is a blind spot. This study aims at estimating the GMP of 1289 cities in non-US and OECD countries, where no official city-level statistics are produced. We perform this estimation through multiple machine learning models, using night-time lights satellite imagery, and other publicly available data. We analyze eight spatial databases and four cross-sectional datasets and derive a feature vector of covariates through various techniques, i.e., downscaling and bootstrap. We specify OLS, Ridge, Lasso, Elastic Net, and Random Forest models, out of which Random Forest generated the most accurate results with 0.3 RMSE for out-of-sample predictions. With this methodology, we produced the first existing data set that groups the 1298 cities into 20 quantiles, with the first quantile denoting the lowest five percent regarding estimated income and the twentieth quantile denoting the highest five percent regarding the estimated economic product.

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LIST OF ABBREVIATIONS

MSA – Metropolitan Statistical Area

GDP – Gross Domestic Product

GMP – Gross Metropolitan Product

NTL – Night Time Lights

VANUI – Vegetation Adjusted Nighttime Light Urban Index

VIIRS – Visible Infrared Imaging Radiometer Suite

RAD – Radiance

CBSA – Core Based Statistical Areas

CRS – Coordination Reference System

C/V – Calibration/Validation

WGS84 – World Geodetic System spheroid of 1984

ESPG – European Petroleum Survey Group

LASSO – Least Absolute Shrinkage and Selection Operator

RF – Random Forest

CARET – Classification And Regression Training

OOB error – Out-of-Bag error

Chapter 1

INTRODUCTION

Gross metropolitan product (GMP) is one the most critical indicators for determining a metropolitan area's economic performance [33]. If GMP data were avaialable for multiple time periods, it could be used for metropolitan growth and poverty analysis [8, 25, 38]. In addition, GMP per capita can be the basis for exploring inequality within a given city as well as between multiple cities [1]. Consequently, GMP is a highly contributing metric in urban and developmental economics research. In addition, metropolitan areas are major contributors to every country's GDP [12]. While GMP data currently exists for major cities in the US and OECD countries, the rest of the world is a blind spot. There is also no commonly agreed upon method for generating reliable GMP estimates (or predictions) for every city in the world. In addition, the inaccuracy and lack of sufficient data in most developing countries' statistical systems make it harder for conducting economic analyses [8]. In fact, when it comes to studying metropolitan areas, because they are bound to the data collecting rules and regulations of their own country, gathering a cohesive dataset that includes cities from multiple countries becomes challenging. Therefore, we aim at creating a method that uses publicly available data, and is generalizable for any city in the world with population over 300,000 people.

Data derived form Luminosity-based satellite imagery can act as a strong proxy for economic activity [8, 25]. These images are publicly available and are gathered from the same source and thus, are cohesive. Therefore, data derived from these images is suitable for machine learning tasks. While some studies [28, 34] use

Machine Learning methods for processing the images, these methods can also be used to derive predictions regarding variables of interest such as the GMP.

Various research studies have been conducted on the use of luminosity-based satellite imagery on growth and development [8, 25]. In addition, some papers focus on specific countries or cities [6,38]. Although the current body of literature covers multiple aspects of both satellite image processing and machine learning algorithm utilization, there is still a gap regarding the use for both for a global GMP estimation.

This study aims to remedy this problem by specifying a reliable supervised machine learning estimation model that uses publicly available data, such as data derived from satellite images (luminocity, urban form, road networks), national-level GDP, metropolitan GMP and population. There are three groups of datasets utilized in the statistical models: calibration (training), validation (testing), and prediction. The calibration and validation datasets include the GMP variable and are used to train and assess each model's performance, respectively. The prediction dataset includes all the independent variables and is used as input to the models. We used three satellite raster images to create the final d ata sets and processed them to derive variables that translate luminosity. In addition, we account for urban form and structure by analyzing each city through a set of derived spatial metrics and luminosity statistics. Using a downscaling technique, we predicted the GMP of each city based on various portions of the GDP (such as non-agricultural and services). A bootstrap technique is then used to capture diversity in the downscaled variables. Moreover, city road segment lengths and counts are included to capture the infrastructure information. We also account for whether or not a city is coastal by using a binary variable. When the feature vectors are derived, we created multiple models, using the ordinary least squares (OLS) model as a baseline. Apart from the OLS, other models such as Lasso, Ridge, Elastic Net, and Random Forests (RF) were used, out of which RF had the best predictions and lowest errors. The result of this study is a prediction data set over the GMP class estimation of 1298 cities in the world. The training and testing data sets include cities from 28 OECD countries including the US. Most of these countries are developed, and it was expected that this data might not be fullt representative of the spectrum of metropolitan economics output. Through utilizing downscaled GMP estimations we discovered that out of an estimated 20 classes of income brackets, the training and testing data only covered the top 11 classes. In addition, the estimation models cannot make predictions of labels that they have not been trained on. As a result, the lowest estimated GMP could only be as low as the lowest GMP in the training data. However, because population is one of the strongest indicators for gross product, and that the population distribution among cities in both training/testing data and the prediciton data is similar, the predicted values of $ln(GMP)$ can be justifiably reliable. The ordinality of the data is also kept. As a result, the predictions are grouped into 20 quantiles to show a sorted list of cities that fall into 5 percent increments of economic output frequency, with the first ventile denoting the lowest GMP and the twentieth showing the highest GMP. We have also included information on per capita GMP in our estimations.this metric can be specifically useful in poverty investigations at the metropolitan scale. [38]

The rest of this thesis is organized as follows. Chapter two discusses related research that has been done in this field and information on the research papers that provide the data for some of the derived explanatory variables in this study. Chapter three discusses the data and its properties. Chapter four describes the methodologies that were used in this research. Chapter five presents information on the implementation of the methods. Finally, chapters six and seven discuss the results of this study, the conclusion , and future work, respectively.

Chapter 2

RELATED WORKS

There is a growing body of literature for the use of Nighttime lights remote sensing imagery as a proxy for socio-economic data. Luminosity-centered satellite imagery has successfully been used as proxies for levels of economic activity and energy use in many studies. The reason for the need for proxies such as luminosity is the lack of information and measurement errors in the developing world's data gathering systems. Although we have adequately reliable data for the developed portion of the world, we are quite in the dark regarding developing countries. This lack of information and data leads to an inability to make accurate and reliable analyses and assessments of the developing world. As a result, scientists have to rely on information available in aggregate and independent of each country's data gathering system. This is why satellite imagery plays an important role. This data is unbiased and globally collected. Especially in the case of luminosity, many studies have proved that this data source translates economic well-being reliably. However, these studies are not without limitations.

Nevertheless, the studies that have been done in this field leave a gap for much further research. Pioneering in the field of satellite image use in economic estimation, Chen and Nordhouse [8], made an initial utilization of luminosity and nighttime light satellite data as a means of regional and one-degree grid cell economic growth estimation. They conclude that although luminosity is a useful proxy, further research needs to be done on the methods of using this data source. They also conclude that luminosity is a poor proxy for countries with moderate to excellent statistic systems. These efforts were followed by Henderson et al. [25], who looked at night lights as a proxy for real GDP growth analysis. They analyzed approximately 177 countries for 17 years and 30 countries that were rated low to middle income by the world bank. Moreover, they conclude that the elasticity of the growth of night light to income growth is close to one for low to medium-income countries. These studies opened the floor to further economics research in this area [6, 14, 16, 35]. Jean et al. [28] worked on using high-resolution satellite images of day time lights for 5 African countries with a convolutional neural network. They aim to predict average household consumption expenditures and assets and wealth, and they were able to explain up to 55% of the economic outcome variety by their model. Building on the research of Jean et al. [28], later, Perez et al. [34] generated one-year predictions using convolutional neural networks and Landsat 7 daytime images. During their analysis, Subash et al. [38] apply a neural networks model to nighttime lights satellite images of rural India to assess the poverty levels due to prolonged data collecting intervals. They found the satellite images were a superior poverty predictor than per capita GDP.

The body of literature in the field of using luminosity-based satellite imagery seems to agree on this data source's validity as a proxy of economic activity and well-being. However, to our knowledge, no research has been done on the use of nighttime light satellite imagery for urban economic outcome in the scale of the study at hand. Other factors that seem to be contributing to economic activity in the literature are urban form and infrastructure [22]. Metropolitan areas' spatial structure is one of the important aspects of a city's growth. Properties such as size (area and perimeter), density, and active urban patches can be valid determinants of a city's economic output. According to the literature, the cities benefit from agglomeration economies as they grow [20, 23]. Lee and Gordon [30] researched the best size of a city for optimized growth. In comparison, John Brotchie et al. [5] note the concentration of economic activity in patches. We have accounted for spatial urban form in this study for these reasons. Gramlich [24], defines infrastructure as "large capital intensive natural monopolies such as highways, other transportation facilities, water and sewer lines, and communications system."

Many studies recognize infrastructure as an impactful variable in GDP growth. Calderon and Serven [7] found a positive relationship between infrastructure and economic growth, while their conclusions also showed a negative relationship between the increase of infrastructure and income inequality. More specifically, in the case of roads and highways, during their instrumental variable design, Durantor and Turner [15], found that a 10 percent increase in a city's initial stock of highways leads to an approximation of one and a half percent increase in its employment. For these reasons, we have considered road map data in our study.

We use the resulting data set from Taubenbock et al. [39] research for deriving our prediction dataset. Their work investigated the world's largest city ranking based on settlement area and settlement population density. Based on this analysis, they generated new morphological boundaries for the cities and compared them to the administrative boundaries. They concluded that the administrative boundaries were wider on average, except in the case of Europe, where the administrative boundaries were in line with the study's outcome boundary.

The roads data was developed by Meijer et al. is [32] research where they analyzed more than 60 geospatial datasets on road infrastructure into a global roads dataset and used a regression model to find the relationship between roads data and GDP, among other variables. They found that wealthier countries have more roads on average and they predicted large road constructions for developing countries. This data covers 222 countries and is claimed to include more roads than the best available country-based global roads datasets by 2018.

In conclusion, the research studies that utilize satellite images, use them as a proxy to estimate poverty, growth, consumption expenditure, and regional economic product. However, the subject of these estimations is often at the country level, and in cases where smaller regions are being investigated, they are not studied over many countries. In other words, if the subject of study is of a smaller level, such as rural areas, the number of countries included in the analysis is limited, and if a large number of countries is included in the study, the subject of the study is at the country level. In addition, while these studies use luminosity-based satellite images in multiple time periods, they do not use multiple images on luminosity. This thesis uses the nighttime satellite images to estimate economic product at the small level of metropolitan areas over 139 countries. We also conduct this research in one time period and we include three different satellite images which let us capture information on radiance and urban structure even in the presence of satellite sensor saturation. Moreover, the research studies that have been conducted on the effect of infrastructure and urban form do not use such variables as predictors for the GMP. After deriving these explanatory variables from spatial data, we train the models on them and finally use them to get GMP predictions.

Chapter 3

DATA

The data set used in this study is put together from nine spatially-explicit sources (specified in Table 3.1) and four cross section data sets (specified in Table 3.2).

The spatial data used in this study can be categorized into three types: raster, vector, geodatabase. A raster image is a two-dimensional grid of square pixels/-cells. Each pixel in a raster image represents a meaningful value. The collection of these cell values creates a set (in some cases more than one set) which is referred to as the raster's band. If there is only one set within which the cell values fall, the raster is addressed as a single band. However, if each cell/pixel corresponds to more than one value, there would be multiple value sets; thus, the raster image is addressed as multi-band. Another spatial file type used in this study is called a vector file. In this study, the vector files were in the format of shapefiles. Vector files are mathematically built images that can appear on a grid. These files can denote lines, points, or polygons (areas). Finally, we use the geodatabase file type. Geodatabases are databases used for storing and working with spatial data and geographic information. Various types of data, such as tabular, vector, or raster, can be stored in these databases. In this study, we used three different night time lights satellite raster images: 1) Stable Night-time Lights (denoted as NTL in table 3.1) 2) Radiance (denoted as RAD in table 3.1) 3) Vegetation Adjusted Night-time Lights (denoted as VANUI in table 3.1) The Satellite images were captured as a part of the Department of Defense's program called the Defense Meteorological Satellite Program (DMSP).

According to the National Centers for Environmental Information (NCEI) website, "Each DMSP satellite has a 101 minute, sun-synchronous near-polar orbit at an altitude of 830km above the surface of the earth. The visible and infrared sensors (OLS) collect images across a 3000km swath, providing global coverage twice per day. The combination of day/night and dawn/dusk satellites allows monitoring of global information such as clouds every 6 hours. The microwave imager (MI) and sounders (T1, T2) cover one half the width of the visible and infrared swath. These instruments cover polar regions at least twice and the equatorial region once per day. The space environment sensors (J4, M, IES) record along-track plasma densities, velocities, composition and drifts." [17]. The stable nighttime lights satellite image used in this study is captured by the Operational Linescan System (OLS), which flys on the DMSP satellites. This image shows cloud-free composites of average visible nighttime lights and "contains the lights from cities, towns, and other sites with persistent lighting, including gas flares" [17] for the calendar year 2010. Figure 3.1 shows the stable nighttime lights raster image. The stable nighttime lights raster is a single gray scale band image with data values ranging from 1 to 63 (zero cloud-free observations were assigned 225). The OLS is capable of capturing low light data. In fact, this system's visible band detector can observe and record radiance levels that are about one million times dimmer compared to most other Earth-observing satellites. Because of light saturation in areas such as city centers, the low gain and high gain satellite images are combined to achieve a global nighttime lights image with no sensor saturation. This newly generated image is called Radiance. Radiance is a unitless single gray scale band raster image, the data value of which ranges from 0.00 to 2165.16. Additionally, due to saturation issues in urban cores, the stable nighttime lights are limited in accounting for urban variation and structure. In order to remedy this issue, Zhang et al. [41] created a new indexing method that decreases NTL saturation effects, increases the NTL signal variation, and accounts for urban area characteristics. This novel indexing method resulted in the production of the Vegetation adjusted nighttime lights raster, which is a single gray scale band image with a pixel value range of -10.00 to 0.98. The raster images of the calendar year 2010-2011 were used in the case of both Radiance and VANUI.

Table 3.1: Spatial data, sources, and derived values

Data Source	Explanation	File Format	Derived Variables
NTL	This is a raster file of global Nighttime Lights. The raster is a single gray-scale band.	Raster	Raster values
VANUI	This is a raster file of global Vegetation Adjusted Nighttime Light Urban Index. The raster is a single gray-scale band	Raster	
RAD	This is a raster file of global Radiance. The raster is a single gray-scale band.	Raster	
US CBSA	This is a global shape file of Core Based Statistical Areas of the US metropolitan polygons and boundaries.	Shape	Boundaries metropolitan ids
OECD Metropolitan Boundaries	These are global shape files of the metropolitan polygons, the Morphological shape file is the result of Taubenböck et al. 2019 study [39] .	Shape	
Morphological Urban Areas			
Countries	This data file contains the boundaries of all the countries in the world	Shape	Country Boundaries
Global Roads	This is a global geo-database of the multilinestring segments of different types of roads. This Geo database is the result of Meijer et al. 2018 research [32].	Geo database table	Road Lengths, road network complexity, count and summation of road segments,
Low Elevation Coastal Zone	This is a raster data on the global coastal zones. This raster image is the result of Meijer et al. 2021 research [31]	Raster	Coastal or not Coastal

Table 3.2: Cross sectional data, sources, and derived values

Data Source	Explanation	File Format	Derived Variables
Data Metro Explorer MSAGDP	These data sets include basic economics variables such as gross metropolitan products for metropolitan areas in the US and in non-US OECD countries	csv	Total population GMP Latitude & Longitude
GDP	The gross metropolitan product of 258 countries in the world	csv	GDP
GDP Economy Sectors	This data set contains the four main sectors of world countries GDP (in percent) which are agriculture, industry, manufacturing, and services.	csv	percent GDP allocated to each sector

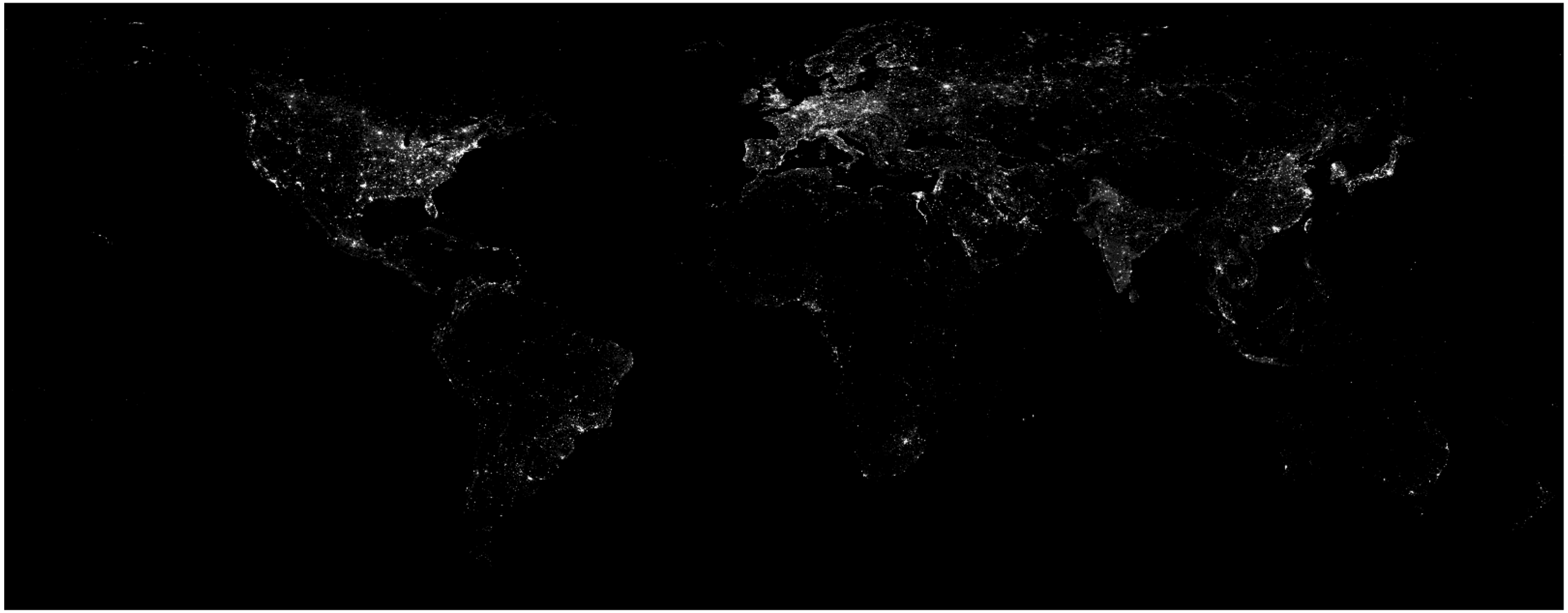


Figure 3.1: Stable Night Time Lights

Our paper combines socio-economic and satellite imagery data with the explicit goal of the estimation of gross metropolitan product in urban areas. We employ four distinct nighttime lights (NTL) data sets for our analysis: (i) stable NTL data from 2010, (ii) radiance (RAD) data from 2006, the closest available date to 2010, (iii) VANUI data for 2010 and (Table 3.3).

Table 3.3: Night-time lights datasets; description and sources

Dataset	Year	Sensor	Sources
Stable NTL	2010	F18	NOAA DMSP
Radiance (RAD)	2010	F16	NOAA DMSP
VANUI	2010	-	Zhang, Schaaf & Seto [41] (2013)

Furthermore, we utilize three urban (metro) area datasets in our analysis: (i) the 375 U.S. metro areas available from the U.S. Census, (ii) 205 non-U.S. OECD metropolitan areas available through the OECD Metro Explorer database; and (iii) the approximately 1300 metropolitan areas estimated by Taubenbock et al. [39]. The first two databases are combined to produce our calibration (C) and validation (V) samples. We will refer to this dataset as our C/V dataset. The third one is used for prediction (P). In this thesis we use the term "city" and "metropolitan area" interchangeably; we avoid a composite definition of a "metropolitan area" and follow the respective definitions of the U.S. and OECD datasets.

The US Office of Management and Budget defines the functioning metropolitan areas as follows"Metropolitan Statistical Areas have at least one urbanized area of 50,000 or more population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties." [29]
The OECD European Commission report, defines functional urban area as follows: " the functional urban area or metropolitan area, captures the full extent of a city's labour market by adding a commuting zone to each city" [10]

We use official geographical administrative and estimated boundaries for the cities in our samples in order to calculate various spatial statistics (such as the aggregate luminosity levels in each city and measures of urban form). Our C/V data sets (U.S and OECD metros) are accompanied by official administrative boundaries. While we have information on administrative boundaries for the cities included in the training/testing data set, such information does not exist for many other cities in the world. In addition, we need city boundaries to be able to calculate many of the explanatory variables used in this study. As a result, we used estimated metro boundaries generated by by Taubenbock et al. [39] for our prediction dataset.

We also collect and use widely available socioeconomic data, such as population and GDP. Given that the training and testing data sets need to include the actual GMP, and they include the US and non-US OECD countries, the GMP metric needed to be collected from different sources. The US GMP metric comes from the US Bureau of Economic Analysis (BEA). Also, we collect the GMP for the OECD countries from the OECD metro explorer database. After calibrating and assessing the models with C/V data, we use the models to estimate the GMP for the cities in the Prediction data set. All GMP data is expressed in real 2005 dollars. Table 3.4 summarises the information on the socioeconomic data sets.

Table 3.4: Urban socioeconomic datasets; description and sources

Dataset	Year	Source	Use	Boundaries
US CBSAs	2010	U.S. BEA	C/V	Official
OECD Metros	2010	OECD Metro Explorer	C/V	Official
Morphological	2019	by Taubenbock et al. [39]	P	Artificial

Note: C: Calibration, V: Validation, P: Prediction

3.0.1 Pre-processing

As mentioned before, we use three NTL satellite images in total. To derive the information we needed for this study from these images, they underwent a series of pre-processing steps. (see the methodology section for how they were done). These processes include reprojecting the images, masking, and generating binary images. Afterward, in order to account for the urban form and luminosity level, we derived various landscape metrics and basic luminosity statistics respectively, for each city. Next, we used a downscaling algorithm to estimate the GMP based on the GDP of the country to which each city belongs. The result of the pre-processing, is a set of explanatory variables. We also add multiple other variables corresponding to coastal status and roads. These steps are further discussed in the following sections. The methods used for these steps are available in the methodology section.

3.0.2 Reprojection

The collected raw images have an EPSG:4326 - WGS 84 projection which is a widely used projection, especially for global mappings. The map units corresponding to this projection are latitudes and longitudes. However, the map units needed for deriving the urban form metrics is meters. As a result, we needed to convert the map units of our images from lat-long to meters. So, an EPSG :3857 - WGS 84 / Pseudo-Mercator reprojection was used for all images. Although the reprojection left the images unchanged concerning the distances, some values in the images change, leading to either a reclassification of these values in different classes or changing the minimum and maximum pixel value of the images. The reprojection does not affect the minimum value (1) and the maximum value (63) in the stable NTL image. However, due to the Pseudo-Mercator, some pixel values get classified under a different value. In RAD and VANUI images, this reprojection causes a reduction in the value range. In short, an insignificant amount of interpolation happens during reprojection, so the number of cells in the raster drops as values get recombined in the reprojected layer. Along with the reprojection of the raster images, the boundaries also underwent this process. Figure 3.2 and 3.3 show luminosity maps of the EPSG:4326 - WGS 84 (original raster) and the EPSG :3857 - WGS 84 (reprojected raster) projections of Astria as an example boundary.

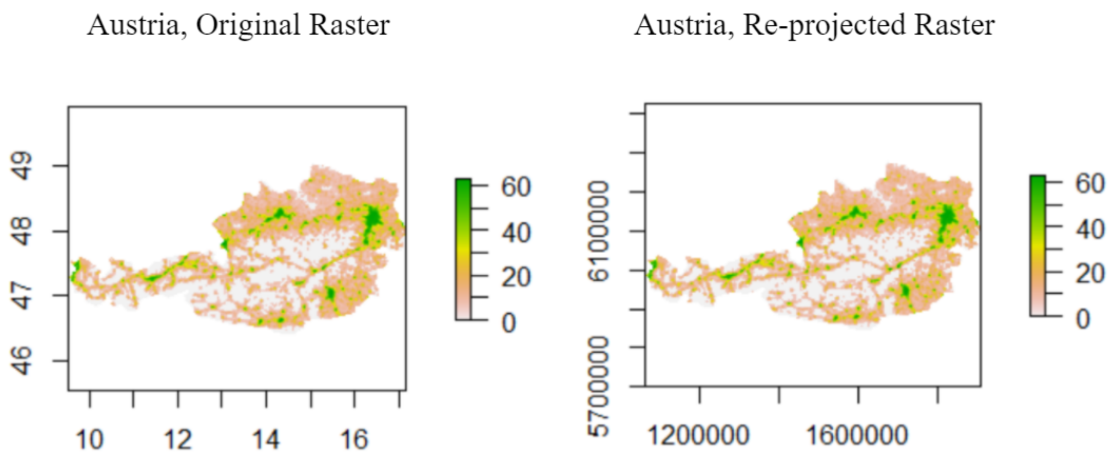


Figure 3.2: re-projection of a boundary, Austria

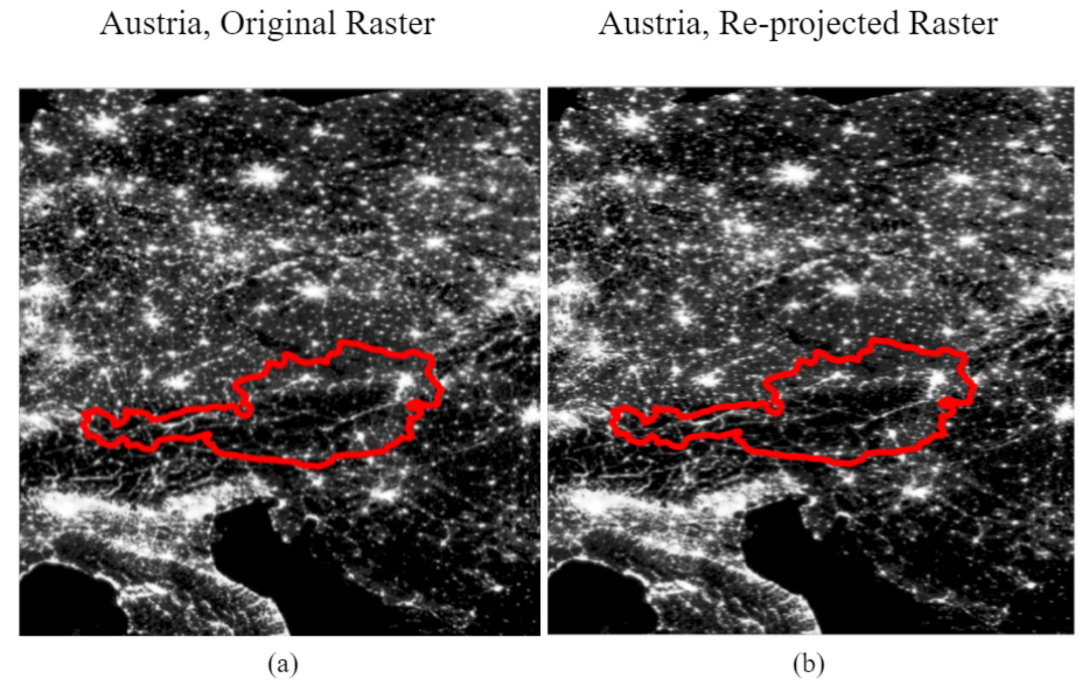


Figure 3.3: Stable Night Time Lights for original vs. re-projected raster images

3.0.3 Masked Rasters

Masking is a process similar to intersection. The goal is to only keep the pixel values that are included within each city boundary. It is important to implement this step because many of the explanatory variables correspond to the information inside, form, or size of a city boundary. The administrative boundary of each metropolitan area was used to create the masked rasters. These boundaries are polygons marking the area and the perimeter of each metropolitan area in our data. We use three distinct files containing city boundary polygons. Table 3.4 shows the sources of these data files. The US CBSA data file has information on 955 metropolitan and micropolitan areas depicted as M1 (metropolitan) and M2 (micropolitan) in the data file. There are a total of 375 metropolitan polygons which were extracted and used in this study. These polygons were reprojected to EPSG:4326 - WGS 84 before being used as a layer for clipping the original raster. Figure 3.4 shows the metropolitan boundary polygons for the US.

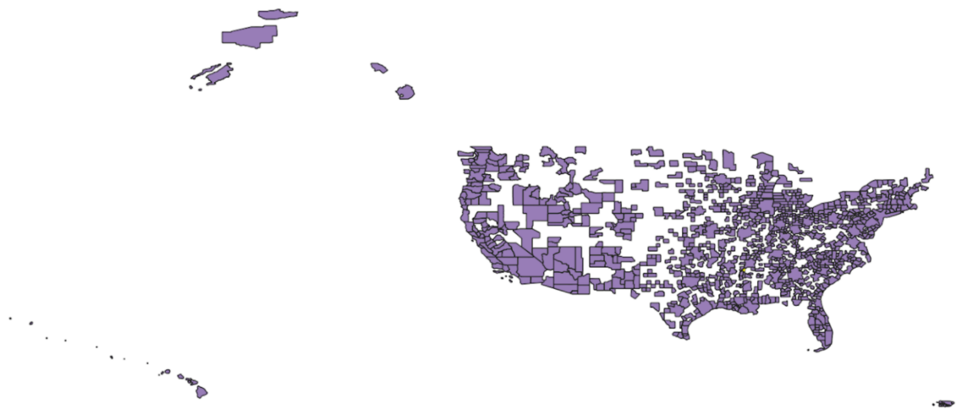


Figure 3.4: United States' metropolitan boundaries

During the masking process, the pixel values inside the polygons are kept while the pixel values outside the polygons are assigned the value of zero. Figure 3.7, 3.5, and 3.6 show an example of the masking process for the metropolitan areas in the US.Figure 3.7 shows an example of stable nighttime lights for North America. Figure 3.5 shows the US city boundaries layered over the stable NTL raster image. Finally, figure 3.5 depicts the result of the masking process for the US metropolitan areas.

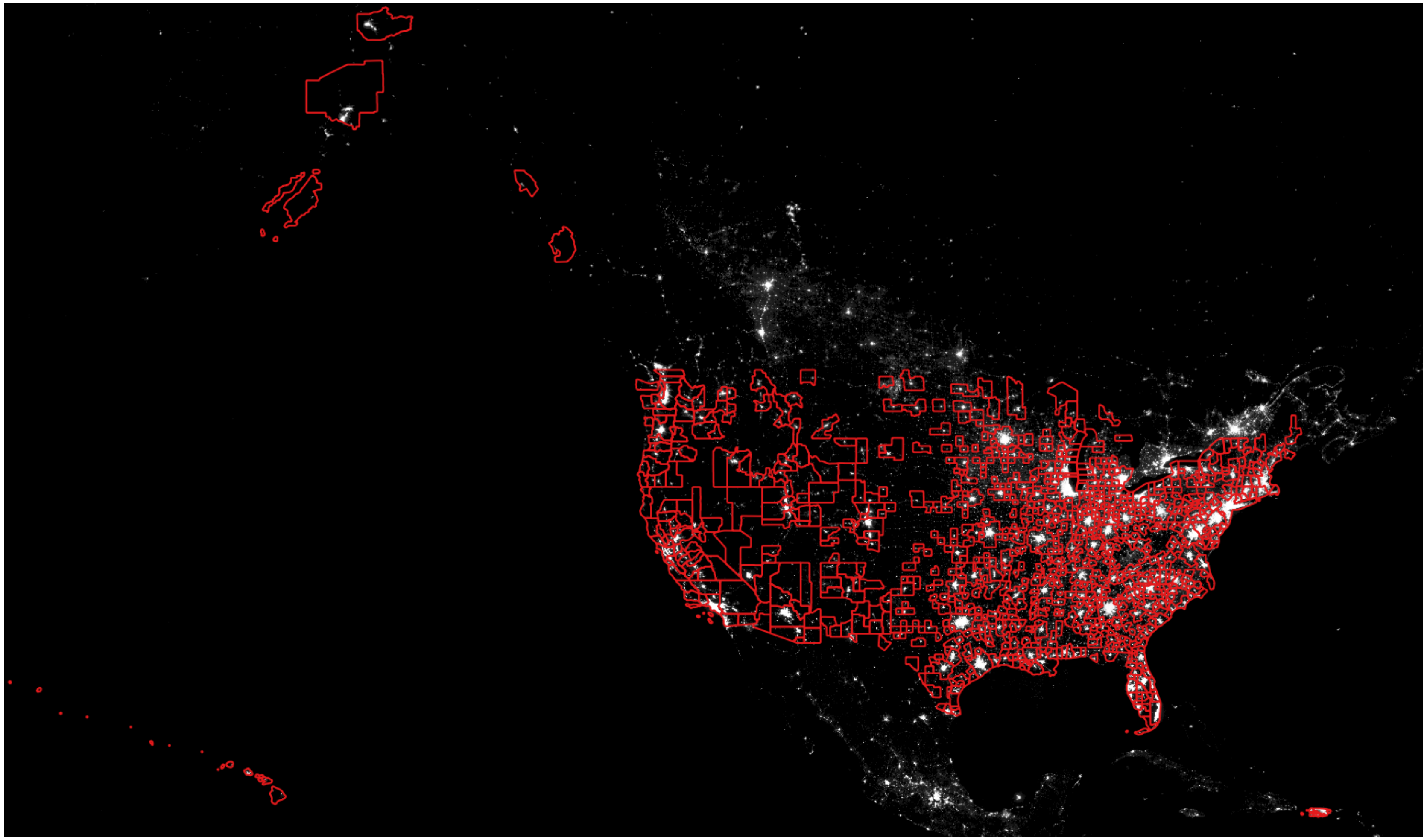


Figure 3.5: United States' metropolitan boundaries layered over the stable night time lights image

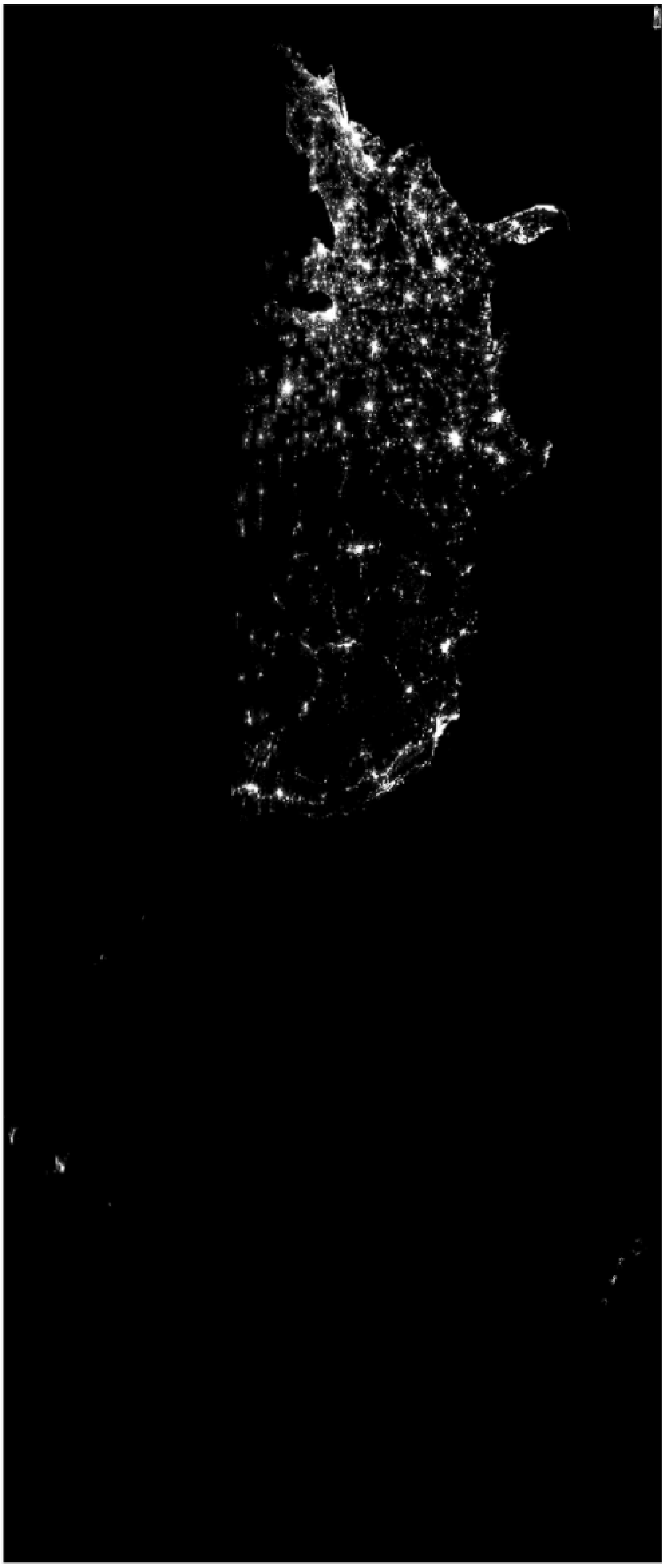


Figure 3.6: Masked stable night time lights image of the United States

Figure 3.7: Original stable night time lights image of the United States

As mentioned before, we used three sets of city boundaries, the US, OECD, and estimated morphological boundaries. The OECD Metro data shapefile includes metropolitan areas in the OECD countries. There are 275 metropolitan areas' boundaries included in this shapefile. 70 of these polygons correspond to the US metropolitan areas. In order to avoid repeated observations and keep metropolitan area definition consistent, we only used the US metropolitan boundaries data for the US cities. Figure 3.8 depicts the the intersection between the OECD and US boundary vector files with the OECD city boundaries in the darker shade and the US city boundaries in the lighter shade. Due to the difference in definition used by the US and OECD for the metropolitan areas, the OECD city boundaries are much tighter than the US city boundaries. Figure 3.9 shows an example of the OECD metropolitan boundary polygons in Europe.

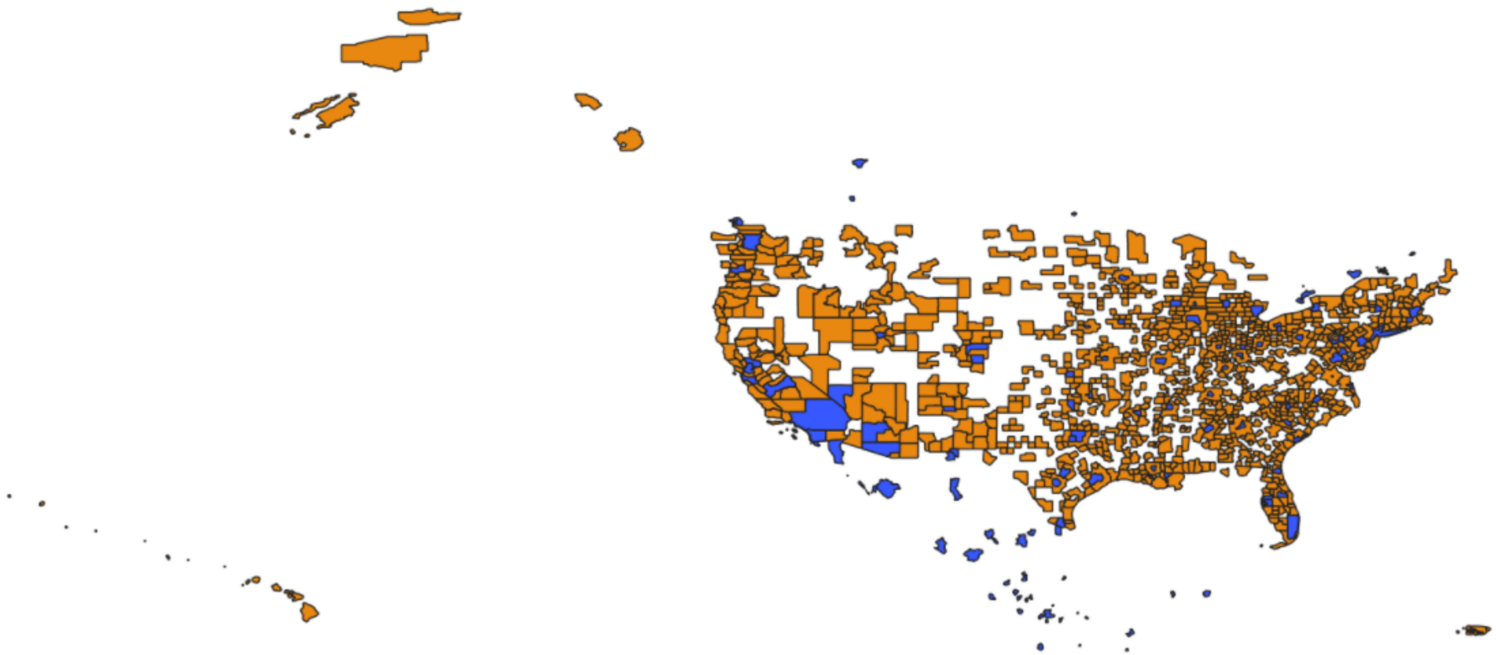


Figure 3.8: The intersection between US and the OECD metropolitan boundaries

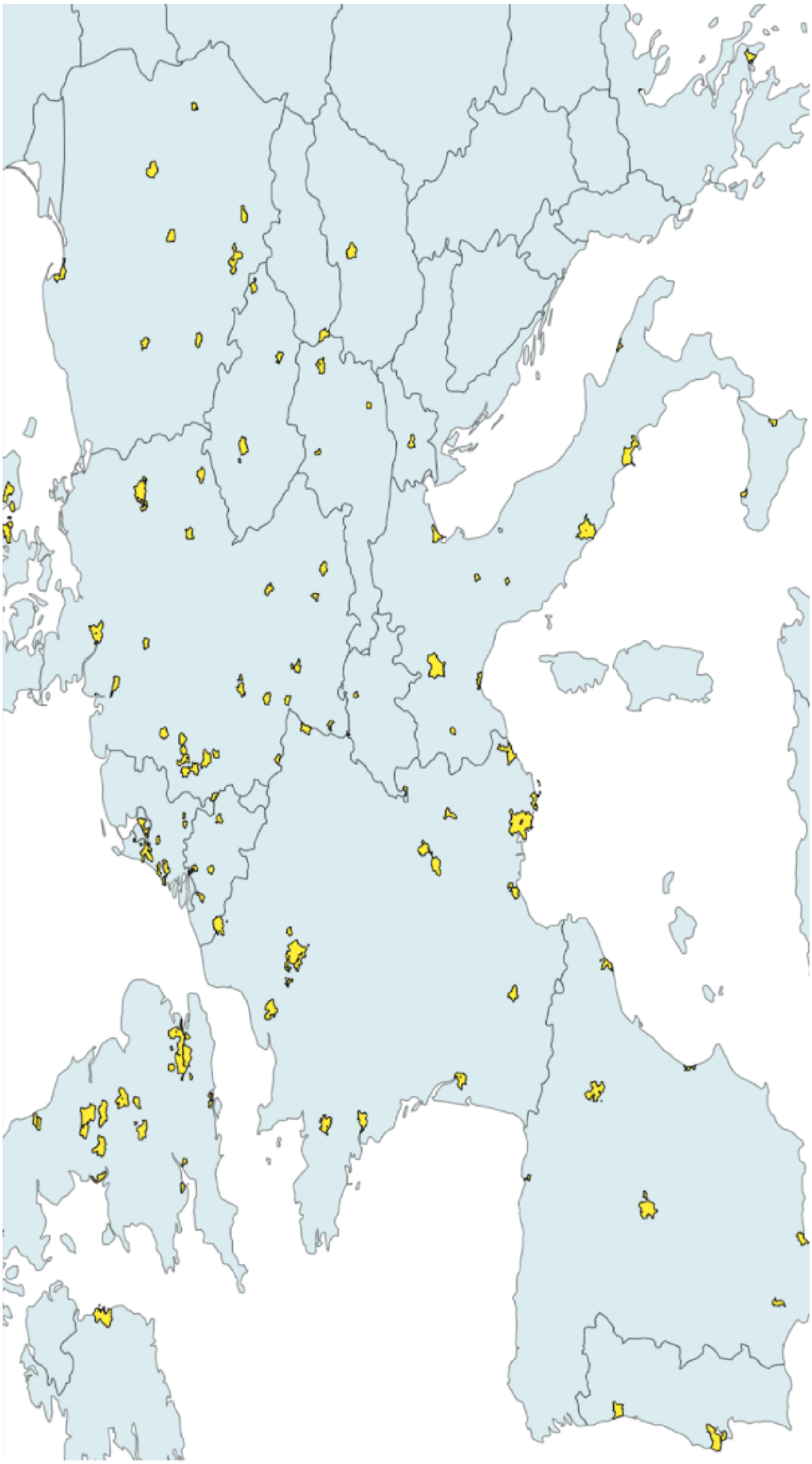


Figure 3.9: A snapshot of the OECD metropolitan boundaries

The US and OECD metropolitan boundaries cover 28 countries. These cities, their corresponding explanatory variables, and GMP construct the C/V data set. 3.5 shows the number of cities per country that we studied for the C/V data set. Finally, we implement the masking process for the estimated morphological metropolitan boundaries, which resulted from the Taubenböck et al. [39] study. This vector covers 1569 cities with a population over 300,000 people [39]. These cities and their corresponding explanatory variables construct the Prediction (P) data set. However, there is an intersection between the cities in the calibration/validation data frame and the prediction data frame. Various ways were tried, including using APIs for finding the same or similar names, latitudes, and longitudes as the cities in the prediction sample on the GeoNames geographical database [9] and matching them to the calibration sample. In order to avoid including cities in the prediction data set that were already used to calibrate and validate the models, we found the coordination for the cities centroids and matched the cities by the latitude and longitude to only to the second decimal degree. Figure 3.10 show the distribution of the cities used for training and testing the models over a global map. Figure 3.11 show the distribution of the cities used for creating the predictions over a global map.

Table 3.5: The countries included in the training and testing data set

Country	**Number of Cities**
United States	307
Japan	36
Mexico	33
Germany	24
France	15
United Kingdom	15
Italy	11

Table 3.5: The countries included in the training and testing data set

Country	**Number of Cities**
South Korea	10
Canada	9
Poland	8
Spain	8
Netherlands	5
Belgium	4
Austria	3
Chile	3
Czech Republic	3
Sweden	3
Switzerland	3
Greece	2
Portugal	2
Denmark	1
Estonia	1
Finland	1
Hungary	1
Ireland	1
Norway	1
Slovakia	1
Slovenia	1

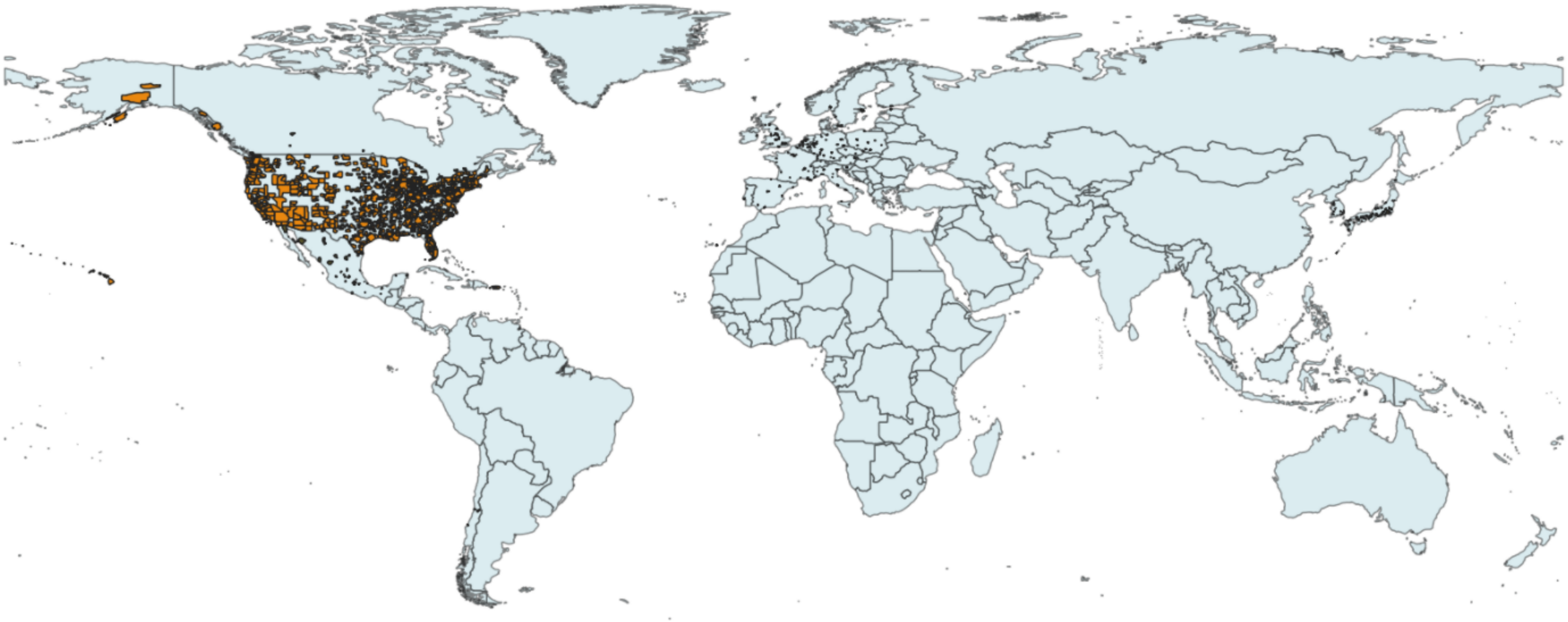


Figure 3.10: The cities used for Calibration/Validation

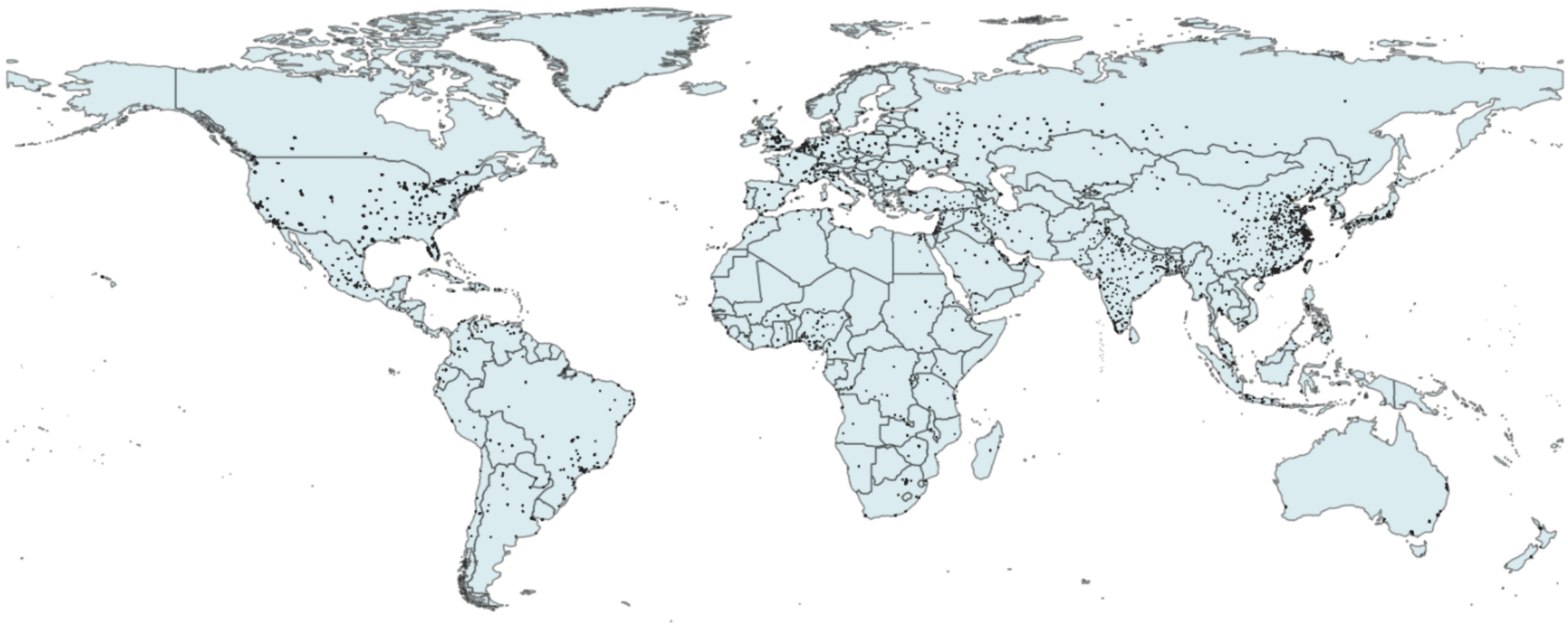


Figure 3.11: The cities used for Prediction

3.0.4 Binary rasters

A binary raster, is an image the pixels of which only take two values, zero or one, based on a threshold. We needed to create binary rasters in this study to avoid creating mismatched data that can overwhelm the models. The problem lies within the process with which we derive urban form's explanatory variables. In short, the process creates the same metric for every unique value in each polygon. For example, if we aim to calculate the number of patches for a city that has a pixel value of {1, 1.4,7}, then the algorithm goes through the pixels withing the boundary of the said city and computes the number of patches corresponding to pixels of value 1, 1.4, and 7. This process causes a number of issues. Firstly, the pixel value range for each raster is highly different. This range difference will cause computing different number of metrics per raster which can lead to the model being biased towards one raster; especially because the pixel value for RAD and VANUI is continuous. In addition, although the cell value range is the same for each raster, the cell value range in each city boundary is not constant. This discrepancy between the distinct cell value sets of different cities will cause mismatched data, meaning some cities will have more metrics than others. On the other hand, when we use binary rasters, we create the same number of metrics per city and per raster, which will make the data clean and less likely to push the model a specific direction. The methodology used to create these images is available in the methods section. During the masking process, any area which is not covered by the boundary polygons, is given the value of zero. As a result, the masked rasters comprise of two main areas: the pitch-black areas with cell values of zero, and the areas of interest within the cities' boundaries, which can have any cell value based on the pixel value range of their corresponding raster. The process of creating binary rasters operates based on the median cell value of the raster in each country. Based on this process, each pixel's value within a city's boundary is compared to the city's country's median pixel value. If the city's pixel had a greater value than the country median cell value, that pixel is assigned the number one as its new value. If the city's pixel had a lower value than the country median cell value, that pixel is assigned the number zero as its new value. The any value in the masked area larger than the median value is assigned the value one, and any value below the median is assigned zero.

Inorder to implement this porcess, we needed to find each country's median cell value per raster. Calculating the median pixel value per country per raster can be challenging. If the masked rasters are considered for this process directly, the large number of pitch-black values (zeros) created due to the masking process will cause the median to be underestimated. On the other hand, if we do not mask the rasters and use the raw images, we would be including the luminosity of all other urban and non-urban areas in the calculation of the median which would lower the representability of the median with regards to the metropolitan areas for which we have the boundaries. Consequently, all the values in the rasters that exclude the areas within the boundaries are set to NA so that the median luminosity level of each country is calculated based on the metropolitan areas of interest. It is important to set the threshold for creating binary rasters based on each country's median cell value instead of seting one median value for the whole map of the world. The reason for this country-based calculation is that the administrative boundaries in the OECD cities are especially tight; this causes a small amount of variation in the cities. Simultanously, the US metropolitan areas' boundaries are wider and thus, have more cell value variation. If all the cities are considered together, the median can be chosen so low that most of the values in one city would be set to one. Calculating the median number for each country allows for a more accurate pixel classification.

3.0.5 Metrics

One of the contributing factors to economic gain is the cities' urban form. For example, a larger city might have more space for building factories and firms or have more infrastructure. However, left unconsidered, the urban form can cause our models to suffer from latent variables. Using the binary rasters, we calculated geological metrics that allow us to capture various aspects of the cities' boundaries.

3.0.6 Corestats

Using the masked rasters, we calculate the sum, count, mean, median, max, and variance of the values within each city. Sum denotes the aggregate luminosity and is calculated by adding the polygon's raster's values. Count denotes the number of cells within each city; the mean, max, median, and variance depict mean luminosity value, the maximum value, the median value, and the variance of the luminosity in each city, respectively.

3.0.7 Downscaling

Using the stable night lights raster and the gross metropolitan product from the socio-economic data sets, we estimated a downscaled GMP. The method for this estimation is available in the Methods section. In short, the equation below is used to achieve the GMP downscaled estimation. In order to add variation to our predictions of the GMP, we consider three variations of GDP. We use the whole GDP, the non-agricultural, and the services portion of the GDP to estimate the downscaled GMP statistic. Using equation 4.7, we utilized a bootstrap technique to find a variation of coefficients. The applied bootstrap technique results in 1000 pairs of coefficients for each GDP portion mentioned above. Figure 4.4 depicts the relationship between the coefficients. The relationship is linear, and an OLS method is used to find the fitted line, depicted in red in figure 4.5. Further, the first coefficient, which denotes the intercept, is clustered into ten bins. An estimated value for the second coefficient is then found based on the fitted line. Consequently, we derive ten pairs of coefficients per GDP portion. These coefficients are later applied within the equation 4.3, for each city.

3.0.8 Coastal Variable

Using the Low Elevation Coastal Zone (LECZ) raster file, which denotes the coastal zones, we derived a binary variable which is 1 if a city is considered coastal and is 0 if a city is not coastal. According to our estimation, we had 164 coastal cities out of 511 metropolitan areas in the training/testing data and 409 coastal cities out of 1298 metropolitan areas in the prediction data. MacManus et al. [31] created this data file. Their study aims to estimate land areas and their different levels of populations (rural to total).

3.0.9 Roads

Created by Meijer et al. [32], the roads data is processed in QGIS against the boundaries for each data set, calibration/validation, and prediction, and the sum of roads and the number of road segments are counted. In our training/testing dataset, the maximum road length and count belonged to Hamburg, Germany, with 3,069 kilometers of roads and 6301 road segments. For the prediction data set, the maximum road length belonged to Baghdad, Iraq, with 7,196 kilometers of roads and the maximum number of road segments Maputo Matola, Mozambique, with 16452 road segments.

Chapter 4

METHODOLOGY

4.0.1 Re-Projection

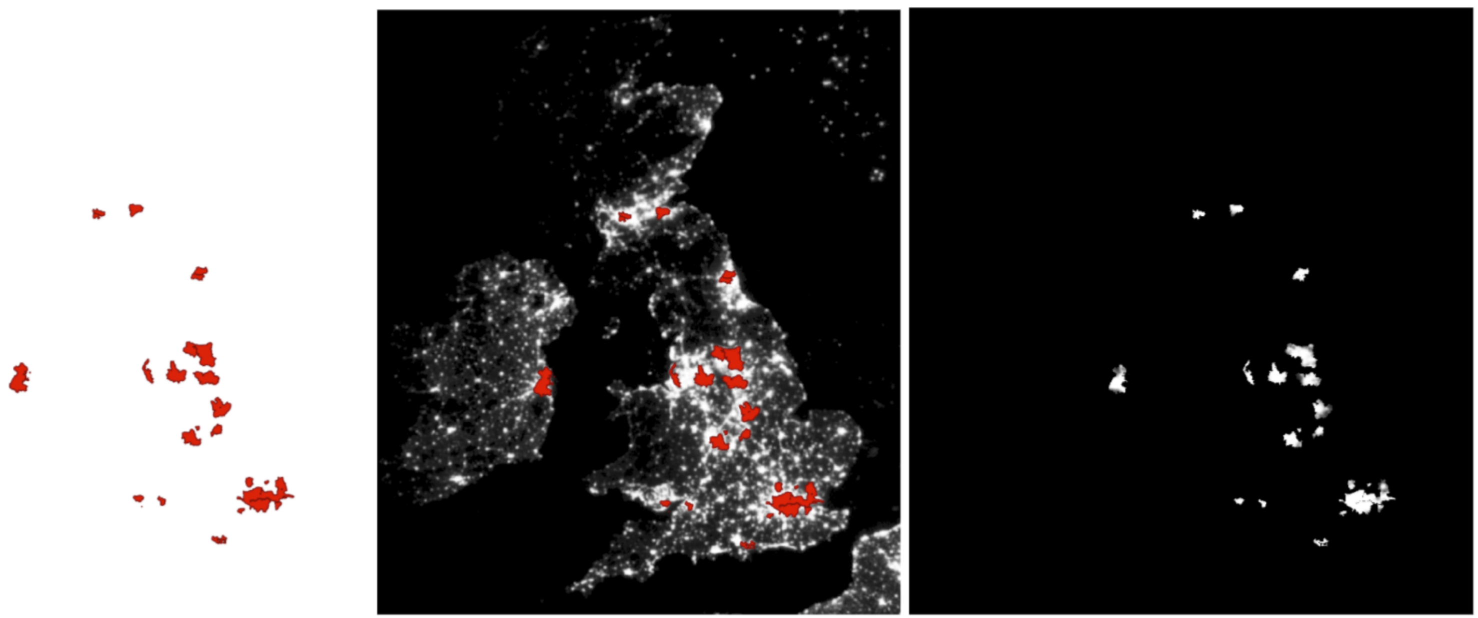
The raw raster data is projected in EPSG:4326 WGS 84 and measured in latitude, longitude, and decimal degrees. However, the library we used for deriving the metrics requires the measurements to be in meters. In order to achieve this meter-based measurement, we decided on using the EPSG:3857 - WGS 84 / Pseudo-Mercator reprojection. This projection, introduced by Google, is also known as the Web Mercator projection, and it is widely used in online maps; i.e., google maps and OpenStreetMap."Web Mercator suggests an ellipsoidal earth based on WGS 84 ellipsoid. All map features are assigned ellipsoidal coordinates". [37] In this projection, the latitude and longitude are converted into X Easting and Northing by the following formulae.

$$Easting \quad E = a(\lambda - \lambda_0) \tag{4.1}$$

$$Northing \quad N = a \ln[\tan(\tfrac{\pi}{4} + \tfrac{\phi}{2})(\tfrac{1 - e\sin\phi}{1 + e\sin\phi})^{\frac{e}{2}}] \tag{4.2}$$

4.0.2 Masking

We use the QGIS raster tools to extract the areas we want by masking layers. The main inputs for this process are a raster and a vector layer (also addressed as the masking layer). We used the nighttime images (rasters) and the boundary shapefiles (vector files) as inputs. The masking process works similar to an intersection; it keeps the cells of the raster that intersect with the polygons of the vector layer and replace any cell that is not included in this intersection are assigned a value of NA (whatever is the NA value in the raster; i.e., 0). Figure 4.1 shows the different stages of clipping a raster by a masked layer.



(a) (b) (c)

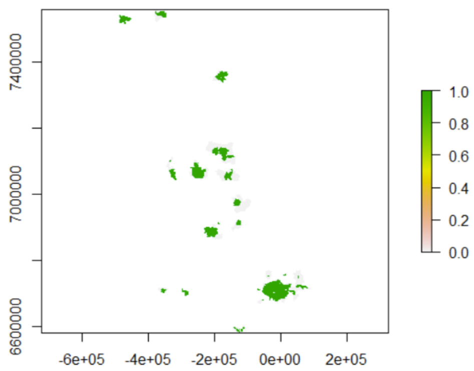
Figure 4.1: Masking Process-case of England and Ireland. (a) the vector layer polygons (b) overlap of the stable NTL raster and metropolitan areas boundaries (c) the resulted masked raster

4.0.3 Creating Binary Rasters

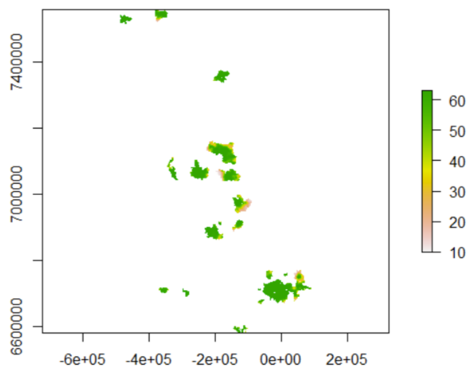
In order to calculate different metrics, we need to turn our masked raster images into binary. This conversion is because when capturing the urban form of these metropolitan areas, the raster values are looked at as different classes. The raw files do not exhibit discrete cell values (apart from the stable NTL). In addition, if we consider all cell values, for example, in the case of stable NTLs, we would end up with 63 classes which is not representative of our analysis. As a result, we decided to convert our cells to light versus light. This would allow us to calculate the metrics more efficiently while adequately accounting for luminosity. Creating binary rasters is done in R and is done per country. In order to create binary rasters, we need to determine a cutoff value so that any cell value in the raster that is greater than the cutoff value is assigned the value of one, and any cell value that is less than the cutoff value is assigned zero. We decided to consider each country's masked raster's median value as the cutoff. Since the automatic assigned NA values for these rasters were considered 0 during the masking process, many cell values in each raster have a value of zero. These values throw off the calculation of the median value, which is why they are assigned to "NA" before the median calculation. Further, we consider all the metropolitan areas in each country in each masked raster. The median raster value is then calculated through the "quantile" function. Next, each cell is evaluated against the cutoff point and assigned either one or zero. Figure 4.2 shows an example of England and fourteen British cities included in the calibration/validation data. This figure shows the difference between a binary raster and the masked raster.

4.0.4 Urban Form Metrics Derivation

In order to derive urban form metrics, we used the "landscapemetrics" package in R. This package "calculates landscape metrics for categorical landscape patterns in a tidy workflow. " landscapemetrics" re-implements the most common metrics from 'FRAGSTATS' and new ones from the current literature on landscape



(a)



(b)

Figure 4.2: Masked vs. Binary raster-case of England. (a) Masked raster of British cities (b) Binary raster of British cities based on the median value of 62

metrics. This package supports 'raster' spatial objects and takes RasterLayer, RasterStacks, RasterBricks or lists of RasterLayer from the 'raster' package as input arguments. It further provides utility functions to visualize patches, select metrics, and building blocks to develop new metrics." [26] The metrics can be calculated in three main ways; class, patches, and landscape. If calculations are done over classes, it means that the metrics are derived based on the different discrete class values of the raster cells for a given raster. If the calculations are done over the patches, the raster is divided into carious patches based on the cell values. Finally, If the calculations are done over the landscape, the metrics are derived from the whole raster without dividing it based on anything. We use the "calculate_lsm" function from this package. This function takes the raster layer (as the landscape) and a set of metrics as inputs, then calculates the metrics and produces a table of the derived metrics as output; Table 4.1 shows a sample of such output for London. To capture the luminosity of the urban areas in this study, we base our calculations on the lit cells (value=1) of the binary rasters and thus, use the class-based calculations in this package. Overall, we derive 15 metrics that cover various aspects of urban form. The list of these metrics, along with their formulae and explanations, are available in the appendix.

Considering that we wanted to account for each city's urban form regarding metrics, each city must be taken into account for the derivation of the metrics table. For this purpose, we came up with a for loop that creates the metrics table, adds the corresponding city's name and index, filters the rows of the output table to include only class=1 rows, and traverses the table for each city. By binding the traversed tables row by row, we arrive at a data set that includes all the cities with their corresponding metrics.

Table 4.1: Example of the landscape metrics table output with class-based calculations for the city of London.

	layer	level	class	metric	value
1	1	class	0	ai	90.93381686
2	1	class	1	ai	95.96823458
3	1	class	0	area_mn	17286.99433
4	1	class	1	area_mn	45448.14289
5	1	class	0	cai_mn	33.9582722
6	1	class	1	cai_mn	27.56688089
7	1	class	0	clumpy	0.9722247977
8	1	class	1	clumpy	0.9807429749
9	1	class	0	cohesion	96.79302755
10	1	class	1	cohesion	99.1671112
11	1	class	0	contig_mn	0.5537249102
12	1	class	1	contig_mn	0.5277165189
13	1	class	0	dcad	0.002187784245
14	1	class	1	dcad	0.001604375113
15	1	class	0	ed	0.5468829007
16	1	class	1	ed	0.5468829007
17	1	class	0	lpi	21.67049369
18	1	class	1	lpi	54.93685419
19	1	class	0	lsi	5.672897196

Table 4.1: Example of the landscape metrics table output with class-based calculations for the city of London.

	layer	level	class	metric	value
20	1	class	1	lsi	3.558139535
21	1	class	0	np	16
22	1	class	1	np	9
23	1	class	0	pd	0.002333636528
24	1	class	1	pd	0.001312670547
25	1	class	0	pladj	96.32190531
26	1	class	1	pladj	97.63221677
27	1	class	0	pland	40.34156142
28	1	class	1	pland	59.65843858
29	1	class	0	shape_mn	1.578895163
30	1	class	1	shape_mn	1.433830413
31	1	class	0	split	18.69766242
32	1	class	1	split	3.298891159
33	1	class	0	te	374956.6956
34	1	class	1	te	374956.6956

Table 4.2: Spatial Metrics used in this study to capture urban form [26]

Indicator	**Formula**	**Range**
Number of patches (Aggregation metric)	$NP = n_i$	$NP \geq 1$
Aggregation index (Aggregation metric)	$AI = [\frac{g_{ii}}{max - g_{ii}}](100)$	$0 \leq AI \leq 100$
Mean of patch area (Area and edge metric)	$AREA_{MN} = mean(AREA[patch_{ij}])$	$AREA\_MN > 0$
Mean of core area index (Core area metric)	$CAI_{MN} = mean(CAI[patch_{ij}]$	$0 \leq CAI_{MN} \leq 100$
Clumpiness index (Aggregation metric)	$Given G_i = (\frac{g_{ii}}{(\sum_{k=1}^{m} g_{ik}) - mine_i})$ $CLUMPY = [\frac{G_i - P_i}{P_i} for G_i < P_i \& P_i < 0.5; else \frac{G_i - P_i}{1 - P_i}]$	$-1 \leq CLUMPY \leq 1$

Table 4.2: Spatial Metrics used in this study to capture urban form [26]

Indicator	**Formula**	**Range**
Patch Cohesion Index (Aggregation metric)	$COHESION = 1 - (\frac{\sum_{j=1}^{n} p_{ij}}{\sum_{j=1}^{n} p_{ij}\sqrt{a_{ij}}}) * (1 - \frac{1}{\sqrt{Z}})^{-1} * 100$	$0 < COHESION < 100$
Mean of Contiguity index (Shape metric)	$CONTIG_{MN} = mean(CONTIG[patch_{ij}])$	$0 \leq CONTIG_M N \leq 1$
Disjunct core area density (core area metric)	$DCAD = (\frac{\sum_{j=1}^{n} n_{ij}^{core}}{A}) * 10000 * 100$	$DCAD \geq 0$
Edge Density (Area and Edge metric)	$ED = \frac{\sum_{k=1}^{m} e_{ik}}{A} * 10000$	$ED \geq 0$
Largest patch index (Area and Edge metric)	$LPI = \frac{\max_{j=1}^{n}(a_{ij})}{A} * 100$	$0 < LPI \leq 100$
Landscape shape index (Aggregation metric)	$LSI = \frac{e_i}{\min e_i}$	$LSI \geq 1$
Patch density (Aggregation metric)	$PD = \frac{n_i}{A} * 10000 * 100$	$0 < PD \leq 1e + 06$

Table 4.2: Spatial Metrics used in this study to capture urban form [26]

Indicator	**Formula**	**Range**
Percentage of Like Adjacencies (Aggregation metric)	$PLADJ = (\frac{g_{ij}}{\sum_{k=1}^{m} g_{ik}}) * 100$	$0 \leq PLADJ \leq 100$
Percentage of landscape of class (Area and Edge metric)	$PLAND = \frac{\sum_{j=1}^{n} a_{ij}}{A} * 100$	$0 < PLAND \leq 100$
Mean shape index (Shape metric)	$SHAPE_{MN} = mean(SHAPE[patch_{ij}])$	$SHAPE\_SD \leq 1$
Splitting index (Aggregation metric)	$SPLIT = \frac{A^2}{\sum_{j=1}^{n} a_{ij}^2}$	$1 \leq SPLIT \leq$ Number of cells squared
Total (class) edge (Area and Edge metric)	$TE = \sum_{k=1}^{m} e_{ik}$	$TE \geq 0$

4.0.5 Luminosity Statistics

Using the masked rasters, we calculate the sum, count, mean, median, max, and variance of the values within each city. Sum denotes the aggregate luminosity. It is calculated by adding up the raster's cell values within each boundary, i.e., the summation of all the cell values within the boundaries of London city. Count denotes the number of cells within each metropolitan boundary. The mean value is the average cell value of the raster, given the making layer polygon, and is equal to the division of the sum value by count. Additionally, max depicts the maximum cell value inside the masking polygon. Median shows the calculated median cell value of all the values inside the boundary polygon. Finally, variance denotes the variance of the luminosity in each city, using the mean cell value and the count of values in each metropolitan area.

4.0.6 Downscaling National GDP with Nighttime Lights

We use a method of GDP downscaling as a country GDP-based prediction method for estimating metro-level GMP. The result of the downscaling process in this study is a prediction for a metro's GMP that we include in our statistical learning models as exlanatory variables. In this method, we calculate a metro-level variable labeled as "downscaled GDP," which we use to derive a predicted GMP using the following regression equation:

$$log(\hat{GMP}) = \hat{\gamma} + \hat{\delta} log(downscaledGDP) \tag{4.3}$$

Equation 4.3 is a general notation of the regression equation used for deriving the estimated GMP. This equation takes two coefficients (gamma and delta) and the "downscaled GDP" statistic as inputs. In order to increase the accuracy of our predictions, we decided to use various sectors' portions of the GDP. In addition, to increase the external validity of our predictions, we applied a bootstrap model and added post-production steps. The following explains the different portions of the GDP that was considered in the calculations, how the "downscaled GDP" statistic is calculated, the bootstrap method, and the post-production process of this method's outcome. We note that since we are using three raster images as sources of nighttime lights, every calculation has been repeated for each image.

GDP Sectors

We understand that not all four major sectors of an economy (agriculture, industry, manufacturing, and services) are majorly affected by the metropolitan area's activity. As a result, we decided to include three central portions of the GDP in the downscaling process. In addition, because we have the actual GMPs in the calibration and validation data, we can assess the accuracy of our predictions. We choose what portions of the GDP to consider based on their predictive performance. First, we use the whole of the GDPs of each country. Next, by subtracting the portion contributed by agriculture, we get the non-agricultural portion of the GDP. Lastly, we consider the services portion of the GDPs of countries.

Deriving the Downscaled GDP Statistic

Every step in the following is repeated for each raster image and GDP portion. First, we calculate each country's luminosity statistics. Next, using equation 4.4, the amount of GDP that can be associated with each unit of luminosity across all countries in the world is calculated.

$$GDPperLumen_{country} := GDP_{country}/sumLights_{country} \tag{4.4}$$

We then create an estimate of GMP for each city in our calibration sample using the $GDPperLumen$ measure and the luminosity statistics of metropolitan areas. This is "downscaling" of national GDP information. The calculation of the downscaled GMP has to be done separately for each city in each country in our data samples. For example, in the case of the U.S., downscaled GMP is calculated as follows:

$$downscaledGMP_{usmetro} := GDPperLumen_{usa} \times sumLights_{usmetro} \tag{4.5}$$

Generally, for any country's metropoltan area, we can express this as:

$$downscaledGMP_{metro} := GDPperLumen_{metro'scountry} \times sumLights_{metro} \tag{4.6}$$

These calculations are repeated for all cities and their respective countries, and they produce a downscaled GMP variable for every metro in our datasets through equation 4.6.

We then base our bootstrap method on the OLS regressions in equation 4.7. Using our calibration sample with $logGMP$ as our dependent variable and $log(downscaledGDP)$ as our independent variable.

$$log(GMP) = \gamma + \delta log(downscaledGDP) + e \tag{4.7}$$

Deriving the Downscaled GDP Statistic

We use the bootstrapping technique to look at a spectrum of coefficients regarding equation 4.7 rather than just one set of coefficients. Because our calibration and validation data only includes OECD countries, and the coefficients in equation 4.3 are calculated based on the calibration and validation data, we decided to use a bootstrap approach to capture a spectrum of coefficients. The bootstrap technique runs a given function, equation, or operator on a set of variables through a selected number of iterations. In this study, we have chosen a regression model as the subject of each iteration and 1000 loops as the number of iterations. In this process, first, we run an OLS model such as 4.7 as a baseline over the population data (calibration/validation data). Second, we create a sample of 20 randomly selected observations from the calibration data and run the model on the new sample data. Next, we create a bootstrap model where 20 different observations are chosen randomly over 1000 iterations, and the regression model 4.7 is estimated over the selected sample in each loop. The coefficients gamma and delta are then derived from each loop as the outcome and saved in a data frame. As a result, when the bootstrap model has successfully run, we end up with a data frame including 1000 pairs of coefficients per GDP portion per raster image. In figure 4.3, we have plotted the OLS regression models both from the population model and the bootstrap model. The black dotted line depicts the population model. The red lines show each estimated bootstrap model, and the dotted green line shows the estimated model made from averaging the coefficients of the bootstrap model. In addition, table 4.3 shows the resulting coefficients of both the population model regression and the bootstrap model over the different portions of GDP, using the calibration/validation model for the radiation raster (RAD); note that the bootstrap coefficients are presented as the average values. All the coefficients are statistically significant at a 1 percent level for the intercepts and less than 0.1 percent for the coefficients of interest

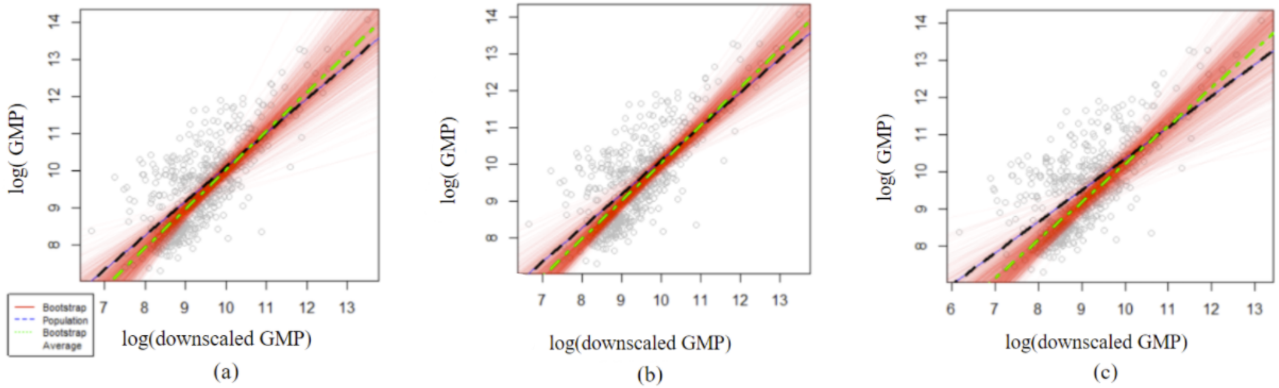


Figure 4.3: Regression vs. bootstrap for the radiation raster over all cities in the calibration/validation data (RAD). (a) whole GDP (b) non-agricultural portion of the GDP (c) services portion of the GDP.

GDP portion	Coefficients	Models	
		Population	Bootstrap
Whole GDP	intercept	0.848	-0.535
	log(downscaled-whole-GMP)	0.925	1.054
Non-agricultural	intercept	0.897	-0.258
	log(downscaled-non-agricultural-GMP)	0.921	1.028
Services	intercept	1.873	-0.082
	log(downscaled-services-GMP)	0.847	1.028

Table 4.3: Regression vs. bootstrap model coefficients over different portions of the GDP for the radiation raster (RAD)

Post-processing the Bootstrap Results

Although we have derived 1000 coefficients per GDP portion per raster image, it is not logical to use all 9 thousand ($1000 \times 3 \times 3 = 9000$) coefficient pairs to create the GMP downscaled predictions. On the other hand, using the averaged coefficient pairs of the bootstrap model defeats the purpose of including diversity in our data set. As a result, we decided to choose ten pairs of coefficients as representatives of the 1000 derived pairs. In this section, we explain how these ten pairs were chosen.

In order to be able to summarize 1000 observations to 10, we take the intercepts and group them into ten discrete groups. Figure 4.4 shows a scatter and box plot of the second coefficients against the grouped intercepts.

Next, we calculate the median value of each group. Note that the relationship between the coefficients is tight and monotone; figure 4.5 shows an example of this relationship for the coefficients derived from non-agricultural GDP and the radiance raster (RAD).

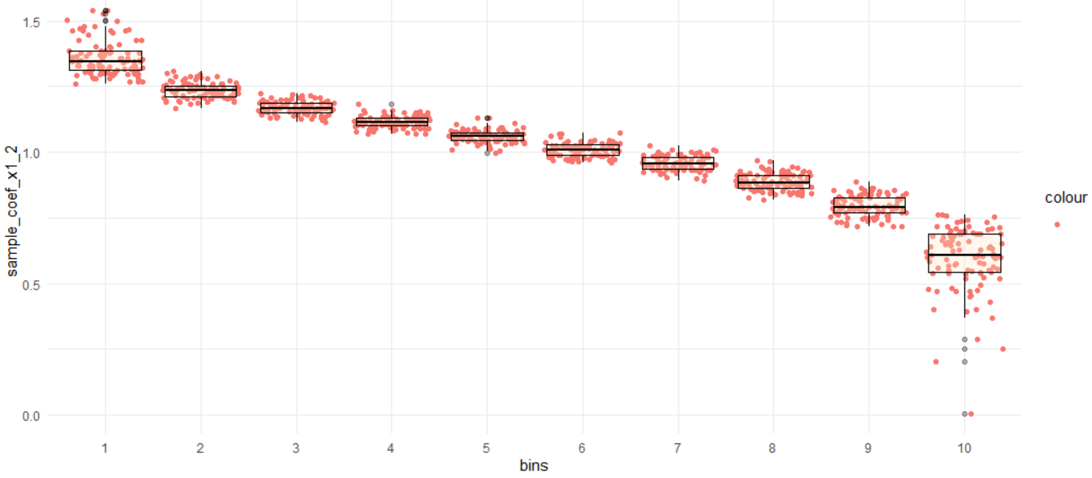


Figure 4.4: scatter and box plot of the second coefficients derived from the bootstrap method against the grouped intercepts

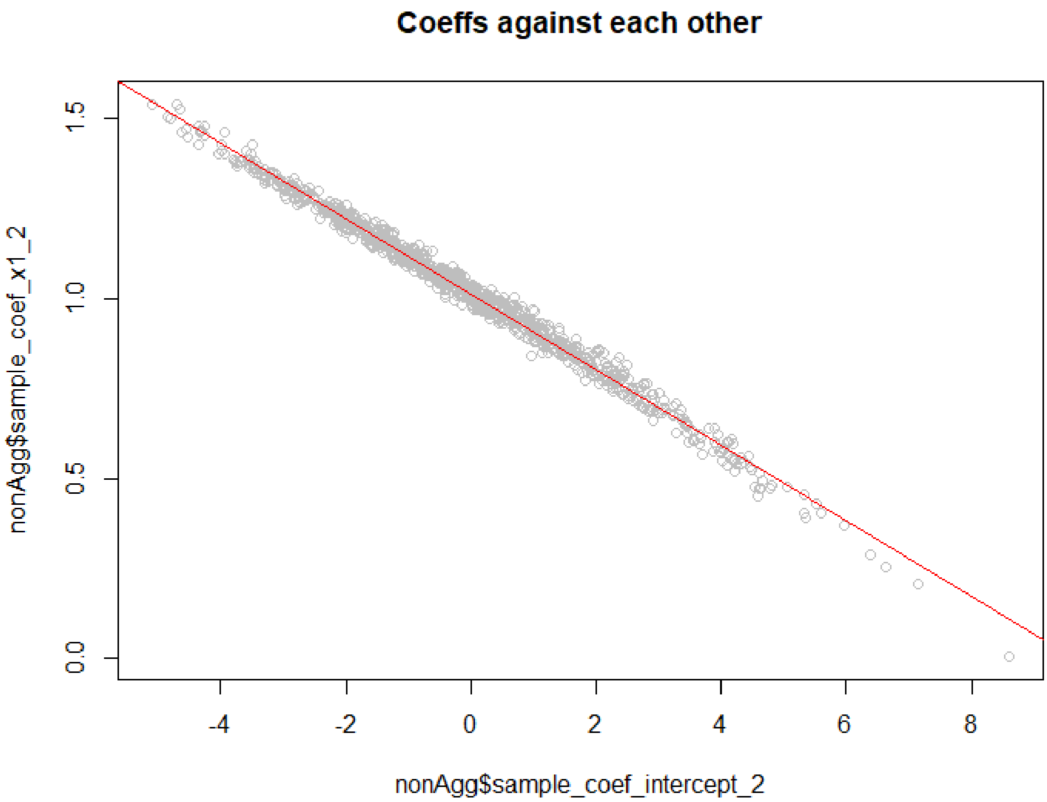


Figure 4.5: scatter the second coefficients derived from the bootstrap method against the intercepts. The red line depicts the regression line from equation 4.8

Based on this evidence, we run a simple OLS regression such as equation 4.8; in figure 4.5, the red line represents the regression line calculated by such equation.

$$second\,coefficient = \alpha_0 + \alpha_1(intercept) + e \tag{4.8}$$

We can calculate the second coefficient based on this regression model, given an intercept through equation 4.9.

$$second\,co\hat{e}\boldsymbol{f}icient = \hat{\alpha_0} + \hat{\alpha_1}(intercept) \tag{4.9}$$

Finally, we use the median group intercepts as inputs for equation 4.9 and estimate the second coefficient. Figure 4.6 shows an example of the ten intercept group medians, and their corresponding estimated coefficients of interest. These pairs are listed in table 4.4.

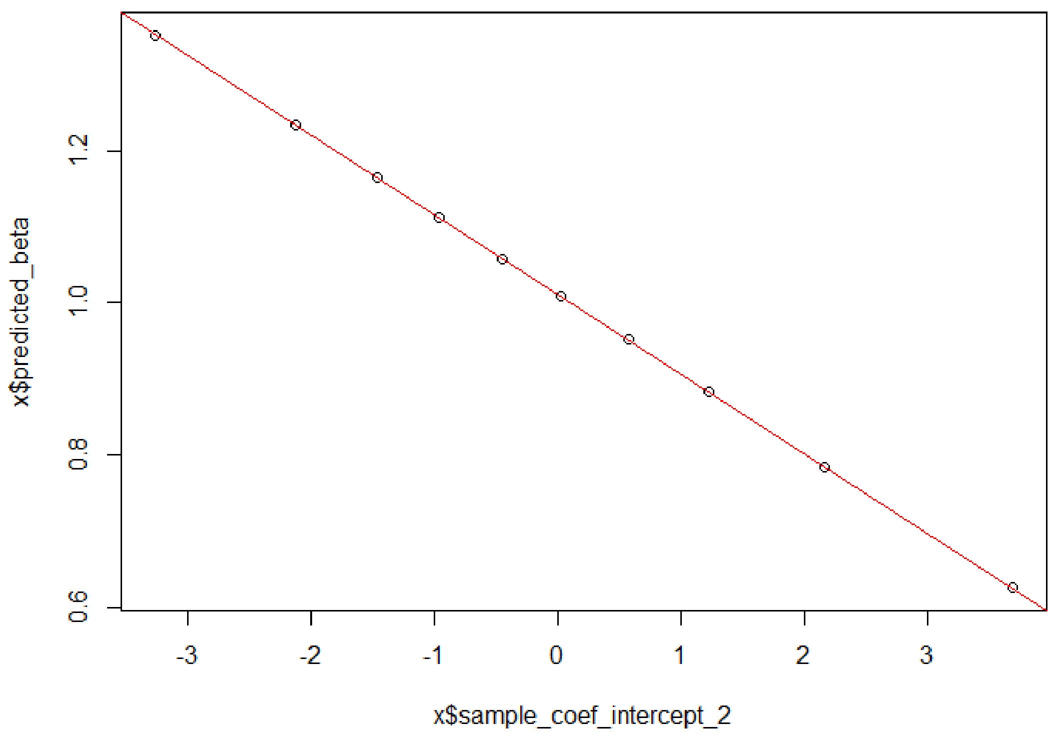


Figure 4.6: plot of intercept group median against estimated coefficients of interest for variables derived from the non-agricultural portion of the GDP and the radiance raster(RAd)

no.	Intercept's Group Median	Predicted Beta
1	-3.258	1.352
2	-2.124	1.234
3	-1.462	1.165
4	-0.962	1.112
5	-0.445	1.058
6	0.031	1.008
7	0.576	0.951
8	1.231	0.883
9	2.168	0.784
10	3.691	0.625

Table 4.4: Intercept group medians and their corresponding estimated Beta coefficient.

Downscaling Results

After the post-processing step is over, we have one data set per GDP portion per raster image, which contains ten pairs of coefficients; such as the dataset shown in table 4.4. These coefficients are then used in equation 4.3 to achieve downscaled predictions of the GMPs for cities. Consequently, after estimating the downscaled GMP with each coefficient pair as inputs for equation 4.3, we add a total of 90 features depicting downscaling to our primary data set.

4.0.7 Grouping GMP into Twenty Ventiles

Our training/testing data set is over OECD cities. This means that if the lowest income range is determined based on this data, we would be grouping many cities from the prediction data set that likely belong to lower-income brackets in much higher income brackets. As a result, it is crucial to consider that our training/testing data set might not include the lowest income bracket. To remedy this situation, we decided to determine the income ranges for each bracket by a GMP estimation over pooled data. First, considering that the average bootstrap regression coefficients driven from the Services portion of countries' GDP in the downscaling method yield sufficiently accurate GMP predictions, we decided to predict every city's GMP through this method. Second, we pooled the training/testing data with the prediction data to have the full spectrum of our data's potential GMP variation. Finally, we used the predicted GMPs to approximate the distribution of GMPs, determining 20 income brackets, from the poorest to the richest, based on cities' frequency. After the GMP ranges are determined, we separate the data sets and use these ranges to group the data. Implementing this method showed that the training and testing data points are not representative of the prediction data because once the twenty income ranges were determined and applied to the data sets, it became clear that the training and testing dataset's lowest observations belonged to the ninth ventile (first ventile denoting the poorest income bracket and the twentieth ventile denoting the wealthiest income range). As a result, the training and testing data set only account for eleven economic output ranges. Because of this, it is not logical to only turn the training and testing data into ventiles, it is also not possible to run the models while some of the classes (the income range between one and 9) are empty. This is why we had to choose the logarithmic form of gmp as the prediction goal.

4.0.8 Ridge, Lasso, and Elastic Nets

When applying linear regression, the Ordinary Least Squares (OLS) method creates a BLUE (best linear unbiased estimator); this means that OLS has the least variance among all other unbiased estimators. However, there exist cases were where OLS estimators have high variance; for example, in the presence of high multi-collinearity or few degrees of freedom. High variance causes over-fitting. Figure 4.7 shows the relationship between bias and variance as a set of darts thrown at a dartboard [13, 18].

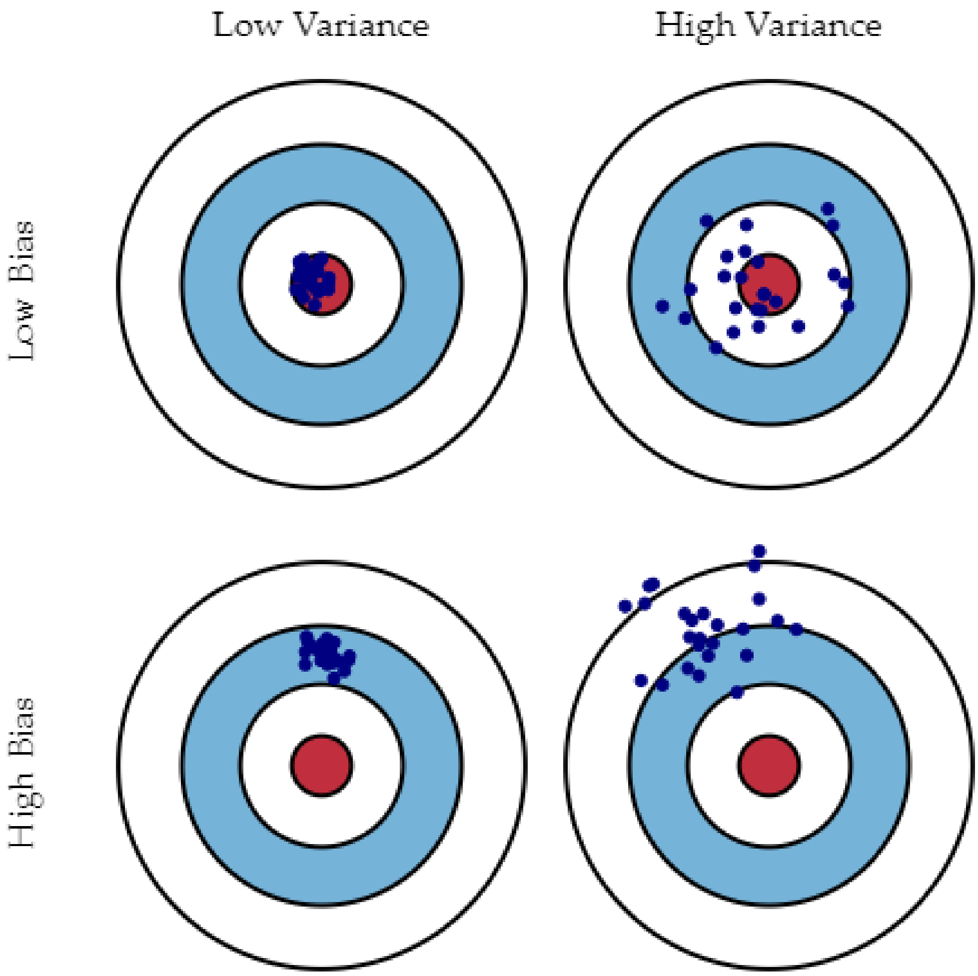


Figure 4.7: Bias and variance as darts thrown at a dartboard Domingos [13], source: [18]

One of the problems in machine learning is over-fitting. In such cases, the model does very well on the training (calibration) data with very low errors and high accuracy, but poorly when applied to the testing (validation) data, with high errors and lower accuracy. Therefore, when specifying a prediction model, the aim is to have the least possible mean squared errors (MSE). We can decompose MSE into bias and variance, such as in equation, [Bishop [3]; Friedman [19]; Geman et al. [21]],:

$$mean\ squared\ errors = bias + variance + noise \tag{4.10}$$

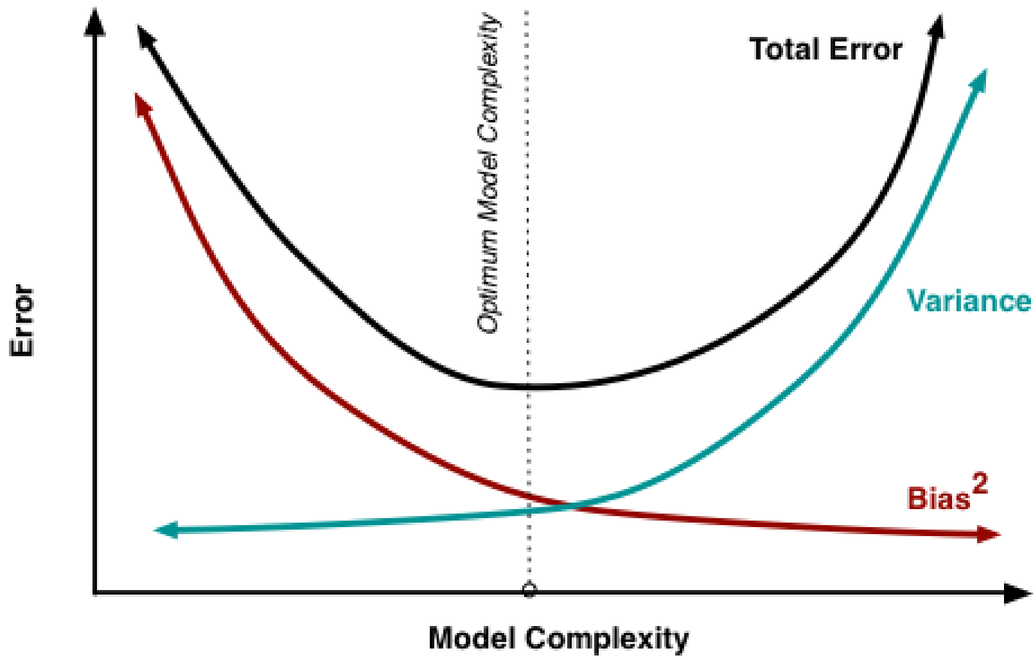


Figure 4.8: Bias vs. variance trade-off Fortmann [18], source: [18]

Equation 4.10 can be written as below [27]:

$$E(y_0 - f(\hat{x}_0))^2 = Var(\hat{f}(x_0)) + [Bias(\hat{f}(x_0))]^2 + Var(e) \tag{4.11}$$

Where the left hand term denotes the expected test MSEs. The the terms from left, on the right hand side are the variance, bias, and the variance of the inherent noise of the data. Note that variance is non-negative by nature and the bias term is square. Consequently, MSE can never be less than $Var(e)$.

Figure 4.8 shows the trade-off between bias and variance. Based on equation 4.11, if we stand at an OLS standpoint where we have very little bias and very high variance, we can increase the bias by a small amount to decrease the variance by a relatively large amount. By introducing bias in the model, we can successfully decrease the MSE value. Ridge, L2 type regularization, tries to introduce this bias in the model to decrease the MSE. Equation 4.12 shows the minimization problem we solve when faced with an OLS model.

$$\textbf{arg min} \sum_{i=1}^{N} (y_i - \sum_j \beta_j x_{ij})^2 \tag{4.12}$$

Ridge adds a penalty term such as in equation 4.13 :

$$\textbf{arg min} \sum_{i=1}^{N} (y_i - \sum_j \beta_j x_{ij})^2 + \lambda \sum_j \beta_j^2 \tag{4.13}$$

This is why regularization is important. Applying the Ridge penalty is a form of implementing regularization in a model. As *lambda* increases, the bias increases and the coefficients shrink further and finally converge to zero. Using the Ridge method, none of the coefficients can actually be assigned a value of zero. Therefore the resulting model will be hard to interpret. The least absolute shrinkage and selection operator (LASSO) sets the coefficients that contribute very little to zero [40]. Equation 4.14 shows the minimization problem that we aim to solve when using LASSO:

$$\textbf{arg min} \sum_{i=1}^{N} (y_i - \sum_j \beta_j x_{ij})^2 + \lambda \sum_j |\beta_j| \tag{4.14}$$

Elastic net tries to mix Ridge and Lasso's penalty terms [42]. Equation **??**hows the elastic net optimizing problem:

$$\textbf{arg min} \sum_{i=1}^{N} (y_i - \sum_j \beta_j x_{ij})^2 + \lambda[\alpha(\sum_j |\beta_j|) + (1-\alpha)(\sum_j \beta_j^2)] \tag{4.15}$$

We can re-write equation 4.15 as:

$$\textbf{arg min}\; MSE + \lambda[\alpha(Lasso\,penalty) + (1-\alpha)(Ridge\,penalty)] \tag{4.16}$$

Where α and λ allow us to use various amounts of each penalty and the entire penalty term respectively. In all models, α and λ can be numerically determined by cross validation.

4.0.9 Random Forests

Random Forests (RF) utilize multiple decision trees through ensemble learning. In this method, we use a collection of decision tree predictors $h(\mathbf{x}; \theta_k)$, $k = 1, 2, ..., K$ where x denotes the independent variable (feature, or covariate) vector of length p and θ_k are independent identically distributed random vectors [36]. It can be proven that over-fitting does not happen when random forests are used. In addition, in order to ensure accurate RF predictions, each decision tree is grown on a bootstrap sample from the training data set with a subset of covariates so that trees' will not share the same errors and they would have low error correlation [36].

Chapter 5

IMPLEMENTATION

In order to run any models on the completed main data sets, there are various steps that we need to follow. In the following, we explain these steps.

5.0.1 Data Partitioning

Data partitioning is the process of breaking our data into a training/calibration set and testing/validation set. We break our data into these two sections because the main data set exclusively on the OECD countries have the final label, GMP, for each city. This means that we can train our models on this data, and also, we can see how well our model does with this data because we can evaluate the predictions against the true values of GMP. To avoid feeding the model the same data it was trained on, it is important that the testing dataset is not included in the training. If we include all or a portion of the testing data in the training process, the evaluations of the predictions lose some of their value. For this reason, we exclude about twenty percent of the main data set from the training process so that we can then use the model predictions as a means of further evaluation.

We randomly select 80 percent of our data for training purposes during data partitioning and 20 percent for testing purposes. Depending on the library we plan to use, this data must be put in different forms. For example, when using the glmnet library, the training and testing data sets must be in the form of Matrices; when using the caret library, the training and testing data must be in the form of data frames and lists. After the initial partitioning, we separate the final label, which is the feature denoting the actual ventile that each city belongs to, from the independent variables.

5.0.2 Libraries

We use three main libraries for our models. The glmnet library is used for the lasso, ridge, elastic networks models. The caret library is used for random forest and and multinomial models. Finally, we used the randomForest library to optimize the RF model and generate variable importance tables.

GLMNET Package

In order to use three of the Supervised machine learning models used in this paper, the Glmnet package in R has been used. The Generalized Linear Models (abbreviated and used as glmnet) package supports the LASSO, Ridge, and Elastic Net Regression methods. Since this package is used for linear models, it can be applied to both linear and logistic regressions. One of the advantages of this packages is its speed, which results from utilizing sparsity in the input matrix. This algorithm is regularized by convex combinations of l_1 and l_2 penalties (elastic net regression) as shown in the term below

$$\lambda[\alpha(\sum_{1}^{k}|var_i|)+(1-\alpha)(\sum_{1}^{k}var_i^2)] \tag{5.1}$$

where $\alpha \in [0,1]$ and allows us to control the ratio of either l_1 or l_2 penalties; for example, to use LASSO penalties only, α can be set to 1 so that the term $(1-\alpha)$ will be omitted. In addition, Since the whole term is a penalty itself designed to prevent overfiting, λ is used to control how much of the pernalty will affect the model.

	λ	α
OLS	0	(0,1)
LASSO	>0	1
RIDGE	>0	0

Table 5.1: Different λ and α combinations in the calculated model result.

CARET Package

We use the "caret" (Classification And Regression Training) package . We used this package for training our elastic net, RF, and Multinomial models. We also make use of a ten fold cross validation technique for all models with numerically determined hyper-parameters (Lasso, Ridge, Elastic net)

RANDOMFOREST Package

The randomForest package, yielded from Breiman and Cutler's original Fortran code [4, 11] , allows us to train an RF model, optimize it, and generate variable importance tables and plots. In addition, it produces out-of-bag (OOB) error measurements which show the testing prediction error against the true label. It uses the square root of the number of predictors as the default number of feature samples for splitting nodes in classification models and one-third of the predictors in regression models. It allows tuning the model by finding the best number of sampled features for splitting nodes by minimizing the OOB. Moreover, using this library, we can generate tables and plots that show the importance of predicting variables by percent increase in MSE and percent increase in node purity.

5.0.3 Evaluation Methods

We evaluate each model in two stages after training and after testing. First, we evaluate each model's training predictions for the GMP ventiles. Next, we use the trained model to make predictions for the testing data and evaluate these predictions. Note that because the models are trained with the training data, the evaluations of the training predictions are always better than the testing data. It is preferred if the training and testing data errors are close because a small error for training predictions and a high error indicates overfitting. We use three main evaluation methods, the RMSE, the distance fromg the correct value, the 45 degree line, and the 5 to 10 billion dollar threshold

Chapter 6

RESULTS

In this chapter, we focus on the results of the implemented models. In the following, we will present our results from our most basic regression analysis to the most data-rich random forest analysis. Finally, we present a prediction data set on the boundaries included in the Morphological boundary shapefile in table 6.7 to table 6.21 which is the main result of this research.

Table 6.1 shows the regression results of preliminary OLS models on the most significant variables. The population variable is in 100,000 people, and the independent variable is ln(GMP), with the GMP in 1,000,000 dollars in all models. All coefficients have expected signs and are statistically significant, except for the count of road segments. Based on model five, for every 100,000 additional inhabitants, we can expect the GMP to increase by 2,500,000 dollars. In addition, if a city is a coastal one, we can expect it to have 31,700,000 dollars more than non-coastal cities on average. For every one degree of moving North, GMP is expected to increase by 1,900,000, and for every one degree of moving East, we expect the GMP to increase by 500,000. Finally, we can expect a 50,000 dollar average increase in GMP per every additional one kilometer of road. Table 6.2 shows the country-level fixed effects model results where the US has been kept as the baseline. With the country binary variables being statistically significant, this model shows there is a meaningful difference in countries effect on the output with regard to the baseline which was the US.

Table 6.1: Preliminary OLS Regression Result

	Dependent variable:				
	log(gmp)				
	(1)	(2)	(3)	(4)	(5)
totpop	0.029^{***}	0.028^{***}	0.027^{***}	0.029^{***}	0.025^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
coastal		0.463^{***}			0.317^{***}
		(0.087)			(0.081)
Latitude			0.016^{***}		0.019^{***}
			(0.004)		(0.004)
Longitude			0.004^{***}		0.005^{***}
			(0.001)		(0.001)
LENGTH				0.0002^{*}	0.0005^{***}
				(0.0001)	(0.0001)
COUNT				0.0003^{***}	0.0001
				(0.0001)	(0.0001)
Constant	9.291^{***}	9.156^{***}	8.885^{***}	9.104^{***}	8.418^{***}
	(0.045)	(0.051)	(0.177)	(0.055)	(0.173)
Observations	511	511	511	511	511
R^2	0.369	0.403	0.460	0.428	0.563
Adjusted R^2	0.368	0.400	0.457	0.425	0.558
Residual Std. Error	0.933 (df = 509)	0.909 (df = 508)	0.865 (df = 507)	0.890 (df = 507)	0.780 (df = 504)
F Statistic	298.035^{***} (df = 1; 509)	171.137^{***} (df = 2; 508)	144.143^{***} (df = 3; 507)	126.405^{***} (df = 3; 507)	108.342^{***} (df = 6; 504)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6.2: Fixed Effects OLS Regression Result

	Dependent variable:				
	log_gmp				
	(1)	(2)	(3)	(4)	(5)
totpop	0.025***	0.025***	0.025***	0.022***	0.022***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
coastal		0.271***			0.249***
		(0.090)			(0.076)
Latitude			−0.003		0.001
			(0.008)		(0.007)
Longitude			0.001		−0.003
			(0.003)		(0.002)
LENGTH				0.001***	0.001***
				(0.0001)	(0.0001)
COUNT				−0.0002*	−0.0002**
				(0.0001)	(0.0001)
Constant	8.983***	8.929***	9.163***	8.406***	8.078***
	(0.047)	(0.050)	(0.379)	(0.056)	(0.322)
Observations	511	511	511	511	511
R^2	0.543	0.551	0.543	0.689	0.697
Adjusted R^2	0.516	0.524	0.514	0.670	0.676
Residual Std. Error	0.817 (df = 482)	0.810 (df = 481)	0.818 (df = 480)	0.674 (df = 480)	0.668 (df = 477)
F Statistic	20.420*** (df = 28; 482)	20.356*** (df = 29; 481)	18.997*** (df = 30; 480)	35.487*** (df = 30; 480)	33.229*** (df = 33; 477)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.3 shows the model evaluation results of a model that uses population as its only independent variable for estimating ln(GMP) and one that uses all the independent variable except for population. The metrics below are achieved without data partitioning.

Table 6.3: Evaluation of an OLS model with only population as an independent variable and an OLS model with all independent variables except for population

OLS Model	**RMSE**	**R-Square**
Population Only	0.931	0.369
All Variables except Population	0.304	0.933

Table 6.4 shows some of the parameters of the models that were implemented in this thesis. Considering the RMSE, the preliminary OLS model has a high error. However, the OLS model that includes all the covariates is the worst model. Although the training data set's RMSE was small, the RMSE increases significantly when we move from the training data to the testing data in an OLS model, which showed that the model did poorly on out of training sample data. This is because the correlation between covariates is high; as a result, the variance of the model is high. So we introduced regulation to our model in the form of the Ridge penalty. This model shows that shrinking the coefficients causes the prediction error to decrease. The Lasso penalty allows for coefficient selection, meaning that some coefficients will be assigned zero. This penalty shows an improvement which means some of our coefficients are not contributing to the model. The Elastic Net model shows that the Lasso penalty is the superior regulation. Finally, the Random Forest has the lowest RMSE, and due to the advantages the model has in general, such as the absence of overfitting, it is the best fit.

Table 6.4: Models Result Parameters

	Optimized Alpha	Optimized Lambda	Training R-squared	Testing R-squared	Training RMSE	Testing RMSE
Ridge	0	0.547	0.873	0.821	0.417	0.499
Lasso	1	0.012	0.896	0.805	0.376	0.519
Elastic Net	0.656	0.025	0.887	0.789	0.393	0.573
Random Forest	N/A	N/A	0.988	0.911	0.128	0.362
Optimized Random Forest	N/A	N/A	0.989	0.988	0.119	0.317

Figures 6.1, 6.2, 6.3, and 6.4 show the accuracy of the implemented models on the testing data. The red line shows the 45-degree line, the green line shows the 5 billion dollar threshold, and the blue line shows 10 billion dollar threshold over a scatter plot of the predicted GMP values against the observed GMP. The closer the fit is to the 45-degree line, the more accurate the model would be on unseen data. Figure 6.5 shows the final tuned RF model with 5000 trees and 202 variables in each node split sample. This model superior in accuracy.

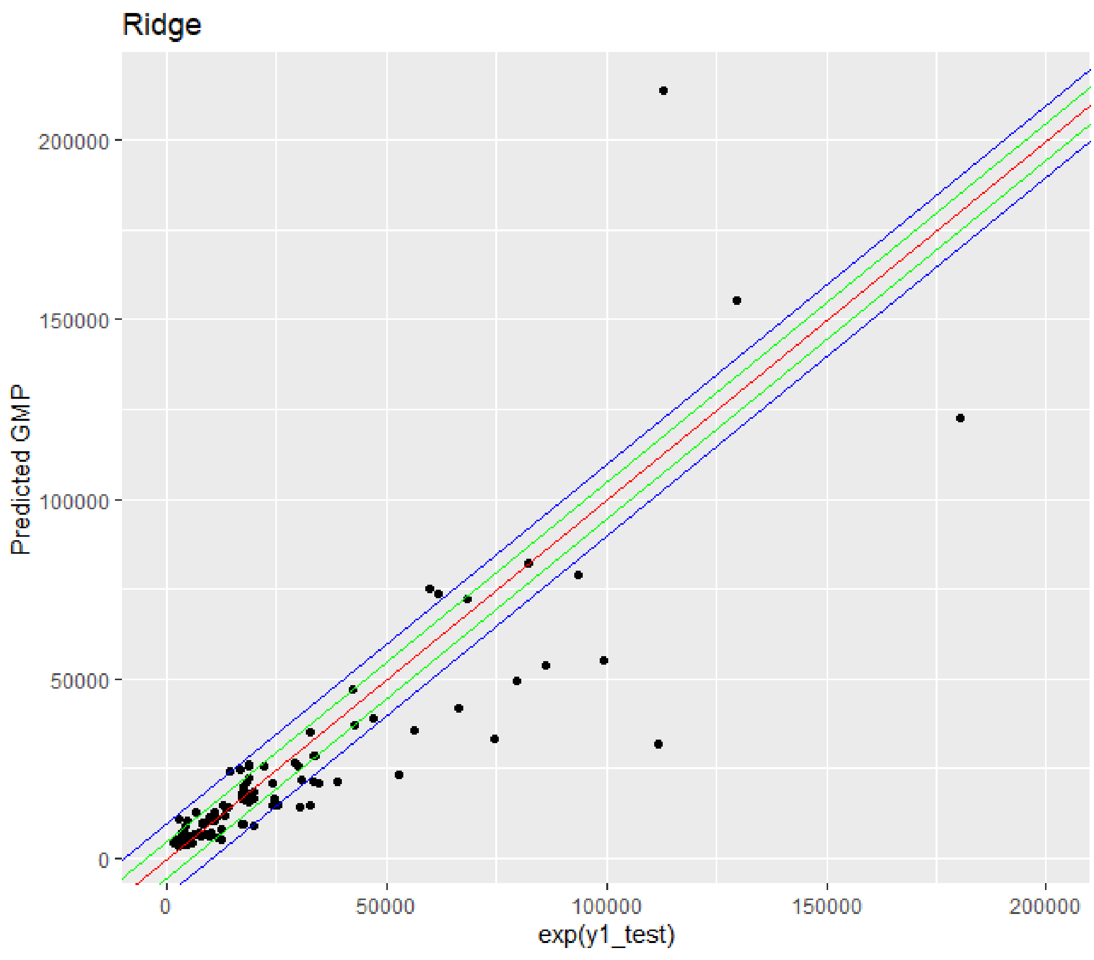


Figure 6.1: The Ridge model. Red line: 100 percent accuracy. Green line: 5 billion dollar threshold. Blue line: 10 billion dollar threshold

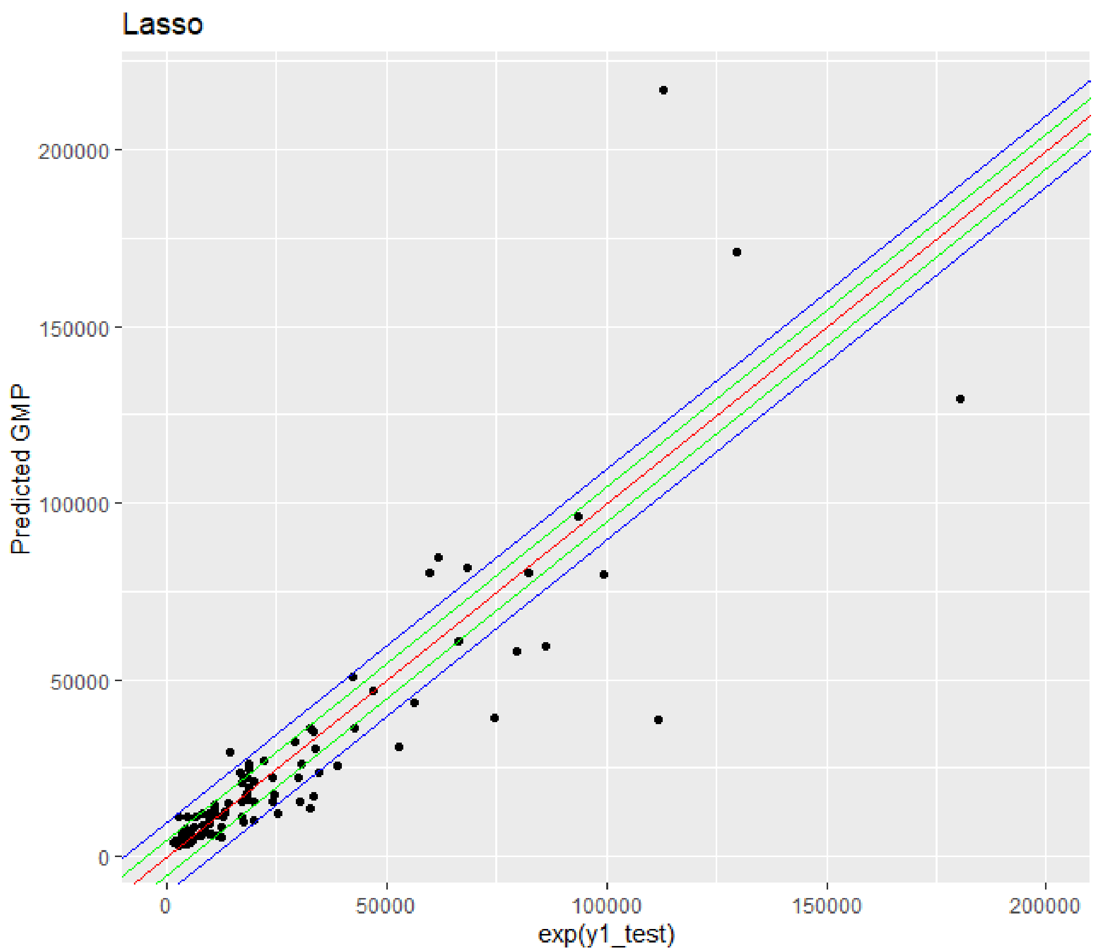


Figure 6.2: The Lasso model. Red line: 100 percent accuracy. Green line: 5 billion dollar threshold. Blue line: 10 billion dollar threshold

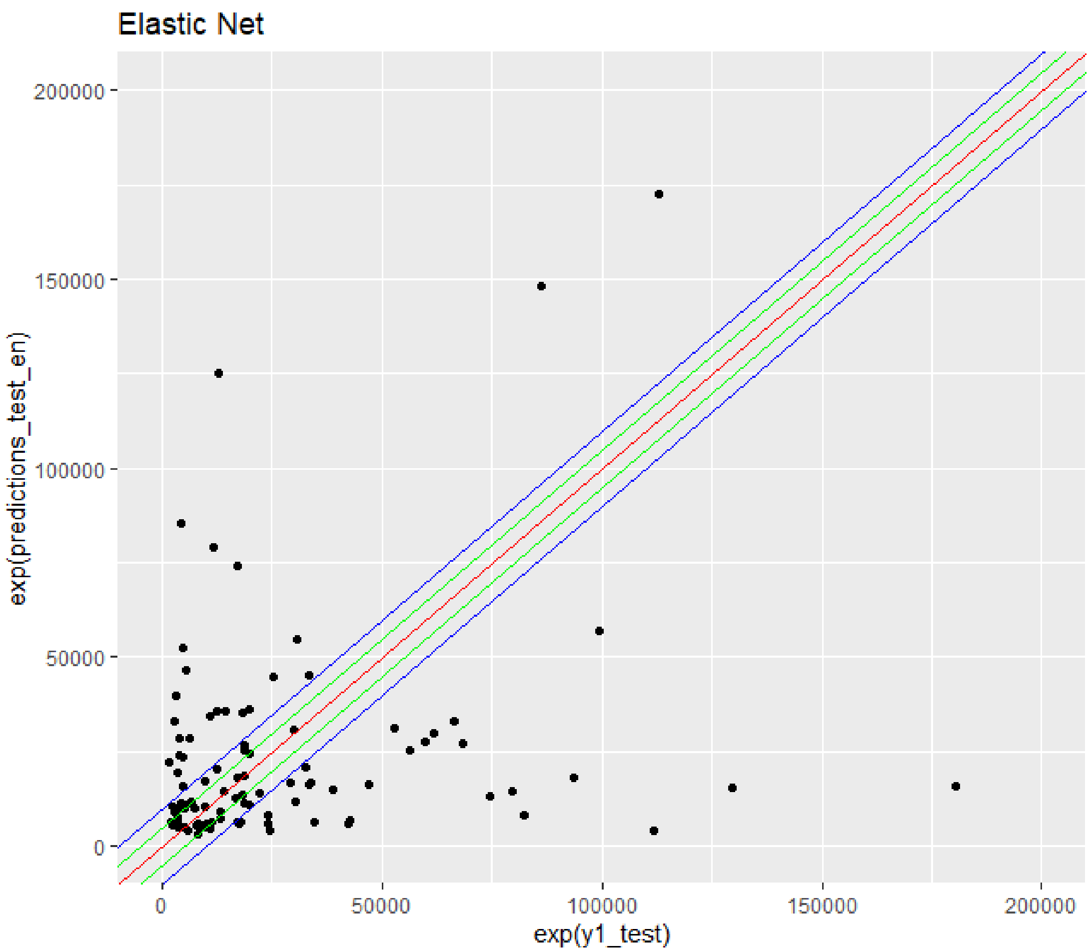


Figure 6.3: The Elastic nets model. Red line: 100 percent accuracy. Green line: 5 billion dollar threshold. Blue line: 10 billion dollar threshold

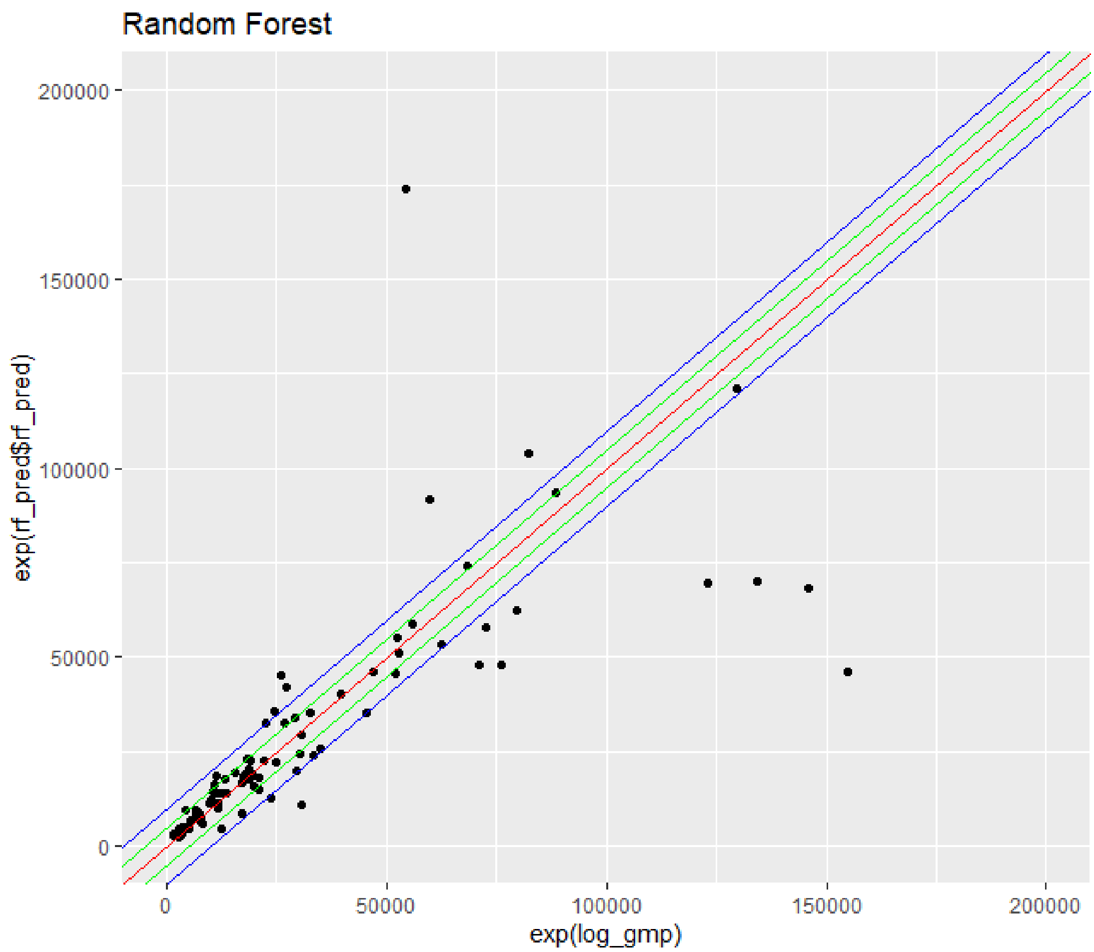


Figure 6.4: The RF model. Red line: 100 percent accuracy. Green line: 5 billion dollar threshold. Blue line: 10 billion dollar threshold

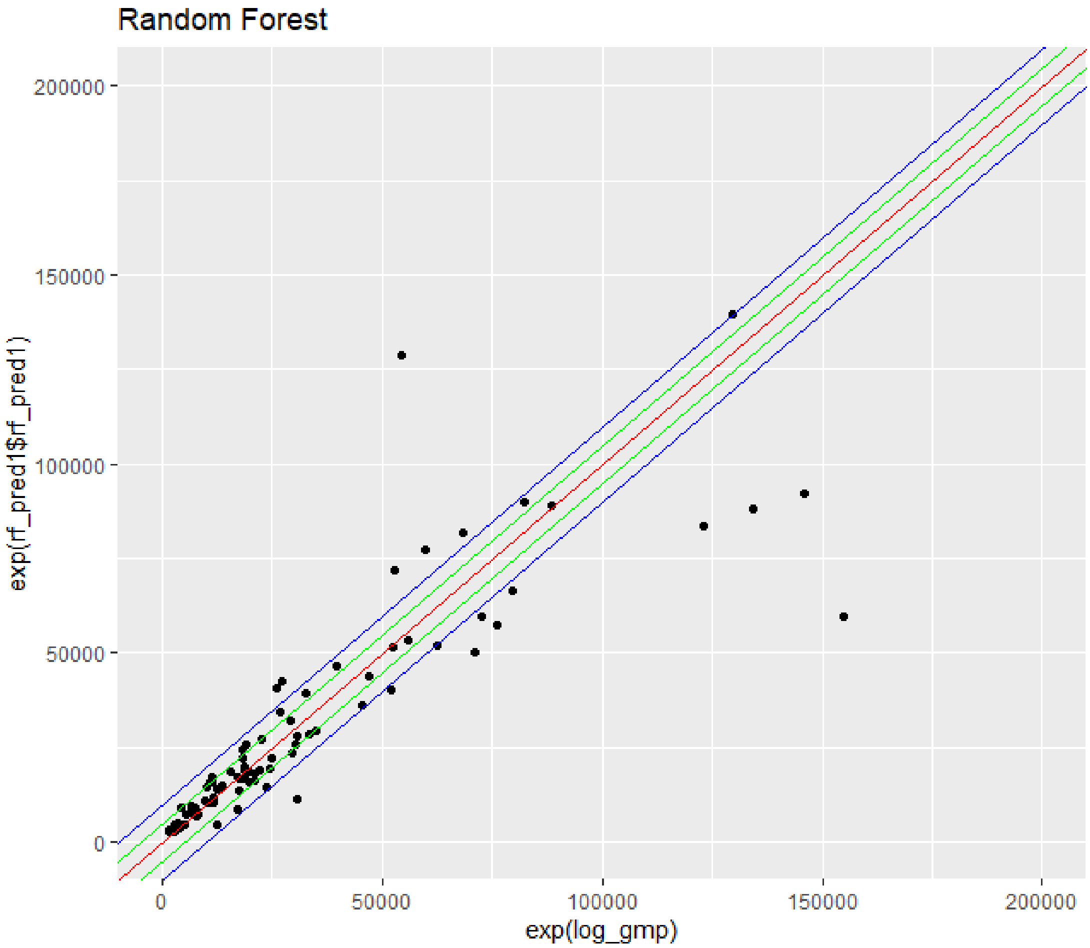


Figure 6.5: The tuned RF model. Red line: 100 percent accuracy. Green line: 5 billion dollar threshold. Blue line: 10 billion dollar threshold

Figure 6.7 shows the tested number of predictive variables tested to achieve the minimum OOB error. This process starts with 90 default variables (one-third of the 270 independent variables we included in our models) and increases this number to achieve the lowest OOB (0.0828), which happens at 202 variable samples.

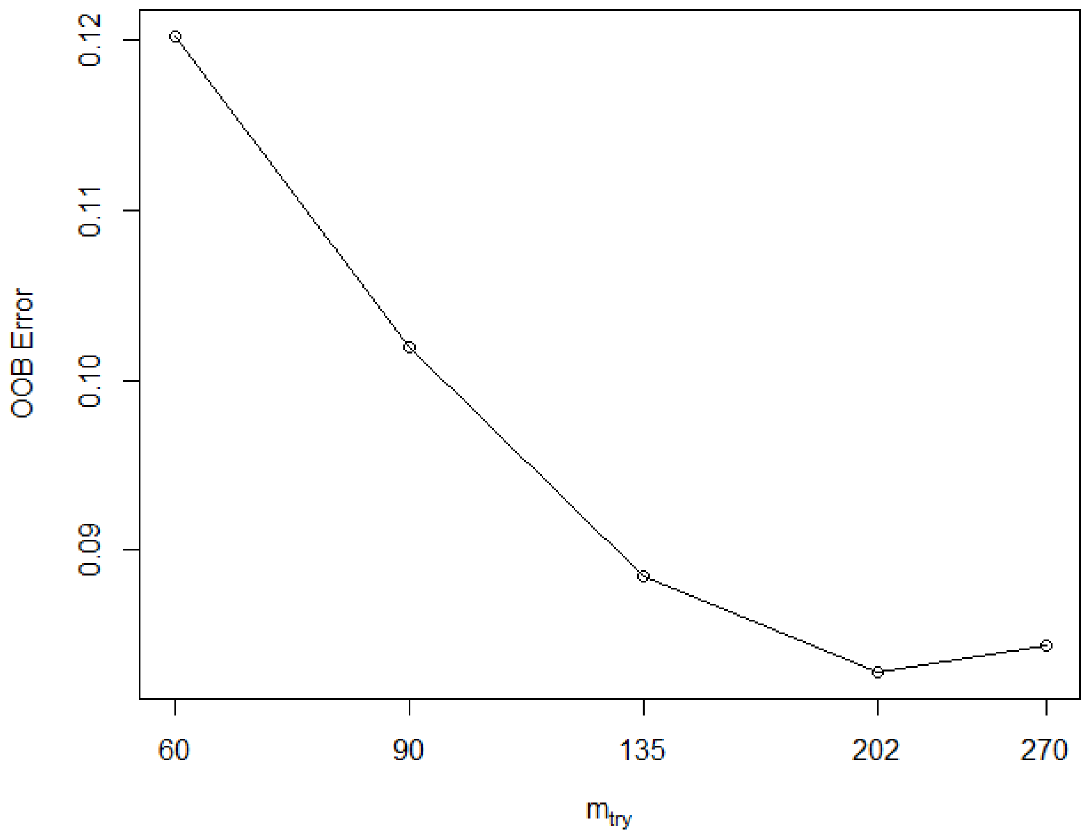


Figure 6.6: The optimal variable sample size for splitting nodes based on OOB error; mtry shows the number of variables sampled

Table 6.5 and figure 6.7 show a list of independent variables in order of importance concerning both percent increase in MSE and increase in node purity. The most influential variable is population and latitude.

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
totpop	123.264	totpop	514.529
Latitude	33.491	rad_variance	56.983
vanui_variance	15.903	rad_sum	16.045
ntl_sum	15.191	Latitude	9.842
rad_variance	14.058	DSgmp_rad_wholeGDP_X2	3.986
rad_sum	11.401	DSgmp_rad_wholeGDP_X8	3.658
COUNT	11.386	DSgmp_rad_wholeGDP_X9	3.484
Longitude	11.179	Longitude	3.452
rad_max	8.220	DSgmp_rad_wholeGDP_X6	3.431
rad_count	7.979	DSgmp_rad_wholeGDP_X4	3.128
LENGTH	7.883	DSgmp_rad_wholeGDP_X10	2.862
ntl_median	7.842	DSgmp_rad_nonsgg_X6	2.829
vanui_te	7.395	DSgmp_rad_wholeGDP_X7	2.678
ntl_count	7.336	DSgmp_rad_nonsgg_X2	2.666

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
DSgmp_rad_service_X4	7.231	DSgmp_rad_wholeGDP_X3	2.622
vanui_shape_mn	6.670	DSgmp_rad_nonsgg_X5	2.525
rad_pladj	6.501	DSgmp_rad_nonsgg_X9	2.501
vanui_count	6.343	DSgmp_rad_wholeGDP_X5	2.472
DSgmp_rad_service_X3	6.274	GDP1000	2.174
ntl_te	6.268	DSgmp_rad_nonsgg_X10	2.145
vanui_cai_mn	6.157	DSgmp_rad_nonsgg_X4	2.140
DSgmp_rad_service_X6	6.132	DSgmp_rad_wholeGDP_X1	2.106
DSgmp_rad_service_X2	6.051	ntl_median	1.824
DSgmp_rad_service_X10	6.014	ntl_sum	1.762
vanui_median	5.998	vanui_variance	1.660
vanui_max	5.948	DSgmp_rad_nonsgg_X3	1.587
vanui_np	5.857	COUNT	1.579
rad_lsi	5.852	DSgmp_rad_nonsgg_X1	1.446

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
DSgmp_rad_service_X1	5.804	vanui_shape_mn	1.365
rad_te	5.753	vanui_median	1.220
DSgmp_rad_nonsgg_X7	5.644	DSgmp_rad_nonsgg_X8	1.212
DSgmp_rad_service_X7	5.624	vanui_max	1.043
DSgmp_rad_wholeGDP_X3	5.429	rad_median	1.014
rad_median	5.395	DSgmp_rad_service_X2	0.999
rad_cohesion	5.385	DSgmp_rad_nonsgg_X7	0.988
ntl_variance	5.357	vanui_cai_mn	0.913
ntl_pland	5.326	ntl_variance	0.880
DSgmp_rad_service_X5	5.208	rad_max	0.872
DSgmp_rad_wholeGDP_X4	5.201	LENGTH	0.832
DSgmp_rad_nonsgg_X5	5.135	vanui_clumpy	0.767
DSgmp_rad_wholeGDP_X8	5.101	vanui_contig_mn	0.750
DSgmp_rad_wholeGDP_X1	5.099	ntl_shape_mn	0.727

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
DSgmp_rad_service_X9	4.994	ntl_clumpy	0.717
rad_dcad	4.949	ntl_cai_mn	0.716
DSgmp_rad_nonsgg_X1	4.757	vanui_lsi	0.715
ntl_clumpy	4.753	DSgmp_rad_service_X6	0.706
vanui_lsi	4.744	ntl_contig_mn	0.704
DSgmp_rad_nonsgg_X2	4.737	vanui_ai	0.661
DSgmp_rad_wholeGDP_X7	4.722	DSgmp_rad_service_X1	0.649
DSgmp_rad_wholeGDP_X5	4.705	vanui_dcad	0.639
DSgmp_rad_wholeGDP_X2	4.695	DSgmp_rad_service_X7	0.629
vanui_sum	4.674	DSgmp_rad_service_X4	0.619
ntl_lsi	4.657	DSgmp_rad_service_X8	0.604
GDP1000	4.636	DSgmp_rad_service_X10	0.600
DSgmp_rad_nonsgg_X10	4.621	rad_shape_mn	0.592
DSgmp_rad_wholeGDP_X9	4.595	rad_dcad	0.568

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
DSgmp_rad_wholeGDP_X6	4.544	DSgmp_rad_service_X5	0.548
DSgmp_rad_wholeGDP_X10	4.498	vanui_te	0.546
DSgmp_vanui_nonagg_X1	4.443	rad_cohesion	0.514
DSgmp_rad_nonsgg_X8	4.338	vanui_pd	0.499
vanui_dcad	4.331	DSgmp_rad_service_X3	0.496
vanui_clumpy	4.308	DSgmp_vanui_nonagg_X1	0.493
rad_pland	4.200	vanui_ed	0.483
DSgmp_rad_nonsgg_X6	4.109	DSgmp_rad_service_X9	0.482
DSgmp_rad_nonsgg_X3	4.063	rad_lsi	0.464
vanui_split	3.912	ntl_pland	0.457
rad_clumpy	3.880	rad_cai_mn	0.447
DSgmp_rad_service_X8	3.766	rad_clumpy	0.444
DSgmp_rad_nonsgg_X9	3.748	ntl_pladj	0.435
DSgmp_vanui_wholeGDP_X7	3.729	rad_pladj	0.431

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
DSgmp_rad_nonsgg_X4	3.646	ntl_lsi	0.425
vanui_pland	3.414	ntl_area_mn	0.425
ntl_split	3.408	rad_ed	0.410
DSgmp_vanui_wholeGDP_X2	3.375	rad_contig_mn	0.408
vanui_contig_mn	3.306	ntl_cohesion	0.402
ntl_np	3.272	rad_ai	0.397
rad_shape_mn	3.259	ntl_te	0.393
rad_np	3.225	vanui_sum	0.391
DSgmp_vanui_nonagg_X3	3.193	vanui_np	0.391
rad_split	3.185	vanui_pladj	0.387
vanui_pladj	3.163	rad_pland	0.386
ntl_pladj	3.162	rad_te	0.385
DSgmp_vanui_service_X5	2.885	ntl_ai	0.384
ntl_dcad	2.865	vanui_pland	0.383

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
ntl_contig_mn	2.859	rad_count	0.374
vanui_ai	2.747	ntl_dcad	0.357
rad_ai	2.629	ntl_count	0.353
DSgmp_vanui_service_X2	2.558	ntl_pd	0.348
rad_lpi	2.553	vanui_area_mn	0.348
ntl_lpi	2.544	vanui_cohesion	0.328
DSgmp_vanui_wholeGDP_X1	2.521	vanui_count	0.322
DSgmp_vanui_service_X9	2.454	rad_area_mn	0.310
ntl_shape_mn	2.433	ntl_ed	0.309
DSgmp_vanui_service_X1	2.323	vanui_split	0.261
vanui_ed	2.310	ntl_split	0.253
DSgmp_vanui_nonagg_X4	2.257	vanui_lpi	0.247
DSgmp_vanui_service_X10	2.202	rad_pd	0.245
ntl_cohesion	2.142	rad_lpi	0.236

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
DSgmp_vanui_service_X6	2.124	ntl_lpi	0.222
rad_ed	2.114	rad_split	0.216
DSgmp_vanui_service_X8	2.063	ntl_np	0.186
vanui_cohesion	2.049	rad_np	0.122
DSgmp_vanui_service_X4	2.013	coastal	0.104
rad_pd	2.004	DSgmp_vanui_wholeGDP_X2	0.099
DSgmp_vanui_wholeGDP_X5	1.967	DSgmp_vanui_wholeGDP_X10	0.097
ntl_area_mn	1.930	DSgmp_vanui_wholeGDP_X5	0.087
DSgmp_vanui_nonagg_X9	1.917	DSgmp_vanui_wholeGDP_X9	0.084
DSgmp_vanui_nonagg_X5	1.915	DSgmp_vanui_service_X10	0.084
DSgmp_vanui_wholeGDP_X6	1.885	DSgmp_vanui_nonagg_X3	0.081
rad_area_mn	1.852	DSgmp_vanui_wholeGDP_X7	0.078
vanui_area_mn	1.752	DSgmp_vanui_wholeGDP_X1	0.076
DSgmp_vanui_service_X3	1.742	DSgmp_vanui_service_X5	0.075

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
DSgmp_vanui_wholeGDP_X8	1.693	DSgmp_vanui_nonagg_X2	0.073
DSgmp_vanui_wholeGDP_X10	1.530	DSgmp_vanui_service_X1	0.072
DSgmp_vanui_wholeGDP_X3	1.468	DSgmp_vanui_nonagg_X5	0.069
DSgmp_vanui_nonagg_X7	1.409	DSgmp_vanui_service_X7	0.067
DSgmp_vanui_nonagg_X6	1.313	DSgmp_vanui_service_X2	0.066
ntl_cai_mn	1.260	DSgmp_vanui_nonagg_X4	0.065
ntl_ai	1.240	DSgmp_vanui_nonagg_X8	0.064
DSgmp_vanui_wholeGDP_X4	1.175	DSgmp_vanui_wholeGDP_X4	0.062
DSgmp_vanui_nonagg_X8	1.082	DSgmp_vanui_service_X6	0.062
DSgmp_vanui_nonagg_X2	1.066	DSgmp_vanui_wholeGDP_X6	0.059
rad_contig_mn	1.022	DSgmp_vanui_service_X8	0.059
DSgmp_vanui_wholeGDP_X9	0.985	DSgmp_vanui_nonagg_X9	0.058
coastal	0.782	DSgmp_vanui_service_X9	0.057
DSgmp_vanui_service_X7	0.669	DSgmp_vanui_service_X3	0.057

Table 6.5: Variable importance in percent increase in MSE and increase in node purity

Variable	**%IncMSE**	**Variable**	**IncNodePurity**
DSgmp_vanui_nonagg_X10	0.466	DSgmp_vanui_nonagg_X6	0.054
vanui_lpi	0.252	DSgmp_vanui_service_X4	0.053
vanui_pd	0.212	DSgmp_vanui_nonagg_X10	0.047
ntl_pd	0.035	DSgmp_vanui_wholeGDP_X8	0.045
rad_cai_mn	-0.083	DSgmp_vanui_wholeGDP_X3	0.045
ntl_ed	-0.306	DSgmp_vanui_nonagg_X7	0.040
ntl_max	-2.000	ntl_max	0.031

Table 6.7 to table 6.21 show the prediction results, categorizing each city within ventiles, based on their predicted GMP. Different tables report the results by subregion: Table 6.7 for Australia and New Zealand. Table 6.8 for Central Asia. Table 6.9 for Eastern Asia. Table 6.10 for Eastern Europe. Table 6.11 for Latin America and the Caribbean. Table 6.12 for Melanesia. Table 6.13 for Northern Africa. Table 6.14 for North America. Table 6.15 for Northern Europe. Table 6.16 for Southeastern Asia. Table 6.17 for South Asia. Table 6.18 for South Europe. Table 6.19 for Sub-Saharan Africa. Table 6.20 for Western Asia. Table 6.21 for Western Europe. It is important to note that in table 6.7 to table 6.21, the population is in number of people, and GMP and GMP per capita are in thousands of dollars.

Table 6.6: The GMP ranges for each ventile.(in millions of dollars)

Ventile	**Max**	**Min**
20	1,294,657	39,475
19	39,332	21,652
18	21,246	14,332
17	14,254	10,579
16	10,576	8,985
15	8,978	8,243
14	8,221	7,784
13	7,784	7,084
12	7,063	5,774
11	5,761	5,156
10	5,155	4,741
9	4,737	4,458
8	4,458	4,249
7	4,249	3,919
6	3,907	3,672
5	3,670	3,522
4	3,522	3,361
3	3,359	3,118
2	3,116	2,801
1	2,801	1,479

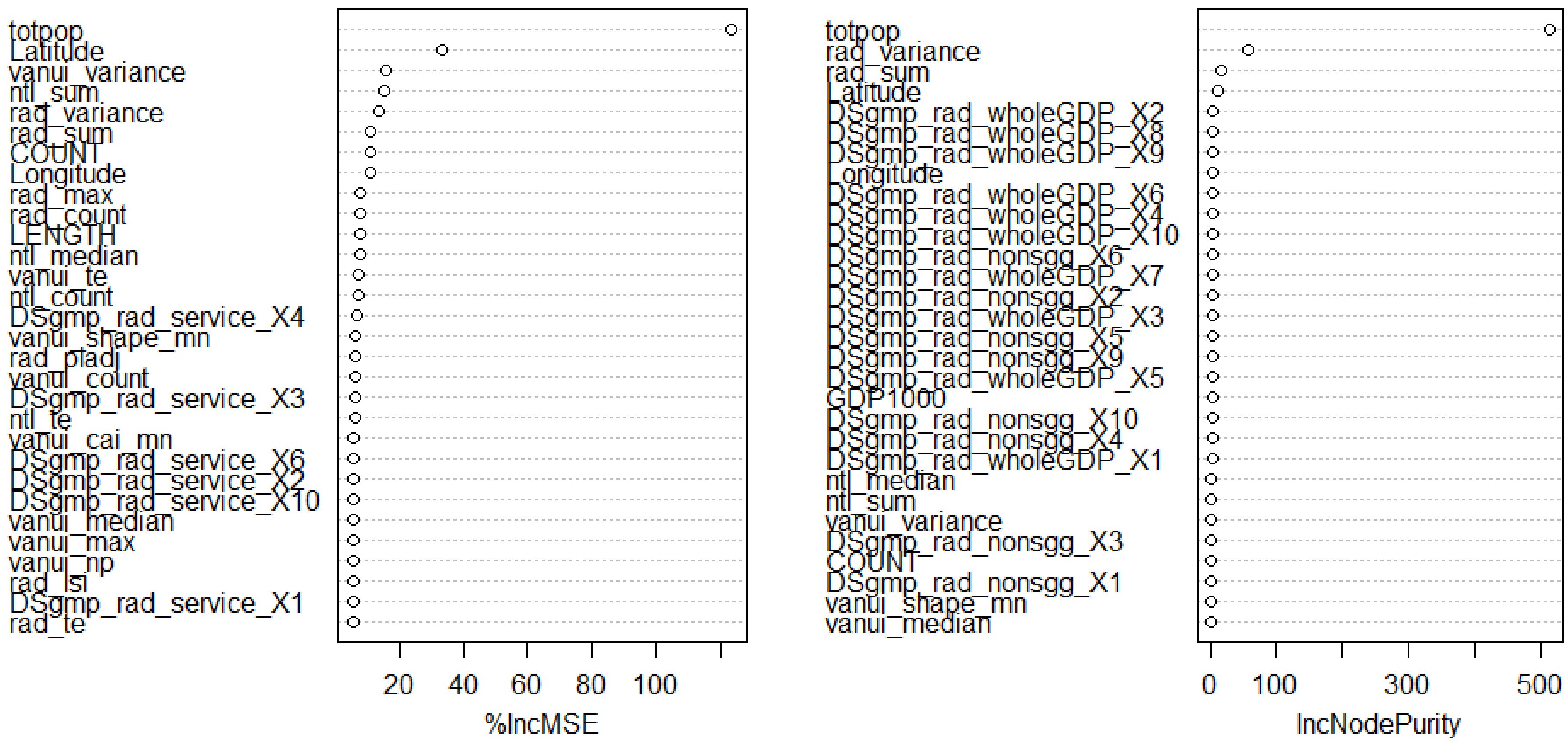


Figure 6.7: Variable importance plot with respect to percent increase in MSE and increase in node purity

Table 6.7: Australia and New Zealand predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Melbourne	Australia	15	8,825,087	2.95	2,996,630	Australia and New Zealand
Prediction	Sydney	Australia	15	8,526,623	2.66	3,206,415	Australia and New Zealand
Prediction	Perth	Australia	14	8,003,557	7.22	1,109,008	Australia and New Zealand
Prediction	Brisbane	Australia	14	7,821,394	5.97	1,310,480	Australia and New Zealand
Prediction	Adelaide	Australia	13	7,578,001	7.55	1,003,519	Australia and New Zealand
Prediction	Auckland	New Zealand	13	7,479,267	6.09	1,227,411	Australia and New Zealand
Prediction	Gold Coast	Australia	10	4,824,359	13.86	348,015	Australia and New Zealand
Prediction	Canberra	Australia	8	4,388,912	11.47	382,716	Australia and New Zealand
Prediction	Sunshine Coast	Australia	5	3,670,278	26.20	140,074	Australia and New Zealand
Prediction	Christchurch	New Zealand	4	3,505,991	11.23	312,208	Australia and New Zealand
Prediction	Newcastle and Lake Macquarie	Australia	3	3,216,091	11.57	277,860	Australia and New Zealand
Prediction	Wellington	New Zealand	3	3,190,176	21.98	145,116	Australia and New Zealand

Table 6.8: Central Asia Prediciton

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Bishkek	Kyrgyzstan	17	11,299,666	11.47	985,221	Central Asia
Prediction	Almaty	Kazakhstan	16	9,264,882	5.49	1,688,854	Central Asia
Prediction	Tashkent	Uzbekistan	16	9,074,209	4.33	2,096,865	Central Asia
Prediction	Ashgabat	Turkmenistan	14	8,153,420	6.35	1,284,243	Central Asia
Prediction	Dushanbe	Tajikistan	14	7,940,168	6.81	1,165,109	Central Asia
Prediction	Shimkent	Kazakhstan	12	5,899,706	7.95	741,711	Central Asia
Prediction	Samarkand	Uzbekistan	9	4,525,852	9.66	468,365	Central Asia
Prediction	Astana	Kazakhstan	7	3,974,445	14.00	283,822	Central Asia
Prediction	Namangan	Uzbekistan	7	3,932,295	11.04	356,333	Central Asia
Prediction	Aktyubinsk	Kazakhstan	5	3,622,297	18.63	194,446	Central Asia
Prediction	Karaganda	Kazakhstan	5	3,608,437	42.98	83,951	Central Asia
Prediction	Pavlodar	Kazakhstan	5	3,595,821	29.63	121,375	Central Asia
Prediction	Ust-Kamenogorsk	Kazakhstan	5	3,579,517	37.86	94,543	Central Asia

Table 6.8: Central Asia Prediciton

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Semipalatinsk	Kazakhstan	5	3,560,053	37.32	95,405	Central Asia
Prediction	Taraz	Kazakhstan	4	3,516,551	34.52	101,880	Central Asia
Prediction	Tashauz	Turkmenistan	4	3,454,809	20.92	165,165	Central Asia
Prediction	Andizhan	Uzbekistan	2	3,047,374	10.66	285,757	Central Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Tokyo	Japan	20	1,294,656,996	37.02	34,970,411	Eastern Asia
Calibration/Validation	Seoul Incheon	South Korea	20	589,192,003	26.24	22,451,402	Eastern Asia
Calibration/Validation	Osaka	Japan	20	516,617,999	29.95	17,247,940	Eastern Asia
Calibration/Validation	Nagoya	Japan	20	215,072,999	33.58	6,405,306	Eastern Asia
Calibration/Validation	Fukuoka	Japan	20	69,050,000	27.36	2523685	Eastern Asia
Calibration/Validation	Busan	South Korea	20	68,353,000	19.83	3,447,182	Eastern Asia
Calibration/Validation	Ulsan	South Korea	20	61,865,000	60.59	1,021,015	Eastern Asia
Calibration/Validation	Sapporo	Japan	20	54,382,000	24.89	2,184,613	Eastern Asia
Calibration/Validation	Daegu	South Korea	20	46,126,000	17.48	2,639,116	Eastern Asia
Calibration/Validation	Hiroshima	Japan	20	42,768,000	30.49	1402833	Eastern Asia
Calibration/Validation	Sendai	Japan	20	42,298,000	26.83	1,576,718	Eastern Asia
Calibration/Validation	Kitakyushu	Japan	19	35,646,000	30.45	1170818	Eastern Asia
Calibration/Validation	Hamamatsu	Japan	19	33,553,000	34.02	986352	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Daejeon	South Korea	19	31,764,000	20.29	1,565,511	Eastern Asia
Calibration/Validation	Gwangju	South Korea	19	30,534,000	19.88	1535944	Eastern Asia
Calibration/Validation	Niigata	Japan	19	29,880,000	28.74	1,039,728	Eastern Asia
Calibration/Validation	Maebashi	Japan	19	29,332,000	29.80	984,416	Eastern Asia
Calibration/Validation	Shizuoka	Japan	19	26,044,000	35.32	737,397	Eastern Asia
Calibration/Validation	Changwon	South Korea	19	25,764,000	34.26	751,964	Eastern Asia
Calibration/Validation	Anjo	Japan	19	25,353,000	33.77	750,787	Eastern Asia
Calibration/Validation	Naha	Japan	19	24,741,000	21.59	1,145,731	Eastern Asia
Calibration/Validation	Utsunomiya	Japan	19	24,551,000	30.69	800,040	Eastern Asia
Calibration/Validation	Kurashiki	Japan	19	24,326,000	42.10	577828	Eastern Asia
Calibration/Validation	Kumamoto	Japan	19	23,221,000	23.86	973384	Eastern Asia
Calibration/Validation	Toyohashi	Japan	19	22,168,000	36.43	608,457	Eastern Asia
Calibration/Validation	Kanazawa	Japan	19	21,652,000	29.12	743647	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Okayama	Japan	18	20,822,000	23.68	879,397	Eastern Asia
Calibration/Validation	Himeji	Japan	18	19,012,000	26.66	713218	Eastern Asia
Calibration/Validation	Takamatsu	Japan	18	18,772,000	35.72	525,518	Eastern Asia
Prediction	Kinki M.M.A. (Osaka)	Japan	18	18,543,677	1.47	12600988.1	Eastern Asia
Calibration/Validation	Numazu	Japan	18	18,360,000	34.67	529,593	Eastern Asia
Calibration/Validation	Cheongju	South Korea	18	18,335,000	24.79	739,558	Eastern Asia
Calibration/Validation	Yokkaichi	Japan	18	17,793,000	31.18	570,666	Eastern Asia
Calibration/Validation	Mito	Japan	18	17,583,000	29.79	590,245	Eastern Asia
Calibration/Validation	Toyama	Japan	18	17,445,000	32.12	543,168	Eastern Asia
Calibration/Validation	Kagoshima	Japan	18	17,301,000	24.64	702127	Eastern Asia
Calibration/Validation	Fukuyama	Japan	18	17,256,000	30.92	558145	Eastern Asia
Calibration/Validation	Matsuyama	Japan	18	17,107,000	26.61	642,841	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Pohang	South Korea	18	16,710,000	32.62	512,246	Eastern Asia
Prediction	Suzhou, Jiangsu Wuxi, Jiangsu Changzhou, Jiangsu Jiangyin Zhangjiagang Jingjiang	China	18	16,518,071	1.14	14,515,129	Eastern Asia
Prediction	Shanghai Kunshan Taicang	China	18	16,509,582	0.68	24,110,036	Eastern Asia
Calibration/Validation	Nagano	Japan	18	16,388,000	30.43	538,526	Eastern Asia
Calibration/Validation	Tokushima	Japan	18	15,879,000	28.32	560,755	Eastern Asia
Prediction	Beijing Sanhe	China	18	15,652,705	0.85	18,403,520	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Oita	Japan	18	15,449,000	28.08	550,265	Eastern Asia
Prediction	Tianjin	China	18	14,790,109	2.05	7,214,797	Eastern Asia
Prediction	Chukyo M.M.A. (Nagoya)	Japan	18	14,744,183	2.07	7,115,975	Eastern Asia
Prediction	Chongqing	China	18	14,736,052	3.10	4,755,705	Eastern Asia
Calibration/Validation	Wakayama	Japan	18	14,689,000	27.77	528,946	Eastern Asia
Calibration/Validation	Kofu	Japan	18	14,657,000	28.53	513797	Eastern Asia
Calibration/Validation	Jeonju	South Korea	17	13,905,000	19.95	697052	Eastern Asia
Prediction	Xi'an, Shaanxi Xianyang, Shaanxi	China	17	12,959,795	2.12	6,105,985	Eastern Asia
Calibration/Validation	Nagasaki	Japan	17	12,810,000	24.81	516,411	Eastern Asia
Prediction	Qingdao Jimo Jiaozhou	China	17	12,714,884	2.42	5255781.227	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Shenyang	China	17	12,551,951	2.22	5,645,447	Eastern Asia
Prediction	Zhengzhou Xingyang	China	17	12,453,232	2.61	4,775,765	Eastern Asia
Prediction	Chengdu	China	17	12,214,577	1.49	8,188,517	Eastern Asia
Prediction	Taiyuan, Shanxi Jinzhong	China	17	12,108,118	2.90	4,172,706	Eastern Asia
Prediction	Dalian	China	17	11,989,898	3.53	3,395,540	Eastern Asia
Prediction	Nanjing, Jiangsu	China	17	11,707,031	2.04	5741530.715	Eastern Asia
Prediction	WenzhouWenzhou Ruian Yueqing	China	17	11,630,441	2.17	5,367,676	Eastern Asia
Prediction	Hefei	China	17	11,551,032	2.92	3,956,116	Eastern Asia
Prediction	Ji'nan, Shandong Zhangqiu	China	17	11,538,371	2.96	3,897,020	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Linyi, Shandong	China	17	11,169,118	8.07	1383174.493	Eastern Asia
Calibration/Validation	Kochi	Japan	17	11,146,000	22.66	491875	Eastern Asia
Prediction	Fuzhou, Fujian	China	17	10,806,287	3.57	3,030,457	Eastern Asia
Prediction	Jilin	China	17	10,648,161	6.98	1,525,249	Eastern Asia
Prediction	Baoding	China	16	10,451,092	6.32	1,654,697	Eastern Asia
Prediction	Haerbin	China	16	10,413,472	2.92	3,564,052	Eastern Asia
Prediction	Changchun	China	16	10,380,678	3.08	3,373,566	Eastern Asia
Prediction	Gimhae	South Korea	16	10,246,161	3.23	3,176,317	Eastern Asia
Prediction	Shijiazhuang	China	16	10,200,929	2.94	3,464,383	Eastern Asia
Prediction	Wuhan	China	16	10,146,059	2.62	3,877,854	Eastern Asia
Prediction	Ningbo	China	16	10,007,047	2.90	3448843.843	Eastern Asia
Prediction	Nanchang	China	16	9,952,869	3.14	3166354.585	Eastern Asia
Prediction	Xining	China	16	9,838,303	8.12	1,212,020	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Xiangyang	China	16	9,572,579	9.95	962,206	Eastern Asia
Prediction	Kaohsiung Kaohsiung Tainan	China	16	9,527,990	2.24	4261897.451	Eastern Asia
Prediction	Taipei	China	16	9,330,869	1.64	5,672,314	Eastern Asia
Prediction	Xiamen Zhangzhou Longhai	China	16	9,325,512	1.64	5,702,594	Eastern Asia
Prediction	Wuhu, Anhui	China	16	9,163,879	9.21	994,845	Eastern Asia
Prediction	Anshan Liaoyang	China	16	9,131,775	4.01	2278228.908	Eastern Asia
Prediction	Quanzhou Shishi Jinjiang	China	16	9,125,668	2.09	4362346.094	Eastern Asia
Prediction	Nantong Haimen	China	16	9,067,580	4.05	2236168.715	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Lanzhou	China	16	9,064,658	3.92	2312983.248	Eastern Asia
Prediction	Luoyang Yanshi	China	15	8,976,010	3.71	2421522.259	Eastern Asia
Prediction	Baotou	China	15	8,963,832	4.17	2,151,363	Eastern Asia
Prediction	Shantou Chaozhou Jieyang	China	15	8,935,929	1.58	5,656,275	Eastern Asia
Prediction	Shouguang	China	15	8,744,452	4.49	1,947,805	Eastern Asia
Prediction	Taizhou, Zhejiang Wenling	China	15	8,721,529	3.28	2,661,145	Eastern Asia
Prediction	Tangshan, Hebei	China	15	8,699,253	4.54	1,916,632	Eastern Asia
Prediction	Hohhot	China	15	8,635,609	4.41	1,956,573	Eastern Asia
Prediction	Yinchuan	China	15	8,509,052	5.65	1,506,200	Eastern Asia
Prediction	Kunming	China	15	8,486,306	2.59	3274226.37	Eastern Asia
Prediction	Xuzhou	China	15	8,470,498	5.72	1,480,049	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Taichung	China	15	8,465,045	2.52	3,353,580	Eastern Asia
Prediction	Zibo	China	15	8,457,265	5.90	1,433,008	Eastern Asia
Prediction	Guiyang	China	15	8,451,077	3.87	2,184,383	Eastern Asia
Prediction	Nanning	China	15	8,442,928	3.22	2624549.999	Eastern Asia
Prediction	Handan	China	15	8,399,145	6.08	1,382,018	Eastern Asia
Prediction	Yantai	China	15	8,335,674	6.38	1,306,106	Eastern Asia
Prediction	Datong	China	15	8,308,415	6.29	1,320,403	Eastern Asia
Prediction	Puning	China	14	8,142,743	3.07	2652438.38	Eastern Asia
Prediction	Huai'an	China	14	8,095,021	6.64	1,218,293	Eastern Asia
Prediction	Liuzhou	China	14	8,060,041	5.38	1498349.42	Eastern Asia
Prediction	Yangzhou	China	14	7,916,088	6.57	1,204,680	Eastern Asia
Prediction	Zhuhai Macao	China	14	7,915,392	4.70	1,684,480	Eastern Asia
Prediction	Haikou	China	14	7,904,282	4.23	1,867,615	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Zhangjiakou	China	14	7,894,518	7.84	1,006,457	Eastern Asia
Prediction	Xinxiang	China	14	7,888,165	6.93	1,138,878	Eastern Asia
Prediction	Yiwu Dongyang	China	14	7,872,478	6.34	1,241,383	Eastern Asia
Prediction	Xiangtan, Hunan	China	14	7,840,638	7.88	994,687	Eastern Asia
Prediction	Changshu	China	13	7,783,622	7.74	1,005,497	Eastern Asia
Prediction	Hengyang	China	13	7,769,238	8.30	936,166	Eastern Asia
Prediction	Huainan	China	13	7,761,681	7.90	982,850	Eastern Asia
Prediction	Zhuzhou	China	13	7,738,519	8.53	907,306	Eastern Asia
Prediction	Putian	China	13	7,656,329	5.84	1311255.912	Eastern Asia
Prediction	Anyang	China	13	7,642,315	7.95	960950.3375	Eastern Asia
Prediction	Qiqihaer	China	13	7,639,992	8.36	913867.5367	Eastern Asia
Prediction	Huaibei	China	13	7,634,422	8.57	891,235	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	P'yongyang	Dem. People's Republic of Korea	13	7,613,042	6.28	1212138.077	Eastern Asia
Prediction	Dandong Sinuiju	China	13	7,604,754	8.77	867,439	Eastern Asia
Prediction	Fushun, Liaoning	China	13	7,560,339	8.69	869,739	Eastern Asia
Prediction	Huizhou	China	13	7,548,902	7.02	1,074,735	Eastern Asia
Prediction	Xingtai	China	13	7,516,427	8.49	885,235	Eastern Asia
Prediction	Ulaanbaatar	Mongolia	13	7,489,407	8.83	847,958	Eastern Asia
Prediction	Huangshi Daye	China	13	7,470,380	8.39	890,908	Eastern Asia
Prediction	Zhanjiang	China	13	7,448,826	7.34	1,015,025	Eastern Asia
Prediction	Changzhi	China	13	7,434,301	8.64	860,455	Eastern Asia
Prediction	Ganzhou Nankang	China	13	7,432,970	5.75	1,292,748	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Ma'anshan	China	13	7,399,043	8.86	834749.3947	Eastern Asia
Prediction	Guilin	China	13	7,340,298	8.08	908,437	Eastern Asia
Prediction	Fuqing	China	13	7,326,449	6.49	1,128,585	Eastern Asia
Prediction	Mianyang, Sichuan	China	13	7,204,884	8.63	834591.5734	Eastern Asia
Prediction	Zhenjiang, Jiangsu	China	13	7,187,679	8.61	834,950	Eastern Asia
Prediction	Qinhuangdao	China	12	7,062,540	8.59	821811.6799	Eastern Asia
Prediction	Shangqiu	China	12	7,036,168	11.01	639,274	Eastern Asia
Prediction	Puyang	China	12	6,887,245	13.35	515791.9274	Eastern Asia
Prediction	Daqing	China	12	6,721,277	8.41	799,513	Eastern Asia
Prediction	Panjin	China	12	6,594,057	8.14	809592.1391	Eastern Asia
Prediction	Rizhao	China	12	6,590,753	8.24	799730.1837	Eastern Asia
Prediction	Jiamusi	China	12	6,510,958	10.75	605,826	Eastern Asia
Prediction	Baoji	China	12	6,505,868	8.23	790,417	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Jining, Shandong	China	12	6,481,650	8.09	801448.566	Eastern Asia
Prediction	Jiaozuo	China	12	6,453,111	8.26	781,691	Eastern Asia
Prediction	Taishan Kaiping	China	12	6,289,974	8.62	730,072	Eastern Asia
Prediction	Yancheng, Jiangsu	China	12	6,287,788	8.18	768,735	Eastern Asia
Prediction	Yueyang	China	12	6,121,458	8.06	759,063	Eastern Asia
Prediction	Nanyang, Henan	China	12	6,120,575	8.19	747661.3668	Eastern Asia
Prediction	Tengzhou	China	12	6,086,370	11.61	524,454	Eastern Asia
Prediction	Jingzhou, Hubei	China	12	6,050,865	7.87	769228.225	Eastern Asia
Prediction	Yichang	China	12	6,046,785	7.93	762,412	Eastern Asia
Prediction	Kaifeng	China	12	6,039,322	8.16	740398.2427	Eastern Asia
Prediction	Laiwu	China	12	5,794,631	7.94	730249.5402	Eastern Asia
Prediction	Jinzhou	China	11	5,760,642	7.93	726330.1023	Eastern Asia
Prediction	Zhuji	China	11	5,538,198	10.89	508,467	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Mudanjiang	China	11	5,419,394	7.88	687803.183	Eastern Asia
Prediction	Dongying	China	11	5,398,397	7.81	691,201	Eastern Asia
Prediction	Nanchong	China	11	5,390,343	7.50	718475.2138	Eastern Asia
Prediction	Weihai	China	11	5,362,824	7.61	704,799	Eastern Asia
Prediction	Benxi	China	11	5,347,193	7.79	686,728	Eastern Asia
Prediction	Jinhua	China	11	5,303,835	7.69	689397.1931	Eastern Asia
Prediction	Taizhou, Jiangsu	China	11	5,295,090	7.99	662,998	Eastern Asia
Prediction	Fuyang	China	11	5,257,340	8.15	644,828	Eastern Asia
Prediction	Xuchang	China	11	5,246,571	8.14	644,717	Eastern Asia
Prediction	Suqian	China	11	5,242,128	7.92	662,070	Eastern Asia
Prediction	Jiaxing	China	11	5,229,016	8.21	637,152	Eastern Asia
Prediction	Changde	China	11	5,226,498	7.58	689,158	Eastern Asia
Prediction	Huzhou	China	11	5,224,207	8.58	608,932	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Chifeng	China	11	5,175,465	8.35	619,646	Eastern Asia
Prediction	Bengbu	China	11	5,160,136	8.23	627,322	Eastern Asia
Prediction	Siping	China	11	5,155,940	10.01	515,192	Eastern Asia
Prediction	Tongliao	China	10	5,149,855	9.54	540,027	Eastern Asia
Prediction	Linfen	China	10	5,117,482	9.23	554302.4883	Eastern Asia
Prediction	Zhaoqing	China	10	5,115,374	8.37	611,054	Eastern Asia
Prediction	Luohe	China	10	5,103,710	8.31	614532.8051	Eastern Asia
Prediction	Hsinchu	China	10	5,099,137	8.41	606,004	Eastern Asia
Prediction	Hengshui	China	10	5,085,531	13.38	380,074	Eastern Asia
Prediction	Yingkou	China	10	5,075,578	9.56	530,977	Eastern Asia
Prediction	Lianyungang	China	10	5,065,760	8.92	567598.9244	Eastern Asia
Prediction	Fuxin	China	10	5,059,649	8.83	573,319	Eastern Asia
Prediction	Dezhou	China	10	5,058,062	9.15	552,651	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Jiujiang	China	10	5,047,875	7.46	677077.1824	Eastern Asia
Prediction	Zhumadian	China	10	5,023,696	8.88	565,871	Eastern Asia
Prediction	Jincheng	China	10	4,994,025	9.59	520,576	Eastern Asia
Prediction	Liaocheng	China	10	4,976,666	9.84	505804.9042	Eastern Asia
Prediction	Qujing	China	10	4,957,786	11.37	435965.0683	Eastern Asia
Prediction	Maoming	China	10	4,956,048	8.77	564871.1026	Eastern Asia
Prediction	Cangzhou	China	10	4,933,263	9.33	528,505	Eastern Asia
Prediction	Yulin, Guangxi	China	10	4,921,717	8.72	564,520	Eastern Asia
Prediction	Hanzhong	China	10	4,894,649	9.79	500,094	Eastern Asia
Prediction	Langfang	China	10	4,848,660	10.11	479737.808	Eastern Asia
Prediction	Deyang	China	10	4,844,339	9.25	523,478	Eastern Asia
Prediction	Keelung	China	10	4,834,871	8.53	567061.6659	Eastern Asia
Prediction	Hegang	China	10	4,820,829	10.39	463,811	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Shiyan	China	10	4,771,981	9.05	527,076	Eastern Asia
Prediction	Zigong	China	10	4,761,749	8.87	537,043	Eastern Asia
Prediction	Ezhou	China	10	4,750,299	8.60	552,187	Eastern Asia
Prediction	Heze	China	9	4,695,776	10.05	467,126	Eastern Asia
Prediction	Anqing	China	9	4,694,761	8.65	542913.1811	Eastern Asia
Prediction	Qitaihe	China	9	4,688,642	9.88	474621.5803	Eastern Asia
Prediction	Xinyu	China	9	4,677,933	9.40	497,415	Eastern Asia
Prediction	Yanji	China	9	4,675,509	9.82	476,185	Eastern Asia
Prediction	Shangrao	China	9	4,664,703	10.99	424,341	Eastern Asia
Prediction	Zunyi	China	9	4,660,024	6.80	685,357	Eastern Asia
Prediction	Zhoukou	China	9	4,627,577	9.64	480,140	Eastern Asia
Prediction	Yixing	China	9	4,593,459	10.02	458,438	Eastern Asia
Prediction	Shaoguan	China	9	4,585,656	7.84	584,979	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Tianshui	China	9	4,577,206	9.15	500,131	Eastern Asia
Prediction	Suzhou, Anhui	China	9	4,552,502	9.44	482,288	Eastern Asia
Prediction	Zaozhuang	China	9	4,534,907	9.12	497,137	Eastern Asia
Prediction	Fuzhou, Jiangxi	China	9	4,519,016	9.51	475,259	Eastern Asia
Prediction	Qingyuan	China	9	4,491,811	9.59	468551.2659	Eastern Asia
Prediction	Tongling	China	9	4,484,791	10.39	431,472	Eastern Asia
Prediction	Liuan	China	9	4,482,191	10.01	447736.0971	Eastern Asia
Prediction	Binzhou	China	9	4,481,062	10.40	430,824	Eastern Asia
Prediction	Yangquan	China	9	4,480,533	10.00	448,217	Eastern Asia
Prediction	Yining	China	8	4,458,034	10.35	430,821	Eastern Asia
Prediction	Chaoyang	China	8	4,455,168	9.89	450,483	Eastern Asia
Prediction	Jixi, Heilongjiang	China	8	4,451,212	10.71	415472.4698	Eastern Asia
Prediction	Kuerle	China	8	4,449,207	9.95	447184.7273	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Cheonan	South Korea	8	4,447,053	10.43	426,418	Eastern Asia
Prediction	Tonghua	China	8	4,415,279	10.50	420,486	Eastern Asia
Prediction	Dazhou	China	8	4,407,833	8.72	505,442	Eastern Asia
Prediction	Shaoyang	China	8	4,404,454	7.35	598,920	Eastern Asia
Prediction	Longyan	China	8	4,384,987	10.07	435532.9997	Eastern Asia
Prediction	Tongxiang	China	8	4,384,303	9.91	442,622	Eastern Asia
Prediction	Pingxiang, Jiangxi	China	8	4,371,226	8.54	511706.206	Eastern Asia
Prediction	Yangjiang	China	8	4,357,914	9.81	444,176	Eastern Asia
Prediction	Beihai	China	8	4,355,889	9.94	438,412	Eastern Asia
Prediction	Yuncheng	China	8	4,339,080	11.36	382,054	Eastern Asia
Prediction	Danyang	China	8	4,334,573	11.66	371,608	Eastern Asia
Prediction	Zhucheng	China	8	4,333,323	10.77	402,320	Eastern Asia
Prediction	Yibin	China	8	4,327,960	8.42	514,158	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Chuzhou	China	8	4,322,854	11.65	370,973	Eastern Asia
Prediction	Xinyang	China	8	4,322,791	11.12	388,748	Eastern Asia
Prediction	Changji	China	8	4,314,518	11.06	390,119	Eastern Asia
Prediction	Zhoushan	China	8	4,300,746	10.48	410,211	Eastern Asia
Prediction	Yiyang, Hunan	China	8	4,291,354	8.66	495,391	Eastern Asia
Prediction	Huludao	China	8	4,284,622	11.40	375,728	Eastern Asia
Prediction	Fuyang	China	8	4,280,651	10.91	392,379	Eastern Asia
Prediction	Sanya	China	8	4,263,328	10.15	419923.7481	Eastern Asia
Prediction	Sanmenxia	China	7	4,246,145	11.83	359040.2079	Eastern Asia
Prediction	Shihezi	China	7	4,245,892	10.37	409,301	Eastern Asia
Prediction	Yuxi	China	7	4,196,727	11.17	375,827	Eastern Asia
Prediction	Meizhou	China	7	4,168,104	11.14	374066.2688	Eastern Asia
Prediction	Huaihua	China	7	4,058,785	8.46	479,703	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Suining, Sichuan	China	7	4,051,745	9.36	432,862	Eastern Asia
Prediction	Qingzhou	China	7	4,038,596	9.92	406957.8066	Eastern Asia
Prediction	Wuzhou	China	7	4,030,272	9.88	407,874	Eastern Asia
Prediction	Haicheng	China	7	3,986,793	10.17	392,164	Eastern Asia
Prediction	Akesu	China	7	3,972,216	10.75	369,530	Eastern Asia
Prediction	Anshun	China	7	3,961,792	12.00	330275.2548	Eastern Asia
Prediction	Kelamayi	China	7	3,956,285	18.05	219160.9098	Eastern Asia
Prediction	Leshan	China	7	3,953,280	8.95	441619.5884	Eastern Asia
Prediction	Jingdezhen	China	7	3,950,399	10.34	382117.2821	Eastern Asia
Prediction	Lishui, Zhejiang	China	7	3,932,926	14.91	263743.0043	Eastern Asia
Prediction	Xiaogan	China	7	3,919,022	9.34	419,757	Eastern Asia
Prediction	Bayannaoer	China	6	3,898,360	11.29	345,439	Eastern Asia
Prediction	Liaoyuan	China	6	3,889,006	11.41	340867.9178	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Shuozhou	China	6	3,857,500	11.75	328,335	Eastern Asia
Prediction	Jiyuan	China	6	3,854,706	11.36	339214.6159	Eastern Asia
Prediction	Asahikawa	Japan	6	3,844,739	11.92	322556.4094	Eastern Asia
Prediction	Gumi	South Korea	6	3,832,026	11.71	327,150	Eastern Asia
Prediction	Loudi	China	6	3,810,942	9.22	413280.6649	Eastern Asia
Prediction	Weinan	China	6	3,807,742	11.18	340,567	Eastern Asia
Prediction	Tongcheng	China	6	3,805,959	45.62	83,429	Eastern Asia
Prediction	Yichun, Jiangxi	China	6	3,804,025	9.40	404,569	Eastern Asia
Prediction	Dujiangyan	China	6	3,772,690	10.65	354,371	Eastern Asia
Prediction	Dongtai	China	6	3,768,885	13.30	283,411	Eastern Asia
Prediction	Neijiang	China	6	3,751,252	9.75	384679.7624	Eastern Asia
Prediction	Luzhou	China	6	3,715,633	9.19	404175.5738	Eastern Asia
Prediction	Shanwei	China	6	3,696,127	10.43	354,276	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Dashiqiao	China	6	3,695,723	11.78	313,604	Eastern Asia
Prediction	Changyi	China	5	3,663,093	23.83	153,700	Eastern Asia
Prediction	Fangchenggang	China	5	3,662,560	34.73	105,457	Eastern Asia
Prediction	Wuhai	China	5	3,582,892	11.87	301,866	Eastern Asia
Prediction	Yulin, Shaanxi	China	5	3,579,711	17.91	199,912	Eastern Asia
Prediction	Shuangyashan	China	5	3,553,408	16.86	210,741	Eastern Asia
Prediction	Baishan	China	5	3,545,655	12.00	295,359	Eastern Asia
Prediction	Leiyang	China	5	3,545,025	10.79	328581.9122	Eastern Asia
Prediction	Tieling	China	5	3,544,674	16.97	208,928	Eastern Asia
Prediction	Liyang	China	5	3,542,369	11.68	303378.5073	Eastern Asia
Prediction	Fuan	China	5	3,539,688	17.88	197,987	Eastern Asia
Prediction	Ankang	China	5	3,536,948	14.11	250610.4292	Eastern Asia
Prediction	Hami	China	5	3,529,961	12.93	273,004	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Chengde	China	4	3,521,172	15.79	222,951	Eastern Asia
Prediction	Jeju	South Korea	4	3,519,325	21.77	161,641	Eastern Asia
Prediction	Gongyi	China	4	3,513,950	12.62	278,357	Eastern Asia
Prediction	Hebi	China	4	3,513,801	14.37	244,523	Eastern Asia
Prediction	Suihua	China	4	3,510,234	14.97	234,424	Eastern Asia
Prediction	Haining	China	4	3,504,176	11.69	299,663	Eastern Asia
Prediction	Lvliang	China	4	3,500,677	13.91	251602.9946	Eastern Asia
Prediction	Erduosi (Ordoss)	China	4	3,499,057	28.15	124,281	Eastern Asia
Prediction	Quzhou	China	4	3,486,677	10.48	332842.0532	Eastern Asia
Prediction	Zhaodong	China	4	3,484,164	12.65	275,388	Eastern Asia
Prediction	Yongin	South Korea	4	3,481,992	38.30	90,907	Eastern Asia
Prediction	Gaomi	China	4	3,475,529	12.41	279,960	Eastern Asia
Prediction	Gongzhuling	China	4	3,473,943	18.34	189,397	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Tongchuan	China	4	3,467,441	18.65	185,968	Eastern Asia
Prediction	Xinzhou	China	4	3,465,792	12.68	273,303	Eastern Asia
Prediction	Guigang	China	4	3,457,740	10.54	327,905	Eastern Asia
Prediction	Taixing	China	4	3,452,683	9.95	346,847	Eastern Asia
Prediction	Zhaoyuan	China	4	3,447,185	19.85	173,652	Eastern Asia
Prediction	Yushu	China	4	3,438,225	17.01	202,125	Eastern Asia
Prediction	Rongcheng	China	4	3,436,761	15.82	217270.2975	Eastern Asia
Prediction	Baicheng	China	4	3,436,653	11.80	291,321	Eastern Asia
Prediction	Renqiu	China	4	3,436,229	14.92	230251.8504	Eastern Asia
Prediction	Heyuan	China	4	3,424,318	11.44	299,200	Eastern Asia
Prediction	Xianning	China	4	3,411,728	12.15	280,744	Eastern Asia
Prediction	Dengfeng	China	4	3,410,813	24.59	138,681	Eastern Asia
Prediction	Anqiu	China	4	3,408,923	10.34	329552.7151	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Zengcheng	China	4	3,402,147	15.95	213,341	Eastern Asia
Prediction	Dali	China	4	3,389,079	13.45	252,034	Eastern Asia
Prediction	Pinghu	China	4	3,376,643	13.36	252782.7741	Eastern Asia
Prediction	Bijie	China	4	3,375,284	12.32	273,887	Eastern Asia
Prediction	Jingmen	China	3	3,350,503	10.05	333367.3257	Eastern Asia
Prediction	Yichun, Heilongjiang	China	3	3,321,705	27.07	122,714	Eastern Asia
Prediction	Linhai	China	3	3,320,979	10.10	328657.8137	Eastern Asia
Prediction	Chuxiong	China	3	3,310,978	12.59	263,066	Eastern Asia
Prediction	Panzhihua	China	3	3,303,042	11.21	294667.8218	Eastern Asia
Prediction	Chenzhou	China	3	3,298,485	10.71	307,931	Eastern Asia
Prediction	Dafeng	China	3	3,289,947	17.35	189,672	Eastern Asia
Prediction	Bozhou	China	3	3,244,161	10.18	318,746	Eastern Asia
Prediction	Meishan	China	3	3,197,446	9.99	320223.1884	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Laizhou	China	3	3,175,325	10.37	306256.88	Eastern Asia
Prediction	Liuyang	China	3	3,166,243	16.96	186706.2163	Eastern Asia
Prediction	Baiyin	China	3	3,161,698	13.49	234,301	Eastern Asia
Prediction	Liupanshui	China	3	3,157,643	9.09	347509.7307	Eastern Asia
Prediction	Huangshan	China	3	3,151,711	11.49	274,376	Eastern Asia
Prediction	Xingyi, Guizhou	China	3	3,150,429	13.81	228,198	Eastern Asia
Prediction	Yanan	China	3	3,142,151	16.45	191,031	Eastern Asia
Prediction	Linqing	China	3	3,130,006	11.78	265672.0718	Eastern Asia
Prediction	Xiantao	China	3	3,127,381	9.83	318,147	Eastern Asia
Prediction	Pizhou	China	2	3,116,247	11.09	280932.7844	Eastern Asia
Prediction	Donggang	China	2	3,116,106	23.18	134,416	Eastern Asia
Prediction	Xintai	China	2	3,103,725	10.28	301,791	Eastern Asia
Prediction	Laiyang	China	2	3,095,390	10.46	295979.5014	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Qufu	China	2	3,093,964	14.94	207044.0326	Eastern Asia
Prediction	Xinzheng	China	2	3,091,687	10.21	302,871	Eastern Asia
Prediction	Zhongxiang	China	2	3,075,563	15.39	199,874	Eastern Asia
Prediction	Guiping	China	2	3,072,562	16.86	182,263	Eastern Asia
Prediction	Dengzhou	China	2	3,059,328	10.06	304,166	Eastern Asia
Prediction	Chaohu	China	2	3,058,101	10.39	294,461	Eastern Asia
Prediction	Chizhou	China	2	3,047,435	17.58	173,303	Eastern Asia
Prediction	Hejian	China	2	3,047,293	22.29	136,697	Eastern Asia
Prediction	Xuancheng	China	2	3,031,862	13.92	217,845	Eastern Asia
Prediction	Guangyuan	China	2	3,030,618	15.20	199,368	Eastern Asia
Prediction	Yingde	China	2	3,020,934	19.86	152,113	Eastern Asia
Prediction	Xinmi	China	2	3,019,616	10.39	290,573	Eastern Asia
Prediction	Shizuishan	China	2	3,018,243	21.77	138,641	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Laixi	China	2	3,017,744	12.32	244859.3833	Eastern Asia
Prediction	Zhuanghe	China	2	3,010,926	24.95	120,676	Eastern Asia
Prediction	Linzhou	China	2	3,006,081	14.62	205662.6325	Eastern Asia
Prediction	Pingdu	China	2	3,005,985	11.68	257361.3632	Eastern Asia
Prediction	Xinyi	China	2	3,005,227	15.17	198,090	Eastern Asia
Prediction	Zhangye	China	2	3,004,912	14.61	205,703	Eastern Asia
Prediction	Pulandian	China	2	2,999,319	21.18	141641.3758	Eastern Asia
Prediction	Xinghua	China	2	2,995,114	11.25	266,177	Eastern Asia
Prediction	Wuwei	China	2	2,983,141	20.50	145,550	Eastern Asia
Prediction	Yongcheng	China	2	2,981,381	13.73	217,182	Eastern Asia
Prediction	Changge	China	2	2,978,570	16.66	178,814	Eastern Asia
Prediction	Suizhou	China	2	2,975,092	12.14	245,039	Eastern Asia
Prediction	Gaoyou	China	2	2,959,949	13.37	221,468	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Jurong	China	2	2,958,604	13.64	216829.1191	Eastern Asia
Prediction	Xiangcheng	China	2	2,953,036	10.45	282,608	Eastern Asia
Prediction	Botou	China	2	2,949,341	15.78	186,924	Eastern Asia
Prediction	Feicheng	China	2	2,944,278	14.82	198,684	Eastern Asia
Prediction	Bazhong	China	2	2,941,569	12.23	240,552	Eastern Asia
Prediction	Gaocheng	China	2	2,931,779	19.24	152,354	Eastern Asia
Prediction	Lin'an	China	2	2,922,464	13.21	221190.6627	Eastern Asia
Prediction	Shengzhou	China	2	2,909,991	9.80	296,847	Eastern Asia
Prediction	Enshi	China	2	2,906,192	13.77	211,035	Eastern Asia
Prediction	Zaoyang	China	2	2,893,529	15.05	192,267	Eastern Asia
Prediction	Macheng	China	2	2,878,152	18.42	156211.7057	Eastern Asia
Prediction	Hanchuan	China	2	2,867,273	17.00	168,710	Eastern Asia
Prediction	Ji'an, Jiangxi	China	2	2,865,542	11.11	257,855	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Guang'an	China	2	2,857,414	16.91	168,983	Eastern Asia
Prediction	Qianjiang	China	2	2,855,588	17.72	161170.5171	Eastern Asia
Prediction	Jianyang	China	2	2,845,159	14.67	193,948	Eastern Asia
Prediction	Ziyang	China	2	2,839,760	10.31	275,470	Eastern Asia
Prediction	Xingning	China	2	2,825,208	9.17	307,946	Eastern Asia
Prediction	Tianmen	China	2	2,823,996	13.55	208,451	Eastern Asia
Prediction	Liling	China	1	2,797,604	9.05	309180.1233	Eastern Asia
Prediction	Gaozhou	China	1	2,789,860	11.09	251,486	Eastern Asia
Prediction	Fengcheng	China	1	2,773,548	14.52	191,016	Eastern Asia
Prediction	Sanming	China	1	2,752,753	10.90	252505.1659	Eastern Asia
Prediction	Leping	China	1	2,745,776	9.56	287214.4844	Eastern Asia
Prediction	Sihui	China	1	2,728,403	14.50	188,221	Eastern Asia
Prediction	Xinyi	China	1	2,719,031	13.26	205,014	Eastern Asia

Table 6.9: Eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Miluo	China	1	2,707,669	29.06	93188.83303	Eastern Asia
Prediction	Qinzhou	China	1	2,705,955	11.76	230072.4824	Eastern Asia
Prediction	Hezhou	China	1	2,698,351	14.88	181,364	Eastern Asia
Prediction	Gaoan	China	1	2,696,808	16.65	161,944	Eastern Asia
Prediction	Laibin	China	1	2,692,411	15.63	172289.2664	Eastern Asia
Prediction	Kaili	China	1	2,687,168	10.87	247172.2555	Eastern Asia
Prediction	Wuchuan	China	1	2,682,815	12.31	217,954	Eastern Asia
Prediction	Luoding	China	1	2,679,409	10.84	247098.628	Eastern Asia
Prediction	Yuanjiang	China	1	2,673,738	16.58	161,280	Eastern Asia
Prediction	Yongzhou	China	1	2,649,401	10.78	245,686	Eastern Asia
Prediction	Cenxi	China	1	2,647,189	18.10	146,244	Eastern Asia

Table 6.10: Eastern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Warsaw	Poland	20	111,665,000	37.46	2,981,198	Eastern Europe
Calibration/Validation	Budapest	Hungary	20	80,888,000	28.42	2846464	Eastern Europe
Calibration/Validation	Prague	Czech Republic	20	76,017,000	41.54	1,829,843	Eastern Europe
Calibration/Validation	Katowice	Poland	20	52,878,000	20.12	2628207	Eastern Europe
Calibration/Validation	Bratislava	Slovakia	19	32,492,000	45.41	715,456	Eastern Europe
Calibration/Validation	Krakow	Poland	19	26,652,000	19.72	1351831	Eastern Europe
Calibration/Validation	Poznan	Poland	19	25,899,000	27.73	934,002	Eastern Europe
Calibration/Validation	Gdansk	Poland	19	22,350,000	20.47	1,091,850	Eastern Europe
Calibration/Validation	Wroclaw	Poland	18	19,734,000	23.69	832,975	Eastern Europe
Calibration/Validation	Lodz	Poland	18	18,780,000	19.64	956,156	Eastern Europe
Prediction	Moskva (Moscow)	Russian Federation	18	15,175,079	1.64	9,236,379	Eastern Europe
Calibration/Validation	Brno	Czech Republic	17	14,146,000	22.14	639,026	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Sankt Peterburg (Saint Petersburg)	Russian Federation	17	11,509,449	2.97	3,870,961	Eastern Europe
Calibration/Validation	Ostrava	Federation	17	11,198,000	19.84	564,380	Eastern Europe
Calibration/Validation	Lublin	Poland	16	10,059,000	14.99	671,101	Eastern Europe
Prediction	Kyiv (Kiev)	Ukraine	16	9,255,902	4.09	2,262,293	Eastern Europe
Prediction	Bucuresti (Bucharest)	Romania	15	8,869,318	4.43	2,002,216	Eastern Europe
Prediction	Kharkiv	Ukraine	15	8,496,791	6.23	1,364,056	Eastern Europe
Prediction	Nizhniy Novgorod	Russian Federation	14	8,120,225	7.50	1082475.717	Eastern Europe
Prediction	Yekaterinburg	Russian Federation	14	8,025,953	8.89	902,805	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Novosibirsk	Russian Federation	14	7,999,494	7.52	1,063,991	Eastern Europe
Prediction	Odesa	Ukraine	14	7,936,968	7.17	1,106,981	Eastern Europe
Prediction	Chelyabinsk	Russian Federation	14	7,930,649	8.36	948,928	Eastern Europe
Prediction	Rostov-na-Donu (Rostov-on-Don)	Russian Federation	14	7,916,515	7.74	1,023,053	Eastern Europe
Prediction	Donetsk Makeyevka	Ukraine	13	7,770,705	8.24	942510.9559	Eastern Europe
Prediction	Kazan	Russian Federation	13	7,739,294	8.70	889,165	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Omsk	Russian Federation	13	7,583,629	8.70	871,662	Eastern Europe
Prediction	Volgograd Volzhsky	Russian Federation	13	7,575,801	8.73	867,931	Eastern Europe
Prediction	Krasnoyarsk	Russian Federation	13	7,554,002	8.99	839,819	Eastern Europe
Prediction	Samara	Russian Federation	13	7,530,015	8.15	923867.7121	Eastern Europe
Prediction	Voronezh	Russian Federation	12	6,435,112	8.48	758877.6112	Eastern Europe
Prediction	Dnipropetrovsk	Ukraine	12	6,397,141	8.47	754,872	Eastern Europe
Prediction	Saratov	Russian Federation	12	5,796,776	7.98	726728.2651	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Ufa	Russian Federation	11	5,498,360	7.74	710,415	Eastern Europe
Prediction	Krasnodar	Russian Federation	11	5,346,715	8.23	649,570	Eastern Europe
Prediction	Sofia	Bulgaria	11	5,334,841	7.65	697245.7271	Eastern Europe
Prediction	Zaporizhzhya	Ukraine	11	5,267,338	8.47	621740.2474	Eastern Europe
Prediction	Astrakhan	Russian Federation	11	5,214,617	10.08	517,575	Eastern Europe
Prediction	Izhevsk	Russian Federation	11	5,169,587	9.68	534,040	Eastern Europe
Prediction	Krivoi Rog	Ukraine	10	5,121,102	9.50	539,054	Eastern Europe
Prediction	Lvov	Ukraine	10	5,075,798	8.64	587,195	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Irkutsk	Russian Federation	10	5,039,373	9.54	528,163	Eastern Europe
Prediction	Naberezhnye Tchelny	Russian Federation	10	5,027,251	9.92	506927.9622	Eastern Europe
Prediction	Makhachkala	Russian Federation	10	5,018,512	7.58	662,207	Eastern Europe
Prediction	Tyumen	Russian Federation	10	4,940,693	9.93	497509.0894	Eastern Europe
Prediction	Orenburg	Russian Federation	9	4,650,880	9.81	474,188	Eastern Europe
Prediction	Khabarovsk	Russian Federation	9	4,636,317	10.00	463429.5399	Eastern Europe
Prediction	Mariupol	Ukraine	9	4,517,489	10.56	427,625	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Ryazan	Russian Federation	9	4,487,633	10.09	444,852	Eastern Europe
Prediction	Barnaul	Russian Federation	9	4,458,448	10.44	426,983	Eastern Europe
Prediction	Tula	Russian Federation	8	4,449,282	10.02	443,857	Eastern Europe
Prediction	Ulyanovsk	Russian Federation	8	4,447,685	10.77	412,910	Eastern Europe
Prediction	Kemerovo	Russian Federation	8	4,439,941	10.53	421836.171	Eastern Europe
Prediction	Vladivostok	Russian Federation	8	4,439,454	10.42	426,140	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Stavropol	Russian Federation	8	4,380,015	10.37	422,354	Eastern Europe
Prediction	Penza	Russian Federation	8	4,372,357	10.45	418,517	Eastern Europe
Prediction	Lipetsk	Russian Federation	8	4,334,640	10.87	398656.1856	Eastern Europe
Prediction	Yaroslavl	Russian Federation	8	4,312,978	10.94	394338.2713	Eastern Europe
Prediction	Kaliningrad, Kaliningrad Oblast	Russian Federation	8	4,300,815	11.36	378,532	Eastern Europe
Prediction	Bryansk	Russian Federation	8	4,270,264	10.92	391,148	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Ivanovo	Russian Federation	8	4,266,141	11.09	384,704	Eastern Europe
Prediction	Tomsk	Russian Federation	8	4,257,270	10.51	405226.4334	Eastern Europe
Prediction	Kursk	Russian Federation	7	4,235,994	11.01	384,900	Eastern Europe
Prediction	Vinnitsa	Ukraine	7	4,225,016	11.25	375,534	Eastern Europe
Prediction	Nikolaev	Ukraine	7	4,208,399	9.22	456278.5207	Eastern Europe
Prediction	Cheboksary	Russian Federation	7	3,941,023	11.30	348,728	Eastern Europe
Prediction	Magnitogorsk	Russian Federation	6	3,883,338	11.40	340789.6672	Eastern Europe
Prediction	Lugansk	Ukraine	6	3,879,798	10.23	379,328	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Belgorod	Russian Federation	6	3,847,195	11.98	321,046	Eastern Europe
Prediction	Tver	Russian Federation	6	3,840,829	11.39	337347.4771	Eastern Europe
Prediction	Plovdiv	Bulgaria	6	3,747,959	11.71	320,003	Eastern Europe
Prediction	Timisoara	Romania	6	3,732,717	11.88	314,087	Eastern Europe
Prediction	Perm	Russian Federation	6	3,729,645	33.04	112,895	Eastern Europe
Prediction	Ulan-Ude	Russian Federation	6	3,722,349	12.11	307392.9597	Eastern Europe
Prediction	Smolensk	Russian Federation	6	3,715,111	11.93	311,407	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Chi?in?u	Russian Federation	6	3,687,912	11.67	315,914	Eastern Europe
Prediction	Bydgoszcz	Poland	5	3,670,330	13.53	271,213	Eastern Europe
Prediction	Kirov	Russian Federation	5	3,643,970	12.99	280,534	Eastern Europe
Prediction	Kurgan	Russian Federation	5	3,627,302	15.87	228,494	Eastern Europe
Prediction	Vladikavkaz	Russian Federation	5	3,619,178	11.77	307,385	Eastern Europe
Prediction	Arkhangelsk	Russian Federation	5	3,603,405	21.58	166972.0946	Eastern Europe
Prediction	Novokuznetsk	Russian Federation	5	3,598,502	14.21	253,169	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Sochi	Russian Federation	5	3,594,949	38.57	93,202	Eastern Europe
Prediction	Vladimir	Russian Federation	5	3,594,376	15.14	237,476	Eastern Europe
Prediction	Orel	Russian Federation	5	3,582,654	12.85	278,825	Eastern Europe
Prediction	Szczecin	Poland	5	3,579,684	13.41	266,863	Eastern Europe
Prediction	Nizhny Tagil	Russian Federation	5	3,574,958	14.76	242,271	Eastern Europe
Prediction	Vologda	Russian Federation	5	3,573,417	13.54	263898.1645	Eastern Europe
Prediction	Chita	Russian Federation	5	3,560,105	18.53	192147.0334	Eastern Europe

Table 6.10: Eastern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Cluj-Napoca	Romania	5	3,559,437	12.40	287,153	Eastern Europe
Prediction	Kaluga	Russian Federation	5	3,555,952	18.46	192593.76	Eastern Europe
Prediction	Yakutsk	Russian Federation	5	3,544,768	23.41	151,431	Eastern Europe
Prediction	Cherepovets	Russian Federation	5	3,523,332	12.71	277,180	Eastern Europe
Prediction	Varna	Bulgaria	4	3,515,393	16.51	212,982	Eastern Europe
Prediction	Surgut	Russian Federation	4	3,477,676	53.38	65,148	Eastern Europe
Prediction	Simferopol	Ukraine	4	3,438,381	10.17	338,065	Eastern Europe
Prediction	Sevastopol	Ukraine	2	3,035,681	19.24	157,820	Eastern Europe

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Mexico City	Mexico	20	309,266,001	16.06	19,255,925	Latin America and the Caribbean
Calibration/Validation	Santiago	Chile	20	105,871,000	16.56	6,393,831	Latin America and the Caribbean
Calibration/Validation	Monterrey	Mexico	20	99,186,000	23.89	4,152,115	Latin America and the Caribbean
Calibration/Validation	Guadalajara	Mexico	20	66,433,000	15.10	4,398,145	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Toluca	Mexico	19	34,666,000	17.90	1,936,126	Latin America and the Caribbean
Calibration/Validation	Puebla	Mexico	19	31,500,000	14.75	2,135,375	Latin America and the Caribbean
Calibration/Validation	Centro	Mexico	19	30,756,000	35.14	875,172	Latin America and the Caribbean
Calibration/Validation	Leon	Mexico	19	21,744,000	13.51	1,609,504	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Queretaro	Mexico	18	21,175,000	18.91	1119642	Latin America and the Caribbean
Calibration/Validation	Tijuana	Mexico	18	19,272,000	12.36	1,559,683	Latin America and the Caribbean
Calibration/Validation	San Luis Potosi	Mexico	18	18,914,000	15.95	1,185,716	Latin America and the Caribbean
Calibration/Validation	Chihuahua	Mexico	18	18,184,000	21.90	830,231	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Torreon	Mexico	18	17,236,000	13.81	1247765	Latin America and the Caribbean
Calibration/Validation	Hermosillo	Mexico	18	17,203,000	21.93	784,342	Latin America and the Caribbean
Calibration/Validation	Merida	Mexico	18	16,809,000	12.77	1,316,633	Latin America and the Caribbean
Prediction	Rio de Janeiro	Brazil	18	14,719,459	1.80	8182469.313	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Saltillo	Mexico	18	14,574,000	20.10	725,123	Latin America and the Caribbean
Calibration/Validation	Juarez	Mexico	17	14,254,000	10.70	1,332,131	Latin America and the Caribbean
Prediction	Buenos Aires	Argentina	17	14,127,174	1.11	12,753,059	Latin America and the Caribbean
Calibration/Validation	Aguascalientes	Mexico	17	13,552,000	14.25	951197	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Benito Juarez	Mexico	17	12,329,000	18.65	661176	Latin America and the Caribbean
Calibration/Validation	Mexicali	Mexico	17	11,913,000	12.72	936,826	Latin America and the Caribbean
Calibration/Validation	Veracruz	Mexico	17	11,713,000	14.97	782,301	Latin America and the Caribbean
Calibration/Validation	Acapulco de Juarez	Mexico	17	11,546,000	14.62	789971	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Cuernavaca	Mexico	17	11,405,000	13.02	876,083	Latin America and the Caribbean
Calibration/Validation	Culiacan	Mexico	17	11,060,000	12.88	858,638	Latin America and the Caribbean
Calibration/Validation	Valparaiso	Chile	17	10,707,000	11.22	954,333	Latin America and the Caribbean
Prediction	Santa Cruz	Bolivia (Plurinational State of)	16	10,479,464	8.68	1206778.796	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Tampico	Mexico	16	10,049,000	13.19	762,129	Latin America and the Caribbean
Calibration/Validation	Pachuca de Soto	Mexico	16	9,574,000	17.52	546513	Latin America and the Caribbean
Prediction	Managua	Nicaragua	15	8,562,941	9.98	858,257	Latin America and the Caribbean
Prediction	Arequipa	Peru	15	8,548,759	10.20	838282.7987	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Guayaquil	Ecuador	15	8,471,349	3.83	2,212,822	Latin America and the Caribbean
Prediction	Salvador	Brazil	15	8,399,776	2.76	3047527.569	Latin America and the Caribbean
Prediction	Recife	Brazil	15	8,356,043	2.88	2,899,625	Latin America and the Caribbean
Prediction	Fortaleza	Brazil	15	8,271,033	2.61	3,166,100	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Morelia	Mexico	15	8,250,000	9.75	846,052	Latin America and the Caribbean
Prediction	Aracaju	Brazil	14	8,200,852	10.12	810075.3789	Latin America and the Caribbean
Prediction	Santo Domingo	Dominican Republic	14	8,077,563	2.50	3,235,832	Latin America and the Caribbean
Calibration/Validation	Reynosa	Mexico	14	8,075,000	11.10	727150	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Ciudad Juarez El Paso	Mexico	14	8,066,228	3.99	2,022,849	Latin America and the Caribbean
Prediction	Mendoza	Argentina	14	7,997,079	10.13	789,176	Latin America and the Caribbean
Prediction	Maracaibo	Venezuela (Bolivarian Republic of)	14	7,967,061	4.07	1956875.117	Latin America and the Caribbean
Prediction	Port-au-Prince	Haiti	14	7,966,927	2.57	3,102,797	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Cali	Colombia	14	7,921,085	3.57	2219548.107	Latin America and the Caribbean
Prediction	Curitiba	Brazil	14	7,898,601	3.17	2,490,460	Latin America and the Caribbean
Prediction	Caracas	Venezuela (Bolivarian Republic of)	14	7,896,705	3.53	2,234,451	Latin America and the Caribbean
Prediction	Manaus	Brazil	14	7,892,151	3.83	2061319.291	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Belo Horizonte Vale do Aco	Brazil	14	7,883,754	2.11	3,731,073	Latin America and the Caribbean
Prediction	Ciudad de Guatemala (Guatemala City)	Guatemala	14	7,877,507	3.47	2273004.259	Latin America and the Caribbean
Prediction	Baixada Santista	Brazil	14	7,820,420	7.97	981594.6623	Latin America and the Caribbean
Prediction	Montevideo	Uruguay	13	7,770,467	5.89	1,318,895	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Quito	Ecuador	13	7,746,939	3.33	2,328,658	Latin America and the Caribbean
Prediction	Valencia	Venezuela (Bolivarian Republic of)	13	7,729,314	5.80	1,332,561	Latin America and the Caribbean
Prediction	Lima	Peru	13	7,722,506	0.86	8,958,034	Latin America and the Caribbean
Prediction	La Paz	Bolivia (Plurinational State of)	13	7,706,414	5.98	1,288,121	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Teresina	Brazil	13	7,626,115	8.58	888,791	Latin America and the Caribbean
Prediction	Natal	Brazil	13	7,552,389	6.41	1,178,234	Latin America and the Caribbean
Prediction	Campinas	Brazil	13	7,550,402	6.44	1,172,950	Latin America and the Caribbean
Prediction	San Juan	Puerto Rico	13	7,485,368	7.30	1,025,795	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Cochabamba	Bolivia (Plurinational State of)	13	7,252,774	8.04	902,539	Latin America and the Caribbean
Calibration/Validation	Oaxaca de Juarez	Mexico	13	7,243,000	9.93	729315	Latin America and the Caribbean
Prediction	La Habana (Havana)	Cuba	13	7,229,063	6.41	1,127,885	Latin America and the Caribbean
Prediction	San Salvador	El Salvador	13	7,143,447	6.75	1,058,270	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Trujillo	Peru	13	7,127,491	7.94	897,871	Latin America and the Caribbean
Prediction	Campo Grande	Brazil	12	7,061,795	8.38	842819.3213	Latin America and the Caribbean
Prediction	Rosario	Argentina	12	7,012,218	8.85	792,436	Latin America and the Caribbean
Prediction	Cartagena	Colombia	12	6,854,455	8.09	847161.8594	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Londrina	Brazil	12	6,806,151	12.49	544,848	Latin America and the Caribbean
Prediction	Bucaramanga	Colombia	12	6,435,288	7.84	820,531	Latin America and the Caribbean
Calibration/Validation	Durango	Mexico	12	6,428,000	11.04	582,267	Latin America and the Caribbean
Prediction	Resistencia Corrientes	Argentina	12	6,138,839	9.82	624979.7502	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Tuxtla Gutierrez	Mexico	12	6,107,000	8.27	738,261	Latin America and the Caribbean
Prediction	Sorocaba	Brazil	12	6,098,942	8.58	710497.9081	Latin America and the Caribbean
Prediction	Salta	Argentina	11	5,585,237	11.99	465,934	Latin America and the Caribbean
Prediction	Juazeiro Do Norte	Brazil	11	5,573,088	15.53	358830.0176	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Petrolina	Brazil	11	5,495,424	13.57	405,081	Latin America and the Caribbean
Prediction	La Plata	Argentina	11	5,423,965	10.32	525,812	Latin America and the Caribbean
Prediction	Santiago	Dominican Republic	11	5,402,046	8.24	655892.6956	Latin America and the Caribbean
Prediction	San Juan	Argentina	11	5,278,867	12.49	422,775	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Joinville	Brazil	11	5,240,923	9.61	545408.9477	Latin America and the Caribbean
Prediction	Ciudad del Este	Paraguay	11	5,157,617	7.80	660,957	Latin America and the Caribbean
Prediction	Montes Claros	Brazil	10	5,149,474	14.30	360,093	Latin America and the Caribbean
Prediction	Juiz De Fora	Brazil	10	5,100,480	10.08	505,973	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Nuevo Laredo	Mexico	10	5,035,881	7.99	630626.2747	Latin America and the Caribbean
Prediction	Barquisimeto	Venezuela (Bolivarian Republic of)	10	5,000,479	8.88	563408.0499	Latin America and the Caribbean
Prediction	Kingston	Jamaica	10	4,989,367	8.06	618664.5422	Latin America and the Caribbean
Prediction	Feira De Santana	Brazil	10	4,931,977	9.12	540,562	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Pereira	Colombia	10	4,927,358	8.82	558,392	Latin America and the Caribbean
Prediction	Chiclayo	Peru	10	4,915,549	8.30	592,058	Latin America and the Caribbean
Prediction	Tegucigalpa	Honduras	10	4,818,816	8.34	577993.9128	Latin America and the Caribbean
Calibration/Validation	Celaya	Mexico	10	4,807,000	7.98	602045	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Villahermosa	Mexico	9	4,730,335	9.11	519,106	Latin America and the Caribbean
Prediction	Santiago Del Estero	Argentina	9	4,710,543	14.53	324,235	Latin America and the Caribbean
Prediction	Temuco	Chile	9	4,698,521	15.78	297,756	Latin America and the Caribbean
Prediction	Monteria	Colombia	9	4,687,633	17.19	272765.7441	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Mar Del Plata	Argentina	9	4,665,513	9.37	498,178	Latin America and the Caribbean
Prediction	Posadas	Argentina	9	4,597,985	12.11	379,739	Latin America and the Caribbean
Prediction	Barcelona-Puerto La Cruz	Venezuela (Bolivarian Republic of)	9	4,476,676	9.56	468,367	Latin America and the Caribbean
Prediction	Ciudad Guayana	Venezuela (Bolivarian Republic of)	8	4,456,464	9.65	461,600	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Cabimas Lagunillas	Venezuela (Bolivarian Republic of)	8	4,382,261	10.00	438079.7432	Latin America and the Caribbean
Prediction	Caxias Do Sul	Brazil	8	4,355,311	10.46	416490.2104	Latin America and the Caribbean
Calibration/Validation	Xalapa	Mexico	8	4,313,000	5.91	729,661	Latin America and the Caribbean
Prediction	Bauru	Brazil	8	4,277,897	11.99	356,744	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Cuenca	Ecuador	8	4,257,734	9.56	445,293	Latin America and the Caribbean
Prediction	Volta Redonda	Brazil	7	4,195,546	10.84	386,970	Latin America and the Caribbean
Prediction	Cusco	Peru	7	4,175,332	10.45	399,723	Latin America and the Caribbean
Prediction	Santa Marta	Colombia	7	4,173,004	11.32	368774.4095	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	La Serena -Coquimbo	Chile	7	4,158,386	11.55	360,025	Latin America and the Caribbean
Prediction	Campina Grande	Brazil	7	4,136,273	10.88	380,087	Latin America and the Caribbean
Prediction	Huancayo	Peru	7	4,123,965	9.10	452,936	Latin America and the Caribbean
Prediction	Manizales	Colombia	7	4,117,445	12.02	342,612	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Piura	Peru	7	4,096,112	10.31	397,313	Latin America and the Caribbean
Prediction	Piracicaba	Brazil	7	4,078,466	11.33	360112.7824	Latin America and the Caribbean
Prediction	Pelotas	Brazil	7	4,072,710	14.88	273683.3748	Latin America and the Caribbean
Prediction	Tepic	Mexico	7	3,982,720	9.85	404,461	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	San Pedro Sula	Honduras	6	3,904,218	8.81	443128.004	Latin America and the Caribbean
Prediction	Boa Vista	Brazil	6	3,864,876	11.57	334112.144	Latin America and the Caribbean
Prediction	Chimbote	Peru	6	3,842,055	12.72	302,153	Latin America and the Caribbean
Prediction	Sucre	Bolivia (Plurinational State of)	6	3,810,426	29.49	129,202	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	San Salvador de Jujuy	Argentina	6	3,763,816	13.88	271,206	Latin America and the Caribbean
Prediction	Uberaba	Brazil	6	3,675,031	11.75	312,764	Latin America and the Caribbean
Prediction	Rio Branco	Brazil	6	3,672,214	10.64	345,266	Latin America and the Caribbean
Prediction	Campos dos Goytacazes	Brazil	5	3,656,087	11.08	329,944	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Franca	Brazil	5	3,648,014	11.06	329,800	Latin America and the Caribbean
Prediction	Iquitos	Peru	4	3,522,063	54.55	64,567	Latin America and the Caribbean
Prediction	Ciudad Victoria	Mexico	4	3,504,380	10.13	345,912	Latin America and the Caribbean
Prediction	Caruaru	Brazil	4	3,501,428	11.07	316,296	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Ponta Grossa	Brazil	4	3,479,454	11.10	313,352	Latin America and the Caribbean
Prediction	Armenia	Colombia	4	3,465,946	9.91	349788.7485	Latin America and the Caribbean
Prediction	Coatzacoalcos	Mexico	4	3,365,452	10.57	318,518	Latin America and the Caribbean
Prediction	Guarenas-Guatire	Venezuela (Bolivarian Republic of)	3	3,342,633	10.95	305,167	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Zacatecas	Mexico	3	3,334,102	10.78	309,315	Latin America and the Caribbean
Prediction	Antofagasta	Chile	3	3,325,285	22.56	147,420	Latin America and the Caribbean
Prediction	Monclova	Mexico	3	3,323,399	10.61	313,374	Latin America and the Caribbean
Prediction	Villavicencio	Colombia	3	3,282,285	11.05	297,137	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Cumana	Venezuela (Bolivarian Republic of)	3	3,273,241	12.41	263,671	Latin America and the Caribbean
Prediction	Colima	Mexico	3	3,267,439	10.72	304719.0494	Latin America and the Caribbean
Prediction	Santo Domingo	Ecuador	3	3,265,954	13.48	242225.5842	Latin America and the Caribbean
Prediction	Maturin	Venezuela (Bolivarian Republic of)	3	3,259,241	16.94	192400.1203	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Ciudad Bolivar	Venezuela (Bolivarian Republic of)	3	3,259,140	13.70	237,907	Latin America and the Caribbean
Prediction	Santa Fe	Argentina	3	3,245,566	11.10	292443.2949	Latin America and the Caribbean
Prediction	Valledupar	Colombia	3	3,241,880	11.69	277,254	Latin America and the Caribbean
Prediction	Acarigua-Aruare	Venezuela (Bolivarian Republic of)	3	3,227,310	16.27	198,341	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Barinas	Venezuela (Bolivarian Republic of)	3	3,217,584	18.52	173,770	Latin America and the Caribbean
Prediction	Punto Fijo	Venezuela (Bolivarian Republic of)	3	3,198,473	14.34	223,011	Latin America and the Caribbean
Prediction	Iquique	Chile	3	3,190,832	15.29	208,634	Latin America and the Caribbean
Prediction	Bahia Blanca	Argentina	3	3,179,698	13.56	234,417	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Blumenau	Brazil	3	3,135,754	10.72	292453.8441	Latin America and the Caribbean
Prediction	Puerto Vallarta	Mexico	3	3,133,897	13.00	241,043	Latin America and the Caribbean
Prediction	Poza Rica de Hidalgo	Mexico	2	3,101,664	10.91	284,375	Latin America and the Caribbean
Prediction	Cuautla Morelos	Mexico	2	3,005,904	12.73	236,179	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Pasto	Colombia	2	2,887,299	9.20	313,754	Latin America and the Caribbean
Prediction	Aguadilla-Isabela-San Sebastian	Puerto Rico	1	2,722,133	25.53	106,615	Latin America and the Caribbean
Prediction	Santiago de Cuba	Cuba	1	2,720,380	12.58	216,304	Latin America and the Caribbean
Prediction	Merida	Venezuela (Bolivarian Republic of)	1	2,705,730	19.44	139203.7636	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Neiva	Colombia	1	2,702,848	9.93	272295.6009	Latin America and the Caribbean
Prediction	Holguin	Cuba	1	2,699,361	13.23	203,990	Latin America and the Caribbean
Calibration/Validation	Irapuato	Mexico	1	2,696,000	5.09	529,440	Latin America and the Caribbean
Prediction	Choloma	Honduras	1	2,688,445	20.28	132,595	Latin America and the Caribbean

Table 6.11: Latin America and the Caribbean predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Orizaba	Mexico	1	2,687,023	11.26	238,566	Latin America and the Caribbean
Prediction	Matamoros	Mexico	1	2,675,336	47.89	55868.95955	Latin America and the Caribbean
Prediction	Camaguey	Cuba	1	2,664,253	15.46	172,302	Latin America and the Caribbean
Prediction	Buenaventura	Colombia	1	2,607,809	10.90	239,250	Latin America and the Caribbean

Table 6.12: Melanesia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Port Moresby	Papua New Guinea	1	2,705,409	14.37	188,256	Melanesia

Table 6.13: Northern Africa predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Al-Qahirah (Cairo)	Egypt	17	13,937,725	0.92	15123129.51	Northern Africa
Prediction	Al-Iskandariyah (Alexandria) Kafr-ad-Dawwar	Egypt	17	12,992,535	2.56	5,080,411	Northern Africa
Prediction	Dar-el-Beida (Casablanca)	Morocco	16	10,147,450	2.96	3,423,511	Northern Africa
Prediction	Tunis	Tunisia	16	9,002,080	4.43	2,033,427	Northern Africa
Prediction	Rabat	Morocco	15	8,493,890	5.36	1585142.792	Northern Africa
Prediction	Tarabulus (Tripoli)	Libya	15	8,243,270	6.51	1,265,403	Northern Africa
Prediction	Al-Khartum (Khartoum)	Sudan	14	8,221,346	3.04	2,702,826	Northern Africa

Table 6.13: Northern Africa predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Wahran (Oran)	Algeria	14	8,016,532	6.88	1,164,816	Northern Africa
Prediction	Tanger	Morocco	14	7,810,179	8.01	974,449	Northern Africa
Prediction	Agadir	Morocco	14	7,784,066	9.02	862797.6921	Northern Africa
Prediction	Marrakech	Morocco	13	7,696,054	7.94	968,741	Northern Africa
Prediction	Asyut	Egypt	12	6,490,676	9.91	654,964	Northern Africa
Prediction	Al-Mansurah	Egypt	12	5,988,398	8.12	737,362	Northern Africa
Prediction	Al-Mahallah al-Kubra	Egypt	11	5,414,314	7.60	712,220	Northern Africa
Prediction	Qacentina	Algeria	11	5,410,714	8.05	672,347	Northern Africa
Prediction	Az-Zaqazig	Egypt	11	5,333,260	7.93	672,918	Northern Africa
Prediction	Tanta	Egypt	11	5,304,094	7.44	713,013	Northern Africa
Prediction	Bur Sa'id	Egypt	11	5,282,992	8.55	618,171	Northern Africa

Table 6.13: Northern Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Safaqis	Tunisia	10	4,962,236	9.38	529,046	Northern Africa
Prediction	Oujda	Morocco	10	4,936,322	9.59	514,689	Northern Africa
Prediction	Al-Fayyum	Egypt	9	4,546,335	9.27	490525.1311	Northern Africa
Prediction	El Djelfa	Algeria	9	4,503,222	13.03	345714.0151	Northern Africa
Prediction	Al-Ismailiyah	Egypt	9	4,463,297	9.80	455,586	Northern Africa
Prediction	Annaba	Algeria	8	4,446,491	11.02	403483.0662	Northern Africa
Prediction	As-Suways	Egypt	8	4,428,157	10.15	436060.5547	Northern Africa
Prediction	Blida	Algeria	8	4,390,452	9.71	452,014	Northern Africa
Prediction	Batna	Algeria	7	4,220,859	13.46	313,518	Northern Africa
Prediction	Aswan	Egypt	7	3,970,239	16.18	245386.1801	Northern Africa
Prediction	Misratah	Libya	6	3,726,684	16.99	219,384	Northern Africa
Prediction	Banghazi	Libya	6	3,679,409	12.25	300,370	Northern Africa
Prediction	Kassala	Sudan	5	3,666,366	9.89	370,853	Northern Africa

Table 6.13: Northern Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Safi	Morocco	4	3,490,122	12.53	278,649	Northern Africa
Prediction	Port Sudan (Bur Sudan)	Sudan	3	3,271,829	9.69	337578.2182	Northern Africa
Prediction	Wad Medani	Sudan	2	2,817,903	9.49	296,943	Northern Africa
Prediction	Nyala	Sudan	1	2,718,269	17.14	158,574	Northern Africa
Prediction	Al Obeid (Al Ubayyid)	Sudan	1	2,670,850	15.96	167,320	Northern Africa
Prediction	Al Gadarif	Sudan	1	2,642,269	11.16	236760.0919	Northern Africa

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Washington-Arlington-Alexandria, DC-VA-MD-WV	United States	20	380,433,001	67.50	5636232	Northern America
Calibration/Validation	Dallas-Fort Worth-Arlington , TX	United States	20	346,197,001	53.87	6426214	Northern America
Calibration/Validation	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	United States	20	303,815,999	50.93	5965343	Northern America
Calibration/Validation	Toronto	Canada	20	228,203,999	35.55	6,418,623	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Seattle-Tacoma-Bellevue, WA	United States	20	210,915,000	61.32	3439809	Northern America
Calibration/Validation	Minneapolis-St. Paul-Bloomington , MN-WI	United States	20	178,428,000	53.28	3,348,859	Northern America
Calibration/Validation	San Jose-Sunnyvale-Santa Clara , CA	United States	20	154,992,999	84.38	1,836,911	Northern America
Calibration/Validation	Montreal	Canada	20	129,443,999	31.04	4169715	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Portland-Vancouver-Hillsboro, OR-WA	United States	20	128,970,000	57.94	2,226,009	Northern America
Calibration/Validation	St. Louis , MO-IL	United States	20	113,007,000	40.54	2,787,701	Northern America
Calibration/Validation	Tampa-St. Petersburg -Clearwater, FL	United States	20	99,569,000	35.77	2783243	Northern America
Calibration/Validation	Pittsburgh , PA	United States	20	99,272,000	42.13	2,356,285	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Riverside-San Bernardino-Ontario, CA	United States	20	95,678,000	22.65	4,224,851	Northern America
Calibration/Validation	Kansas City, MO-KS	United States	20	94,964,000	47.26	2,009,342	Northern America
Calibration/Validation	Orlando-Kissimmee-Sanford, FL	United States	20	88,383,000	41.41	2134411	Northern America
Calibration/Validation	Columbus, OH	United States	20	82,210,000	43.22	1901974	Northern America
Calibration/Validation	Vancouver	Canada	20	81,613,000	35.29	2312497	Northern America
Calibration/Validation	Milwaukee-Waukesha-West Allis, WI	United States	20	76,126,000	48.93	1,555,908	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Nashville-Davidson –Murfreesboro–Franklin, TN	United States	20	76,106,000	45.55	1,670,890	Northern America
Calibration/Validation	Bridgeport-Stamford-Norwalk, CT	United States	20	74,432,000	81.18	916,829	Northern America
Calibration/Validation	San Antonio-New Braunfels , TX	United States	20	73,339,000	34.23	2,142,508	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Virginia Beach -Norfolk- Newport News, VA-NC	United States	20	70,985,000	42.33	1676822	Northern America
Calibration/Validation	Calgary	Canada	20	70,967,000	55.80	1,271,737	Northern America
Calibration/Validation	Hartford- West Hartford -East Hartford , CT	United States	20	69,488,000	57.32	1,212,381	Northern America
Calibration/Validation	Edmonton	Canada	20	66,210,000	56.60	1,169,701	Northern America
Calibration/Validation	Salt Lake City, UT	United States	20	57,778,000	53.11	1,087,873	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Memphis , TN-MS-AR	United States	20	55,985,000	42.26	1324829	Northern America
Calibration/Validation	Richmond , VA	United States	20	55,970,000	46.33	1,208,101	Northern America
Calibration/Validation	Oklahoma City, OK	United States	20	52,607,000	41.99	1252987	Northern America
Calibration/Validation	Jacksonville , FL	United States	20	52,029,000	38.67	1,345,596	Northern America
Calibration/Validation	Louisville/ Jefferson County, KY-IN	United States	20	51,077,000	41.33	1235708	Northern America
Calibration/Validation	Ottawa-Gatineau	Canada	20	47,761,000	34.45	1,386,544	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Birmingham -Hoover, AL	United States	20	47,103,000	41.76	1,128,047	Northern America
Calibration/Validation	Honolulu, HI	United States	20	46,073,000	48.33	953,207	Northern America
Calibration/Validation	Omaha- Council Bluffs , NE-IA	United States	20	42,828,000	49.49	865350	Northern America
Calibration/Validation	Tulsa, OK	United States	20	40,541,000	43.24	937478	Northern America
Calibration/Validation	Rochester , NY	United States	20	40,264,000	37.29	1,079,671	Northern America
Calibration/Validation	Baton Rouge , LA	United States	19	36,646,000	45.67	802484	Northern America
Calibration/Validation	Durham-Chapel Hill, NC	United States	19	36,631,000	72.63	504,357	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Albany-Schenectady-Troy, NY	United States	19	35,156,000	40.38	870,716	Northern America
Calibration/Validation	Grand Rapids-Wyoming, MI	United States	19	35,049,000	35.44	988,938	Northern America
Calibration/Validation	Albuquerque , NM	United States	19	34,765,000	39.19	887,077	Northern America
Calibration/Validation	New Haven-Milford, CT	United States	19	34,482,000	39.98	862477	Northern America
Calibration/Validation	Des Moines-West Des Moines, IA	United States	19	34,347,000	60.30	569,633	Northern America
Calibration/Validation	Madison, WI	United States	19	32,823,000	54.21	605,435	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Oxnard-Thousand Oaks-Ventura, CA	United States	19	32,455,000	39.42	823,318	Northern America
Calibration/Validation	Greensboro-High Point, NC	United States	19	30,401,000	42.00	723801	Northern America
Calibration/Validation	Knoxville, TN	United States	19	30,075,000	35.91	837571	Northern America
Calibration/Validation	Little Rock-North Little Rock-Conway, AR	United States	19	28,905,000	41.31	699,757	Northern America
Calibration/Validation	Dayton, OH	United States	19	28,828,000	36.07	799,232	Northern America
Calibration/Validation	Tucson, AZ	United States	19	27,922,000	28.48	980,263	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Columbia, SC	United States	19	27,867,000	36.30	767,598	Northern America
Calibration/Validation	Winnipeg	Canada	19	27,287,000	33.96	803,601	Northern America
Calibration/Validation	Fresno, CA	United States	19	26,965,000	28.98	930450	Northern America
Calibration/Validation	Allentown-Bethlehem-Easton, PA-NJ	United States	19	26,206,000	31.91	821,173	Northern America
Calibration/Validation	Quebec	Canada	19	25,652,000	31.26	820,529	Northern America
Calibration/Validation	Harrisburg-Carlisle, PA	United States	19	24,696,000	44.94	549,475	Northern America
Calibration/Validation	Anchorage , AK	United States	19	24,412,000	64.10	380821	Northern America
Calibration/Validation	Syracuse , NY	United States	19	24,239,000	36.58	662577	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Wichita, KS	United States	19	24,202,000	38.36	630,919	Northern America
Calibration/Validation	Akron, OH	United States	19	24,169,000	34.37	703,200	Northern America
Calibration/Validation	El Paso, TX	United States	19	24,002,000	29.85	804,123	Northern America
Calibration/Validation	Lafayette , LA	United States	19	23,665,000	50.70	466,750	Northern America
Calibration/Validation	Colorado Springs, CO	United States	19	23,515,000	36.42	645,613	Northern America
Calibration/Validation	Winston-Salem, NC	United States	19	23,467,000	36.63	640,595	Northern America
Calibration/Validation	Jackson, MS	United States	19	22,463,000	39.61	567122	Northern America
Calibration/Validation	Hamilton	Canada	19	22,301,000	37.19	599,712	Northern America
Calibration/Validation	Toledo, OH	United States	19	22,026,000	36.11	610,001	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Lexington-Fayette, KY	United States	18	20,765,000	43.98	472,099	Northern America
Calibration/Validation	Shreveport-Bossier City , LA	United States	18	20,030,000	45.54	439,811	Northern America
Calibration/Validation	Manchester-Nashua, NH	United States	18	19,474,000	48.60	400721	Northern America
Calibration/Validation	Huntsville, AL	United States	18	19,319,000	46.26	417,593	Northern America
Calibration/Validation	Chattanooga , TN-GA	United States	18	18,574,000	35.17	528143	Northern America
Calibration/Validation	Springfield , MA	United States	18	18,387,000	29.58	621,570	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Ogden-Clearfield, UT	United States	18	17,964,000	30.08	597,159	Northern America
Calibration/Validation	Lancaster, PA	United States	18	17,781,000	34.23	519,445	Northern America
Calibration/Validation	Cape Coral-Fort Myers, FL	United States	18	17,572,000	28.40	618,754	Northern America
Calibration/Validation	Fayetteville-Springdale-Rogers, AR-MO	United States	18	17,433,000	37.64	463,204	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Palm Bay -Melbourne- Titusville, FL	United States	18	17,235,000	31.72	543,376	Northern America
Calibration/Validation	Boulder, CO	United States	18	17,185,000	58.34	294,567	Northern America
Calibration/Validation	Augusta-Richmond County, GA-SC	United States	18	16,909,000	29.93	564,873	Northern America
Calibration/Validation	Lansing-East Lansing, MI	United States	18	16,786,000	36.17	464036	Northern America
Calibration/Validation	Beaumont-Port Arthur , TX	United States	18	16,472,000	40.85	403,190	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Ann Arbor , MI	United States	18	16,411,000	47.60	344791	Northern America
Calibration/Validation	Fort Wayne , IN	United States	18	16,169,000	38.84	416257	Northern America
Calibration/Validation	Corpus Christi, TX	United States	18	16,115,000	37.64	428,185	Northern America
Calibration/Validation	Peoria, IL	United States	18	15,445,000	40.73	379,186	Northern America
Calibration/Validation	Salinas, CA	United States	18	15,274,000	36.80	415,057	Northern America
Calibration/Validation	Davenport-Moline-Rock Island, IA-IL	United States	18	15,252,000	40.17	379,690	Northern America
Calibration/Validation	Fayetteville , NC	United States	18	15,233,000	41.58	366,383	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Mobile, AL	United States	18	14,534,000	35.19	412,992	Northern America
Calibration/Validation	Lakeland-Winter Haven, FL	United States	18	14,392,000	23.90	602,095	Northern America
Calibration/Validation	Youngstown-Warren-Boardman, OH-PA	United States	18	14,332,000	25.33	565,773	Northern America
Calibration/Validation	Sioux Falls, SD	United States	17	13,713,000	60.08	228,261	Northern America
Calibration/Validation	Provo-Orem, UT	United States	17	13,612,000	25.84	526,810	Northern America
Calibration/Validation	Modesto, CA	United States	17	13,480,000	26.20	514,453	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	York-Hanover, PA	United States	17	13,281,000	30.53	434,972	Northern America
Calibration/Validation	Springfield, MO	United States	17	13,179,000	30.18	436712	Northern America
Calibration/Validation	McAllen-Edinburg-Mission, TX	United States	17	13,170,000	17.00	774,769	Northern America
Calibration/Validation	Montgomery, AL	United States	17	13,137,000	35.08	374,536	Northern America
Calibration/Validation	Cedar Rapids, IA	United States	17	13,044,000	50.57	257,940	Northern America
Calibration/Validation	Green Bay, WI	United States	17	13,038,000	42.57	306,241	Northern America
Calibration/Validation	Lincoln, NE	United States	17	12,934,000	42.81	302,157	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Evansville , IN-KY	United States	17	12,641,000	40.57	311552	Northern America
Calibration/Validation	Asheville , NC	United States	17	12,577,000	29.60	424,858	Northern America
Calibration/Validation	Reading, PA	United States	17	12,561,000	30.53	411,442	Northern America
Calibration/Validation	Midland, TX	United States	17	12,494,000	88.19	141,671	Northern America
Calibration/Validation	Pensacola-Ferry Pass-Brent, FL	United States	17	12,107,000	26.96	448991	Northern America
Calibration/Validation	Vallejo-Fairfield , CA	United States	17	11,970,000	28.96	413,344	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Norwich-New London, CT	United States	17	11,698,000	42.68	274,055	Northern America
Calibration/Validation	Atlantic City-Hammonton, NJ	United States	17	11,553,000	42.08	274549	Northern America
Calibration/Validation	Tallahassee, FL	United States	17	11,517,000	31.35	367,413	Northern America
Calibration/Validation	Deltona-Daytona Beach-Ormond Beach, FL	United States	17	11,486,000	19.46	590289	Northern America
Calibration/Validation	Roanoke, VA	United States	17	11,477,000	37.18	308,707	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Savannah , GA	United States	17	11,413,000	32.83	347,611	Northern America
Calibration/Validation	South Bend -Mishawaka , IN-MI	United States	17	11,051,000	34.62	319,224	Northern America
Calibration/Validation	Canton- Massillon, OH	United States	17	10,971,000	27.13	404,422	Northern America
Calibration/Validation	Rockford, IL	United States	17	10,954,000	31.35	349431	Northern America
Calibration/Validation	Salem, OR	United States	17	10,947,000	28.02	390,738	Northern America
Calibration/Validation	Lake Charles , LA	United States	17	10,852,000	54.37	199,607	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Huntington-Ashland, WV-KY-OH	United States	17	10,691,000	29.30	364,908	Northern America
Calibration/Validation	Kalamazoo-Portage, MI	United States	17	10,618,000	32.51	326,589	Northern America
Calibration/Validation	Charleston , WV	United States	16	10,576,000	46.57	227,078	Northern America
Calibration/Validation	Fargo, ND-MN	United States	16	10,498,000	50.28	208,777	Northern America
Calibration/Validation	Columbus , GA-AL	United States	16	10,394,000	35.25	294865	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Burlington -South Burlington , VT	United States	16	10,198,000	48.27	211,261	Northern America
Calibration/Validation	Hickory- Lenoir- Morganton , NC	United States	16	10,180,000	27.85	365497	Northern America
Calibration/Validation	Flint, MI	United States	16	10,039,000	23.58	425,790	Northern America
Calibration/Validation	Visalia- Porterville , CA	United States	16	9,970,000	22.55	442,179	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Crestview-Fort Walton Beach-Destin, FL	United States	16	9,814,000	41.61	235,865	Northern America
Calibration/Validation	Spartanburg, SC	United States	16	9,678,000	30.89	313,268	Northern America
Calibration/Validation	Port St. Lucie, FL	United States	16	9,657,000	22.77	424,107	Northern America
Calibration/Validation	Wilmington, NC	United States	16	9,653,000	37.87	254,884	Northern America
Calibration/Validation	Lubbock, TX	United States	16	9,417,000	32.38	290,805	Northern America
Calibration/Validation	Rochester, MN	United States	16	9,097,000	43.97	206877	Northern America
Calibration/Validation	Clarksville, TN-KY	United States	16	8,985,000	34.47	260,625	Northern America
Calibration/Validation	Amarillo, TX	United States	15	8,920,000	35.41	251,933	Northern America
Calibration/Validation	Gainesville, FL	United States	15	8,912,000	33.72	264275	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Longview, TX	United States	15	8,891,000	41.48	214369	Northern America
Calibration/Validation	Charlottesville, VA	United States	15	8,856,000	40.49	218,705	Northern America
Calibration/Validation	Elkhart-Goshen, IN	United States	15	8,686,000	43.97	197,559	Northern America
Calibration/Validation	Appleton, WI	United States	15	8,584,000	38.04	225666	Northern America
Calibration/Validation	Springfield, IL	United States	15	8,460,000	40.25	210170	Northern America
Calibration/Validation	Kingsport-Bristol-Bristol, TN-VA	United States	15	8,382,000	27.08	309,544	Northern America
Calibration/Validation	Duluth, MN-WI	United States	15	8,369,000	29.91	279,771	Northern America
Calibration/Validation	Fort Smith, AR-OK	United States	15	8,280,000	29.52	280,467	Northern America
Calibration/Validation	Champaign-Urbana, IL	United States	14	8,210,000	35.40	231,891	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Santa Cruz-Watsonville, CA	United States	14	8,162,000	31.11	262,382	Northern America
Calibration/Validation	Utica-Rome, NY	United States	14	8,114,000	27.10	299,397	Northern America
Calibration/Validation	Topeka, KS	United States	14	8,085,000	34.57	233,870	Northern America
Calibration/Validation	Waco, TX	United States	14	8,082,000	31.97	252772	Northern America
Calibration/Validation	Erie, PA	United States	14	7,978,000	28.44	280566	Northern America
Calibration/Validation	Tyler, TX	United States	14	7,977,000	38.04	209714	Northern America
Calibration/Validation	Bellingham, WA	United States	14	7,916,000	39.36	201140	Northern America
Calibration/Validation	Bremerton-Silverdale, WA	United States	13	7,780,000	30.98	251133	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Tuscaloosa, AL	United States	13	7,766,000	33.74	230162	Northern America
Calibration/Validation	Binghamton, NY	United States	13	7,669,000	30.47	251725	Northern America
Calibration/Validation	Lynchburg, VA	United States	13	7,486,000	29.63	252,634	Northern America
Calibration/Validation	Jacksonville, NC	United States	13	7,432,000	41.81	177,772	Northern America
Calibration/Validation	Barnstable Town, MA	United States	13	7,286,000	33.75	215,888	Northern America
Calibration/Validation	Brownsville-Harlingen, TX	United States	12	7,035,000	17.32	406220	Northern America
Calibration/Validation	Oshkosh-Neenah, WI	United States	12	6,921,000	41.44	166994	Northern America
Calibration/Validation	Sioux City , IA-NE-SD	United States	12	6,773,000	40.18	168,563	Northern America
Calibration/Validation	Macon, GA	United States	12	6,752,000	29.07	232,293	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Yakima, WA	United States	12	6,713,000	27.60	243,231	Northern America
Calibration/Validation	Hagerstown-Martinsburg, MD-WV	United States	12	6,696,000	26.61	251,599	Northern America
Calibration/Validation	Waterloo-Cedar Falls, IA	United States	12	6,648,000	39.61	167819	Northern America
Calibration/Validation	Iowa City, IA	United States	12	6,647,000	43.56	152,586	Northern America
Calibration/Validation	St. Cloud, MN	United States	12	6,570,000	34.74	189,093	Northern America
Calibration/Validation	Greeley, CO	United States	12	6,349,000	25.11	252,825	Northern America
Calibration/Validation	Billings, MT	United States	12	6,314,000	39.73	158,934	Northern America
Calibration/Validation	Ocala, FL	United States	12	6,203,000	18.72	331298	Northern America
Calibration/Validation	College Station-Bryan, TX	United States	12	6,142,000	26.86	228660	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Florence, SC	United States	12	6,109,000	29.72	205,566	Northern America
Calibration/Validation	Napa, CA	United States	12	6,020,000	44.11	136484	Northern America
Calibration/Validation	Casper, WY	United States	12	5,857,000	77.63	75,450	Northern America
Calibration/Validation	Eau Claire, WI	United States	11	5,757,000	35.72	161151	Northern America
Calibration/Validation	Monroe, LA	United States	11	5,733,000	32.49	176,441	Northern America
Calibration/Validation	Athens-Clarke County, GA	United States	11	5,721,000	29.71	192,541	Northern America
Calibration/Validation	Columbia, MO	United States	11	5,714,000	35.13	162,642	Northern America
Calibration/Validation	Racine, WI	United States	11	5,706,000	29.20	195,408	Northern America
Calibration/Validation	Gainesville, GA	United States	11	5,675,000	31.58	179684	Northern America
Calibration/Validation	Harrisonburg, VA	United States	11	5,662,000	45.21	125,228	Northern America
Calibration/Validation	Santa Fe, NM	United States	11	5,589,000	38.77	144170	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Warner Robins, GA	United States	11	5,498,000	30.61	179,605	Northern America
Calibration/Validation	Corvallis, OR	United States	11	5,496,000	64.22	85579	Northern America
Calibration/Validation	Laredo, TX	United States	11	5,432,000	21.70	250304	Northern America
Calibration/Validation	Medford, OR	United States	11	5,402,000	26.58	203,206	Northern America
Calibration/Validation	Chico, CA	United States	11	5,396,000	24.53	220,000	Northern America
Calibration/Validation	Morgantown, WV	United States	11	5,367,000	41.38	129,709	Northern America
Calibration/Validation	Greenville, NC	United States	11	5,337,000	31.74	168,148	Northern America
Calibration/Validation	Odessa, TX	United States	11	5,298,000	38.63	137,130	Northern America
Calibration/Validation	Dover, DE	United States	11	5,293,000	32.61	162310	Northern America
Calibration/Validation	State College, PA	United States	11	5,287,000	34.33	153,990	Northern America
Calibration/Validation	Merced, CA	United States	11	5,244,000	20.50	255,793	Northern America
Calibration/Validation	Rocky Mount, NC	United States	11	5,224,000	34.28	152,392	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Johnson City, TN	United States	11	5,220,000	26.27	198,716	Northern America
Calibration/Validation	Bloomington, IN	United States	11	5,186,000	32.50	159,549	Northern America
Calibration/Validation	Jefferson City, MO	United States	11	5,175,000	34.54	149,807	Northern America
Calibration/Validation	Terre Haute, IN	United States	10	5,155,000	29.90	172,425	Northern America
Calibration/Validation	Las Cruces, NM	United States	10	5,138,000	24.56	209,233	Northern America
Calibration/Validation	Joplin, MO	United States	10	5,117,000	29.15	175518	Northern America
Calibration/Validation	Wichita Falls, TX	United States	10	5,104,000	33.73	151,306	Northern America
Calibration/Validation	Wausau, WI	United States	10	5,016,000	37.42	134,063	Northern America
Calibration/Validation	Daphne-Fairhope -Foley, AL	United States	10	4,985,000	27.35	182,265	Northern America
Calibration/Validation	Niles-Benton Harbor, MI	United States	10	4,849,000	30.92	156,813	Northern America
Calibration/Validation	Abilene, TX	United States	10	4,798,000	29.03	165,252	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Decatur, IL	United States	10	4,781,000	43.16	110768	Northern America
Calibration/Validation	Farmington, NM	United States	10	4,771,000	36.69	130,044	Northern America
Calibration/Validation	Bangor, ME	United States	10	4,741,000	30.80	153,923	Northern America
Calibration/Validation	Alexandria, LA	United States	9	4,737,000	30.78	153,922	Northern America
Calibration/Validation	Watertown-Fort Drum, NY	United States	9	4,684,000	40.30	116,229	Northern America
Calibration/Validation	Rapid City, SD	United States	9	4,658,000	34.61	134,598	Northern America
Calibration/Validation	Dalton, GA	United States	9	4,625,000	32.52	142,227	Northern America
Calibration/Validation	Blacksburg-Christiansburg-Radford, VA	United States	9	4,594,000	25.77	178237	Northern America
Calibration/Validation	Pittsfield, MA	United States	9	4,544,000	34.63	131219	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Mount Vernon-Anacortes, WA	United States	9	4,538,000	38.82	116,901	Northern America
Prediction	Kitchener	Canada	9	4,536,013	9.46	479698.1967	Northern America
Calibration/Validation	Winchester , VA-WV	United States	9	4,535,000	35.30	128,472	Northern America
Calibration/Validation	Sheboygan, WI	United States	9	4,529,000	39.21	115,507	Northern America
Calibration/Validation	Idaho Falls, ID	United States	9	4,525,000	33.95	133,265	Northern America
Calibration/Validation	Bismarck, ND	United States	9	4,510,000	39.29	114,778	Northern America
Calibration/Validation	Wheeling, WV-OH	United States	9	4,504,000	30.44	147,950	Northern America
Calibration/Validation	Bowling Green, KY	United States	9	4,494,000	28.34	158,599	Northern America
Calibration/Validation	Yuma, AZ	United States	9	4,486,000	22.92	195,751	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Jackson, TN	United States	8	4,434,000	34.10	130,011	Northern America
Prediction	London	Canada	8	4,396,490	11.68	376282.7356	Northern America
Calibration/Validation	Grand Junction , CO	United States	8	4,395,000	29.95	146,723	Northern America
Calibration/Validation	Hattiesburg, MS	United States	8	4,390,000	30.73	142842	Northern America
Calibration/Validation	Battle Creek, MI	United States	8	4,346,000	31.92	136,146	Northern America
Calibration/Validation	Redding, CA	United States	8	4,334,000	24.46	177,223	Northern America
Calibration/Validation	Lawton, OK	United States	8	4,277,000	32.83	130,291	Northern America
Calibration/Validation	East Stroudsburg, PA	United States	8	4,276,000	25.18	169,842	Northern America
Calibration/Validation	Cheyenne, WY	United States	8	4,274,000	46.59	91,738	Northern America
Calibration/Validation	Jackson, MI	United States	8	4,258,000	26.57	160,248	Northern America
Calibration/Validation	Albany, GA	United States	7	4,224,000	26.85	157,308	Northern America
Calibration/Validation	Decatur, AL	United States	7	4,195,000	27.27	153829	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Kingston, NY	United States	7	4,195,000	22.99	182,493	Northern America
Calibration/Validation	Flagstaff, AZ	United States	7	4,185,000	31.13	134421	Northern America
Calibration/Validation	Fairbanks, AK	United States	7	4,171,000	42.74	97,581	Northern America
Calibration/Validation	New Bern, NC	United States	7	4,088,000	32.24	126,802	Northern America
Calibration/Validation	Dothan, AL	United States	7	4,079,000	28.01	145,639	Northern America
Calibration/Validation	El Centro, CA	United States	7	4,046,000	23.18	174,528	Northern America
Calibration/Validation	Yuba City, CA	United States	7	4,017,000	24.07	166892	Northern America
Calibration/Validation	Burlington, NC	United States	7	4,010,000	26.53	151,131	Northern America
Calibration/Validation	St. Joseph, MO-KS	United States	7	3,975,000	31.22	127329	Northern America
Calibration/Validation	Missoula, MT	United States	6	3,896,000	35.65	109,299	Northern America
Calibration/Validation	Staunton-Waynesboro, VA	United States	6	3,887,000	32.80	118502	Northern America
Calibration/Validation	Dubuque, IA	United States	6	3,882,000	41.45	93653	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Lima, OH	United States	6	3,849,000	36.20	106,331	Northern America
Calibration/Validation	Owensboro, KY	United States	6	3,844,000	33.50	114752	Northern America
Calibration/Validation	Valdosta, GA	United States	6	3,782,000	27.09	139588	Northern America
Calibration/Validation	Coeur d'Alene, ID	United States	6	3,780,000	27.29	138,494	Northern America
Calibration/Validation	Jonesboro, AR	United States	6	3,774,000	31.18	121026	Northern America
Prediction	Oshawa	Canada	6	3,715,518	12.49	297,509	Northern America
Calibration/Validation	Columbus, IN	United States	6	3,698,000	48.15	76,794	Northern America
Calibration/Validation	Ocean City, NJ	United States	6	3,692,000	37.96	97,265	Northern America
Calibration/Validation	Prescott, AZ	United States	6	3,680,000	17.44	211,033	Northern America
Calibration/Validation	Altoona, PA	United States	5	3,653,000	28.74	127,089	Northern America
Calibration/Validation	Pueblo, CO	United States	5	3,569,000	22.44	159063	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Florence-Muscle Shoals, AL	United States	5	3,567,000	24.24	147,137	Northern America
Prediction	Halifax	Canada	5	3,558,377	15.69	226,817	Northern America
Calibration/Validation	Sebastian-Vero Beach, FL	United States	5	3,539,000	25.64	138,028	Northern America
Calibration/Validation	Ames, IA	United States	5	3,528,000	39.40	89542	Northern America
Calibration/Validation	Goldsboro, NC	United States	5	3,528,000	28.77	122,623	Northern America
Prediction	St. Catharines-Niagara	Canada	4	3,499,007	23.71	147563.8022	Northern America
Calibration/Validation	Grand Forks , ND-MN	United States	4	3,499,000	35.54	98,461	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Hanford-Corcoran, CA	United States	4	3,494,000	22.84	152,982	Northern America
Calibration/Validation	Johnstown, PA	United States	4	3,474,000	24.18	143,679	Northern America
Calibration/Validation	Sierra Vista-Douglas, AZ	United States	4	3,464,000	26.37	131,346	Northern America
Calibration/Validation	Glens Falls, NY	United States	4	3,459,000	26.83	128,923	Northern America
Calibration/Validation	Mankato-North Mankato, MN	United States	4	3,429,000	35.45	96,740	Northern America
Calibration/Validation	Auburn-Opelika, AL	United States	4	3,425,000	24.42	140,247	Northern America
Calibration/Validation	Victoria, TX	United States	4	3,400,000	36.17	94,003	Northern America
Calibration/Validation	Ithaca, NY	United States	4	3,388,000	33.36	101,564	Northern America
Calibration/Validation	Lewiston-Auburn, ME	United States	4	3,381,000	31.39	107,702	Northern America
Calibration/Validation	San Angelo, TX	United States	4	3,380,000	30.23	111,823	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Lebanon, PA	United States	3	3,359,000	25.15	133,568	Northern America
Calibration/Validation	Monroe, MI	United States	3	3,309,000	21.77	152,021	Northern America
Calibration/Validation	Beckley, WV	United States	3	3,303,000	26.45	124898	Northern America
Calibration/Validation	Williamsport, PA	United States	3	3,286,000	28.30	116,111	Northern America
Calibration/Validation	Sherman-Denison, TX	United States	3	3,267,000	27.03	120,877	Northern America
Calibration/Validation	Logan, UT-ID	United States	3	3,265,000	26.03	125,442	Northern America
Calibration/Validation	Fond du Lac, WI	United States	3	3,172,000	31.21	101,633	Northern America
Calibration/Validation	Mansfield, OH	United States	3	3,172,000	25.48	124,475	Northern America
Calibration/Validation	Hammond, LA	United States	3	3,167,000	26.15	121,097	Northern America
Calibration/Validation	Lawrence, KS	United States	3	3,167,000	28.58	110,826	Northern America
Calibration/Validation	Kokomo, IN	United States	3	3,161,000	38.20	82,752	Northern America
Calibration/Validation	St. George, UT	United States	3	3,119,000	22.58	138,115	Northern America

Table 6.14: North America prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Lake Havasu City-Kingman , AZ	United States	2	3,114,000	15.56	200,186	Northern America
Calibration/Validation	Michigan City -La Porte, IN	United States	2	3,081,000	27.64	111467	Northern America
Calibration/Validation	Springfield, OH	United States	2	3,061,000	22.13	138,333	Northern America
Calibration/Validation	Grand Island, NE	United States	2	3,042,000	37.17	81,850	Northern America
Calibration/Validation	Muncie, IN	United States	2	2,992,000	25.43	117671	Northern America
Calibration/Validation	Cleveland, TN	United States	2	2,926,000	25.27	115788	Northern America
Calibration/Validation	Midland, MI	United States	2	2,881,000	34.45	83,629	Northern America
Calibration/Validation	Bloomsburg-Berwick, PA	United States	2	2,877,000	33.62	85562	Northern America
Calibration/Validation	Morristown, TN	United States	2	2,847,000	24.98	113,951	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Punta Gorda, FL	United States	2	2,811,000	17.57	159978	Northern America
Calibration/Validation	Brunswick, GA	United States	1	2,801,000	24.93	112370	Northern America
Calibration/Validation	Homosassa Springs, FL	United States	1	2,797,000	19.80	141236	Northern America
Calibration/Validation	Rome, GA	United States	1	2,770,000	28.76	96317	Northern America
Calibration/Validation	Pine Bluff, AR	United States	1	2,702,000	26.95	100258	Northern America
Calibration/Validation	Sumter, SC	United States	1	2,678,000	24.92	107,456	Northern America
Calibration/Validation	Great Falls, MT	United States	1	2,666,000	32.78	81,327	Northern America
Calibration/Validation	Longview, WA	United States	1	2,648,000	25.86	102,410	Northern America
Calibration/Validation	Bay City, MI	United States	1	2,563,000	23.78	107,771	Northern America
Calibration/Validation	Elmira, NY	United States	1	2,558,000	28.80	88,830	Northern America
Calibration/Validation	Manhattan, KS	United States	1	2,499,000	26.95	92719	Northern America
Calibration/Validation	Hot Springs, AR	United States	1	2,404,000	25.04	96024	Northern America

Table 6.14: North America prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Carson City, NV	United States	1	2,389,000	43.22	55,274	Northern America
Calibration/Validation	Cumberland , MD-WV	United States	1	2,366,000	22.90	103,299	Northern America
Calibration/Validation	Gadsden, AL	United States	1	2,312,000	22.14	104,430	Northern America
Calibration/Validation	Gettysburg, PA	United States	1	2,196,000	21.66	101,407	Northern America
Calibration/Validation	Pocatello, ID	United States	1	2,174,000	26.24	82,839	Northern America
Calibration/Validation	Danville, IL	United States	1	2,112,000	25.87	81625	Northern America
Calibration/Validation	Walla Walla, WA	United States	1	2,010,000	31.98	62,859	Northern America
Calibration/Validation	Lewiston, ID-WA	United States	1	1,728,000	28.38	60,888	Northern America
Calibration/Validation	Grants Pass, OR	United States	1	1,606,000	19.42	82,713	Northern America
Calibration/Validation	Sebring, FL	United States	1	1,577,000	15.96	98,786	Northern America
Calibration/Validation	The Villages, FL	United States	1	1,479,000	15.83	93420	Northern America

Table 6.15: Northern Europe prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	London	United Kingdom	20	548,778,002	46.53	11793530	Northern Europe
Calibration/Validation	Stockholm	Sweden	20	95,028,000	48.36	1964829	Northern Europe
Calibration/Validation	Dublin	Ireland	20	79,510,000	48.18	1,650,202	Northern Europe
Calibration/Validation	Copenhagen	Denmark	20	74,485,000	37.43	1989871	Northern Europe
Calibration/Validation	Helsinki	Finland	20	62,713,000	43.08	1455677	Northern Europe
Calibration/Validation	Manchester	United Kingdom	20	59,653,000	32.40	1,841,382	Northern Europe
Calibration/Validation	Oslo	Norway	20	59,030,000	48.18	1225202	Northern Europe
Calibration/Validation	Birmingham	United Kingdom	20	53,267,000	28.27	1,884,199	Northern Europe
Calibration/Validation	Leeds	United Kingdom	19	37,894,000	32.49	1,166,267	Northern Europe
Calibration/Validation	Glasgow	United Kingdom	19	34,878,000	36.80	947,809	Northern Europe
Calibration/Validation	Edinburgh	United Kingdom	19	31,564,000	43.38	727,620	Northern Europe
Calibration/Validation	Bristol	United Kingdom	19	30,422,000	38.24	795,481	Northern Europe
Calibration/Validation	Gothenburg	Sweden	19	28,371,000	32.34	877,150	Northern Europe

Table 6.15: Northern Europe prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Newcastle	United Kingdom	19	26,216,000	24.95	1050561	Northern Europe
Calibration/Validation	Liverpool	United Kingdom	19	24,954,000	26.74	933,127	Northern Europe
Calibration/Validation	Nottingham	United Kingdom	19	23,826,000	28.51	835625	Northern Europe
Calibration/Validation	Sheffield	United Kingdom	19	22,433,000	25.49	880,237	Northern Europe
Calibration/Validation	Malmo	Sweden	18	19,870,000	30.25	656,835	Northern Europe
Calibration/Validation	Portsmouth	United Kingdom	18	19,562,000	33.89	577,191	Northern Europe
Calibration/Validation	Leicester	United Kingdom	18	19,256,000	29.14	660817	Northern Europe
Calibration/Validation	Cardiff	United Kingdom	18	18,600,000	29.03	640,632	Northern Europe
Calibration/Validation	Tallinn	Estonia	17	13,272,000	25.01	530,760	Northern Europe
Calibration/Validation	Bradford	United Kingdom	17	13,149,000	24.34	540,172	Northern Europe
Prediction	West Yorkshire	United Kingdom	17	10,967,992	12.50	877,195	Northern Europe

Table 6.15: Northern Europe prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Southampton/ Portsmouth (South Hampshire)	United Kingdom	15	8,535,777	11.15	765824.1917	Northern Europe
Prediction	Glasgow	United Kingdom	15	8,500,086	7.85	1082286.215	Northern Europe
Prediction	Coventry-Bedworth	United Kingdom	10	4,857,599	11.29	430076.251	Northern Europe
Prediction	Belfast	United Kingdom	9	4,689,925	9.93	472,527	Northern Europe
Prediction	Riga	Latvia	9	4,515,284	10.01	450,854	Northern Europe
Prediction	Bournemouth /Poole	United Kingdom	8	4,426,432	9.98	443,456	Northern Europe
Prediction	Teeside (Middlesbrough)	United Kingdom	7	3,983,675	11.76	338,809	Northern Europe
Prediction	Southend-On-Sea	United Kingdom	7	3,982,334	11.06	359,918	Northern Europe

Table 6.15: Northern Europe prediction

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Kingston upon Hull	United Kingdom	7	3,931,093	12.04	326,428	Northern Europe
Prediction	Stoke-on-Trent (The Potteries)	United Kingdom	6	3,903,274	11.66	334,705	Northern Europe
Prediction	Swansea	United Kingdom	6	3,875,019	21.81	177636.1517	Northern Europe
Prediction	Brighton-Worthing-Littlehampton	United Kingdom	5	3,668,622	12.35	297,041	Northern Europe
Prediction	Preston	United Kingdom	5	3,640,104	16.26	223,851	Northern Europe
Prediction	Vilnius	Lithuania	5	3,586,955	16.22	221,148	Northern Europe
Prediction	Reading-Wokingham	United Kingdom	4	3,511,623	18.61	188,655	Northern Europe
Prediction	Tampere	Finland	4	3,498,589	25.48	137286.8728	Northern Europe

Table 6.15: Northern Europe prediction

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Newport	United Kingdom	4	3,490,258	21.08	165,536	Northern Europe

Table 6.16: South-eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Jakarta Bogor	Indonesia	16	10,180,025	0.38	26,451,441	South-eastern Asia
Prediction	Kuala Lumpur	Malaysia	16	9,801,259	1.44	6,805,920	South-eastern Asia
Prediction	Krung Thep (Bangkok Krung Thep (Bangkok) Samut Prakan Nonthaburi)	Thailand	16	9,522,965	0.59	16,206,744	South-eastern Asia
Prediction	Surakarta	Indonesia	16	9,100,560	10.22	890,546	South-eastern Asia
Prediction	Surabaya	Indonesia	15	8,966,308	1.87	4785056.336	South-eastern Asia
Prediction	Yangon	Myanmar	15	8,629,574	1.86	4,639,010	South-eastern Asia
Prediction	Bandung	Indonesia	15	8,595,463	1.64	5255851.47	South-eastern Asia
Prediction	Denpasar	Indonesia	15	8,353,774	6.41	1304064.405	South-eastern Asia
Prediction	Semarang	Indonesia	15	8,330,913	5.18	1,607,067	South-eastern Asia

Table 6.16: South-eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Cebu City Lapu-Lapu City Mandaue City	Philippines	14	7,998,043	3.75	2134033.79	South-eastern Asia
Prediction	Medan	Indonesia	14	7,992,076	2.92	2740258.368	South-eastern Asia
Prediction	Palembang	Indonesia	14	7,927,133	5.09	1557823.167	South-eastern Asia
Prediction	Makassar (Ujung Pandang)	Indonesia	14	7,870,139	4.76	1,653,771	South-eastern Asia
Prediction	Yogyakarta	Indonesia	14	7,805,794	5.81	1,342,604	South-eastern Asia
Prediction	Da Nang	Viet Nam	14	7,801,520	8.71	895,323	South-eastern Asia
Prediction	Mandalay	Myanmar	13	7,693,047	5.77	1,333,860	South-eastern Asia
Prediction	Bandar Lampung	Indonesia	13	7,499,646	7.06	1,062,262	South-eastern Asia
Prediction	Malang	Indonesia	13	7,430,905	6.20	1,199,018	South-eastern Asia
Prediction	Pekan Baru	Indonesia	13	7,425,779	8.57	866,586	South-eastern Asia

Table 6.16: South-eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Davao City	Philippines	13	7,394,263	7.67	964,219	South-eastern Asia
Prediction	Cirebon	Indonesia	13	7,316,102	6.68	1,095,536	South-eastern Asia
Prediction	Banjarmasin	Indonesia	12	6,274,418	8.79	713,753	South-eastern Asia
Prediction	Ipoh	Malaysia	12	6,163,474	8.34	739,211	South-eastern Asia
Prediction	Padang	Indonesia	12	5,774,118	9.31	620,507	South-eastern Asia
Prediction	Kota Kinabalu	Malaysia	10	4,920,893	9.16	537332.5119	South-eastern Asia
Prediction	Vungtau	Viet Nam	10	4,792,923	17.43	275,056	South-eastern Asia
Prediction	Jambi	Indonesia	9	4,660,543	6.83	681,932	South-eastern Asia
Prediction	Samarinda	Indonesia	9	4,651,884	7.68	605,565	South-eastern Asia
Prediction	Chon Buri	Thailand	9	4,647,325	9.45	491,997	South-eastern Asia
Prediction	Vientiane	Lao People's Democratic Republic		9	4,560,633	8.74	522,092

Table 6.16: South-eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
South-eastern Asia							
Prediction	Kuching	Malaysia	9	4,500,096	10.45	430784.5087	South-eastern Asia
Prediction	Balikpapan	Indonesia	9	4,479,580	9.47	472795.0726	South-eastern Asia
Prediction	Cagayan de Oro City	Philippines	8	4,416,748	8.07	547,314	South-eastern Asia
Prediction	Nha Trang	Viet Nam	8	4,323,114	10.57	409,151	South-eastern Asia
Prediction	Pontianak	Indonesia	8	4,288,074	8.59	499118.8965	South-eastern Asia
Prediction	Mataram	Indonesia	8	4,263,530	6.80	627,362	South-eastern Asia
Prediction	Seremban	Malaysia	7	4,246,989	9.43	450,333	South-eastern Asia
Prediction	Can Tho	Viet Nam	7	4,183,695	10.21	409,794	South-eastern Asia
Prediction	Tasikmalaya	Indonesia	7	4,180,593	7.42	563340.3861	South-eastern Asia
Prediction	Kota Bharu	Malaysia	7	4,107,088	10.35	396,872	South-eastern Asia
Prediction	Bacolod	Philippines	7	3,987,096	8.37	476,623	South-eastern Asia
Prediction	Zamboanga City	Philippines	7	3,955,303	8.28	477775.2387	South-eastern Asia

Table 6.16: South-eastern Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Iloilo City	Philippines	6	3,899,949	8.81	442,441	South-eastern Asia
Prediction	Sukabumi	Indonesia	6	3,890,397	8.08	481444.6545	South-eastern Asia
Prediction	Baguio City	Philippines	6	3,874,795	9.12	425,056	South-eastern Asia
Prediction	Hue	Viet Nam	6	3,776,819	9.98	378,439	South-eastern Asia
Prediction	Nay Pyi Taw	Myanmar	6	3,765,394	10.51	358,154	South-eastern Asia
Prediction	Angeles City	Philippines	6	3,705,142	9.83	376,760	South-eastern Asia
Prediction	Rayong	Thailand	5	3,605,546	10.61	339,836	South-eastern Asia
Prediction	Hat Yai	Thailand	3	3,245,092	12.31	263547.6732	South-eastern Asia
Prediction	Nakhon Ratchasima	Thailand	3	3,208,640	13.52	237,314	South-eastern Asia
Prediction	Udon Thani	Thailand	3	3,198,884	20.82	153,640	South-eastern Asia
Prediction	Kuantan	Malaysia	3	3,195,310	14.16	225,601	South-eastern Asia
Prediction	Manado	Indonesia	2	3,113,142	9.03	344,621	South-eastern Asia
Prediction	General Santos City	Philippines	2	3,031,031	9.53	318155.7317	South-eastern Asia

Table 6.16: South-eastern Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Batangas City	Philippines	2	2,837,015	9.37	302,743	South-eastern Asia
Prediction	Sandakan	Malaysia	2	2,822,981	9.24	305,677	South-eastern Asia
Prediction	Lampang	Thailand	1	2,731,394	24.57	111173.2703	South-eastern Asia
Prediction	Ambon	Indonesia	1	2,730,506	12.30	222,074	South-eastern Asia
Prediction	Mawlamyine	Myanmar	1	2,712,409	12.13	223,673	South-eastern Asia
Prediction	Butuan	Philippines	1	2,708,375	14.64	185,012	South-eastern Asia
Prediction	Bengkulu	Indonesia	1	2,682,238	10.26	261390.261	South-eastern Asia
Prediction	Kuala Terengganu	Malaysia	1	2,662,257	11.75	226,552	South-eastern Asia
Prediction	Lipa City	Philippines	1	2,658,032	12.82	207323.7454	South-eastern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Tehran Tehran Karaj Eslamshahr Malard Qods	Iran (Islamic Republic of)	18	15,019,009	1.26	11,910,073	Southern Asia
Prediction	Delhi	India	17	13,556,500	0.76	17,843,028	Southern Asia
Prediction	Mumbai (Bombay) Bhiwandi	India	17	12,823,394	0.72	17709132.6	Southern Asia
Prediction	Lahore	Pakistan	17	12,244,601	2.11	5,802,571	Southern Asia
Prediction	Agra	India	17	11,957,705	5.99	1995729.408	Southern Asia
Prediction	Bhopal	India	17	11,435,610	6.92	1,651,966	Southern Asia
Prediction	Ranchi	India	17	11,348,326	10.26	1,106,168	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Coimbatore	India	17	11,343,930	8.09	1,401,987	Southern Asia
Prediction	Nagpur	India	17	11,333,929	4.48	2,527,800	Southern Asia
Prediction	Jaipur	India	17	11,227,837	3.77	2,975,523	Southern Asia
Prediction	Chittagong	Bangladesh	17	10,983,518	3.57	3,077,719	Southern Asia
Prediction	Surat	India	17	10,865,162	2.03	5360547.613	Southern Asia
Prediction	Dhaka	Bangladesh	17	10,675,361	0.84	12,686,440	Southern Asia
Prediction	Ahmadabad	India	17	10,578,970	1.61	6572548.025	Southern Asia
Prediction	Kabul	Afghanistan	16	10,513,435	2.87	3,659,578	Southern Asia
Prediction	Jabalpur	India	16	10,469,689	9.98	1,048,876	Southern Asia
Prediction	Vijayawada	India	16	10,413,631	8.69	1197849.902	Southern Asia
Prediction	Asansol	India	16	10,374,909	6.13	1,693,187	Southern Asia
Prediction	Vadodara	India	16	10,323,016	6.23	1,656,515	Southern Asia
Prediction	Karachi	Pakistan	16	10,102,103	0.75	13,418,499	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Faisalabad	Pakistan	16	9,895,712	2.78	3,565,253	Southern Asia
Prediction	Salem	India	16	9,840,355	9.70	1,014,921	Southern Asia
Prediction	Kota	India	16	9,698,035	12.23	793,201	Southern Asia
Prediction	Kathmandu	Nepal	16	9,651,214	2.49	3871431.214	Southern Asia
Prediction	Nashik	India	16	9,623,006	6.68	1439984.719	Southern Asia
Prediction	Patna	India	16	9,245,880	4.72	1,958,354	Southern Asia
Prediction	Rawalpindi Islamabad	Pakistan	16	9,240,637	3.21	2,878,358	Southern Asia
Prediction	Kochi (Cochin)	India	16	9,194,167	5.96	1,541,577	Southern Asia
Prediction	Chennai (Madras)	India	16	9,176,231	1.07	8539160.535	Southern Asia
Prediction	Lucknow	India	16	9,117,764	3.14	2906136.577	Southern Asia
Prediction	Durg-Bhilainagar	India	16	9,039,383	9.03	1,000,741	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Jodhpur	India	15	8,895,666	9.83	905024.4541	Southern Asia
Prediction	Varanasi (Benares)	India	15	8,844,927	4.43	1,995,268	Southern Asia
Prediction	Raipur	India	15	8,807,102	9.44	932,465	Southern Asia
Prediction	Peshawar	Pakistan	15	8,759,035	5.75	1,523,845	Southern Asia
Prediction	Multan	Pakistan	15	8,672,904	3.97	2,185,943	Southern Asia
Prediction	Sialkot	Pakistan	15	8,654,892	10.41	831566.4686	Southern Asia
Prediction	Colombo	Sri Lanka	15	8,583,280	3.01	2,855,452	Southern Asia
Prediction	Thiruvana-nthapuram Kollam Kayamkulam	India	15	8,568,235	2.04	4,190,440	Southern Asia
Prediction	Chandigarh	India	15	8,551,143	4.75	1799201.029	Southern Asia

Table 6.17: Southern Asia

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Mashhad	Iran (Islamic Republic of)	15	8,536,707	5.15	1,659,051	Southern Asia
Prediction	Gujranwala	Pakistan	15	8,474,927	6.05	1,401,025	Southern Asia
Prediction	Bhubaneswar	India	15	8,455,249	9.53	887,391	Southern Asia
Prediction	Kanpur	India	15	8,453,595	3.00	2,816,901	Southern Asia
Prediction	Indore	India	15	8,392,577	3.84	2,184,115	Southern Asia
Prediction	Esfahan	Iran (Islamic Republic of)	15	8,349,166	6.06	1,377,121	Southern Asia
Prediction	Ludhiana	India	15	8,344,824	5.74	1455051.104	Southern Asia

Table 6.17: Southern Asia

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Bangalore	India	15	8,306,888	0.96	8,631,086	Southern Asia
Prediction	Pune (Poona)	India	14	8,220,228	1.37	6016708.407	Southern Asia
Prediction	Jammu	India	14	8,197,534	11.25	728,381	Southern Asia
Prediction	Hyderabad	Pakistan	14	8,173,604	5.06	1,615,107	Southern Asia
Prediction	Allahabad	India	14	8,086,623	5.28	1,531,309	Southern Asia
Prediction	Rajahmundry Rajahmundry Kakinada	India	14	8,061,521	5.39	1494298.157	Southern Asia
Prediction	Guwahati (Gauhati)	India	14	8,040,577	7.68	1,046,666	Southern Asia
Prediction	Hyderabad	India	14	8,030,601	1.07	7494320.102	Southern Asia
Prediction	Jamshedpur	India	14	8,008,051	5.37	1491503.288	Southern Asia
Prediction	Gwalior	India	14	7,983,320	8.53	935,636	Southern Asia
Prediction	Madurai	India	14	7,915,927	5.64	1,403,278	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Khulna	Bangladesh	14	7,889,224	10.36	761,187	Southern Asia
Prediction	Meerut	India	14	7,884,243	6.78	1,163,554	Southern Asia
Prediction	Visakhapatnam	India	14	7,861,205	5.52	1,423,626	Southern Asia
Prediction	Bareilly	India	13	7,768,448	7.26	1,069,941	Southern Asia
Prediction	Bhubaneswar	India	13	7,744,242	4.96	1,562,792	Southern Asia
Prediction	Dhanbad	India	13	7,683,337	7.98	962520.4036	Southern Asia
Prediction	Tiruchirappalli	India	13	7,663,948	7.83	978,875	Southern Asia
Prediction	Aurangabad	India	13	7,626,676	6.13	1,243,201	Southern Asia
Prediction	Rajkot	India	13	7,618,739	6.90	1103459.804	Southern Asia
Prediction	Jalandhar	India	13	7,613,786	8.08	942,832	Southern Asia
Prediction	Mysore	India	13	7,474,183	7.98	936,625	Southern Asia
Prediction	Gorakhpur	India	13	7,442,844	8.18	909,496	Southern Asia
Prediction	Saharanpur	India	13	7,428,034	8.22	904046.162	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Moradabad	India	13	7,203,136	8.41	856467.8915	Southern Asia
Prediction	Kozhikode (Calicut)	India	13	7,083,569	7.70	920,004	Southern Asia
Prediction	Aligarh	India	12	7,034,820	8.40	837,644	Southern Asia
Prediction	Nellore	India	12	6,747,650	12.52	538,791	Southern Asia
Prediction	Tiruppur	India	12	6,613,191	8.65	764,571	Southern Asia
Prediction	Amritsar	India	12	6,375,342	8.00	796813.5586	Southern Asia
Prediction	Dehradun	India	12	6,235,160	8.13	766,887	Southern Asia
Prediction	Solapur	India	12	6,095,587	7.57	805,634	Southern Asia
Prediction	Warangal	India	12	6,070,158	8.95	678522.6919	Southern Asia
Prediction	Tabriz	Iran (Islamic Republic of)	12	5,909,052	8.11	728,871	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Ahvaz	Iran (Islamic Republic of)	12	5,887,537	10.30	571782.7287	Southern Asia
Prediction	Panipat	India	11	5,546,692	11.90	465,969	Southern Asia
Prediction	Gaya	India	11	5,527,848	10.61	520,832	Southern Asia
Prediction	Hubli-Dharwad	India	11	5,513,856	10.83	509,124	Southern Asia
Prediction	Begusarai	India	11	5,491,041	11.94	459970.4697	Southern Asia
Prediction	Amravati	India	11	5,464,607	12.36	442139.383	Southern Asia
Prediction	Anand	India	11	5,425,247	8.16	664,490	Southern Asia
Prediction	Bilaspur	India	11	5,378,068	11.67	460,793	Southern Asia
Prediction	Mangalore	India	11	5,348,739	7.40	722,534	Southern Asia
Prediction	Mardan	Pakistan	11	5,303,881	7.16	740325.9323	Southern Asia

Table 6.17: Southern Asia

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Rajshahi	Bangladesh	11	5,197,979	11.28	460,690	Southern Asia
Prediction	Bikaner	India	11	5,188,647	7.92	655,226	Southern Asia
Prediction	Guntur	India	10	5,153,884	7.38	697,926	Southern Asia
Prediction	Shiraz	Iran (Islamic Republic of)	10	5,105,057	8.81	579,246	Southern Asia
Prediction	Puducherry	India	10	5,071,722	7.78	651,665	Southern Asia
Prediction	Quetta	Pakistan	10	5,035,834	8.90	565,609	Southern Asia
Prediction	Raurkela	India	10	4,985,834	8.08	616,947	Southern Asia
Prediction	Comilla	Bangladesh	10	4,962,301	9.38	528,910	Southern Asia
Prediction	Sylhet	Bangladesh	10	4,945,946	7.20	687,099	Southern Asia
Prediction	Hardwar	India	10	4,941,871	7.46	662,093	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Srinagar	India	10	4,854,333	9.10	533269.4051	Southern Asia
Prediction	Udaipur	India	10	4,847,694	9.45	512,724	Southern Asia
Prediction	Tirupati	India	10	4,834,946	13.50	358,177	Southern Asia
Prediction	Akola	India	10	4,810,006	13.39	359,173	Southern Asia
Prediction	Jhansi	India	9	4,721,930	10.10	467,480	Southern Asia
Prediction	Durgapur	India	9	4,669,905	14.38	324,646	Southern Asia
Prediction	Muzaffarpur	India	9	4,625,539	7.61	607857.6592	Southern Asia
Prediction	Thrissur	India	9	4,571,621	13.02	351,126	Southern Asia
Prediction	Kolhapur	India	9	4,560,053	8.08	564282.9042	Southern Asia
Prediction	Bahawalpur	Pakistan	9	4,503,984	8.35	539,305	Southern Asia
Prediction	Nanded Waghala	India	9	4,461,885	7.97	559,821	Southern Asia
Prediction	Muzaffarnagar	India	8	4,446,980	9.18	484,178	Southern Asia
Prediction	Ajmer	India	8	4,441,319	10.43	425762.9392	Southern Asia

Table 6.17: Southern Asia

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Sargodha	Pakistan	8	4,424,178	8.31	532,509	Southern Asia
Prediction	Patiala	India	8	4,421,785	8.91	496,527	Southern Asia
Prediction	Yazd	Iran (Islamic Republic of)	8	4,394,307	10.40	422554.5502	Southern Asia
Prediction	Qom	Iran (Islamic Republic of)	8	4,346,809	10.51	413,397	Southern Asia
Prediction	Vellore	India	8	4,301,866	8.53	504206.2117	Southern Asia
Prediction	Baharampur	India	8	4,295,393	8.38	512,643	Southern Asia
Prediction	Yamunanagar	India	8	4,286,932	9.14	468,897	Southern Asia

Table 6.17: Southern Asia

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Kermanshah	Iran (Islamic Republic of)	8	4,270,534	11.85	360319.3424	Southern Asia
Prediction	Sangali	India	7	4,248,895	8.57	495,883	Southern Asia
Prediction	Erode	India	7	4,243,413	10.12	419426.8384	Southern Asia
Prediction	Firozabad	India	7	4,233,121	8.50	498192.8642	Southern Asia
Prediction	Jamnagar	India	7	4,188,546	10.38	403575.0034	Southern Asia
Prediction	Rohtak	India	7	4,165,483	11.91	349,772	Southern Asia
Prediction	Sukkur	Pakistan	7	4,125,618	11.50	358884.5109	Southern Asia
Prediction	Herat	Afghanistan	7	4,122,322	14.21	290,150	Southern Asia
Prediction	Wah	Pakistan	7	4,117,678	9.24	445,772	Southern Asia
Prediction	Alwar	India	7	4,110,015	9.64	426497.4681	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Larkana	Pakistan	7	4,086,915	10.74	380,623	Southern Asia
Prediction	Dhule	India	7	4,075,686	12.61	323,295	Southern Asia
Prediction	Rampur	India	7	4,032,032	9.92	406492.9415	Southern Asia
Prediction	Qazvin	Iran (Islamic Republic of)	7	4,020,685	31.95	125,839	Southern Asia
Prediction	Brahmapur	India	7	4,002,311	8.64	463,367	Southern Asia
Prediction	Bhavnagar	India	7	4,001,628	9.08	440,870	Southern Asia
Prediction	Mymensingh	Bangladesh	7	3,961,181	9.53	415620.9059	Southern Asia
Prediction	Bhilwara	India	7	3,941,078	13.20	298666.3112	Southern Asia
Prediction	Agartala	India	7	3,936,369	9.21	427,394	Southern Asia
Prediction	Gulbarga	India	6	3,891,176	9.08	428,771	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Bogra	Bangladesh	6	3,869,141	8.42	459,717	Southern Asia
Prediction	Kannur	India	6	3,865,823	10.69	361,569	Southern Asia
Prediction	Imphal	India	6	3,863,958	8.40	460,260	Southern Asia
Prediction	Dera Ghazikhan	Pakistan	6	3,844,395	9.53	403,477	Southern Asia
Prediction	Hosur	India	6	3,789,923	20.01	189,384	Southern Asia
Prediction	Malegaon	India	6	3,786,188	9.34	405428.659	Southern Asia
Prediction	Shahjahanpur	India	6	3,779,090	10.17	371,671	Southern Asia
Prediction	Shimoga	India	6	3,773,291	14.04	268800.8549	Southern Asia
Prediction	Hamadan	Iran (Islamic Republic of)	6	3,763,599	11.84	317,970	Southern Asia
Prediction	Jalgaon	India	6	3,736,314	9.34	400,226	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Kurnool	India	6	3,726,510	9.86	377,998	Southern Asia
Prediction	Sari	Iran (Islamic Republic of)	6	3,723,045	30.84	120,740	Southern Asia
Prediction	Rangpur	Bangladesh	6	3,713,445	8.85	419,806	Southern Asia
Prediction	Nizamabad	India	6	3,683,105	11.68	315,257	Southern Asia
Prediction	Satna	India	5	3,668,407	10.18	360,433	Southern Asia
Prediction	Darbhanga	India	5	3,646,009	9.09	400,896	Southern Asia
Prediction	Barisal	Bangladesh	5	3,640,774	10.02	363364.5345	Southern Asia
Prediction	Bellary	India	5	3,640,371	11.62	313,162	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Khorramabad	Iran (Islamic Republic of)	5	3,631,407	26.09	139,206	Southern Asia
Prediction	Orumiyeh	Iran (Islamic Republic of)	5	3,627,481	12.54	289,277	Southern Asia
Prediction	Ujjain	India	5	3,622,729	10.47	345,903	Southern Asia
Prediction	Anantapur	India	5	3,613,656	11.93	302969.2496	Southern Asia

Table 6.17: Southern Asia

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Sanandaj	Iran (Islamic Republic of)	5	3,592,535	20.45	175,678	Southern Asia
Prediction	Ardabil	Iran (Islamic Republic of)	5	3,573,201	13.22	270,317	Southern Asia
Prediction	Zanjan	Iran (Islamic Republic of)	5	3,548,554	20.04	177,096	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Arak	Iran (Islamic Republic of)	5	3,547,642	16.78	211,446	Southern Asia
Prediction	Hisar	India	5	3,540,036	11.64	304,139	Southern Asia
Prediction	Ahmadnagar	India	5	3,534,879	13.00	272,010	Southern Asia
Prediction	Rasht	Iran (Islamic Republic of)	5	3,525,487	14.65	240,688	Southern Asia
Prediction	Dewas	India	4	3,518,353	16.50	213,287	Southern Asia
Prediction	Rahim Yar Khan	Pakistan	4	3,515,637	10.16	346,055	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Kerman	Iran (Islamic Republic of)	4	3,492,356	17.31	201782.3453	Southern Asia
Prediction	Gorgan	Iran (Islamic Republic of)	4	3,473,815	17.93	193736.7394	Southern Asia
Prediction	Jhang	Pakistan	3	3,348,386	9.66	346,554	Southern Asia
Prediction	Zahedan	Iran (Islamic Republic of)	3	3,334,258	13.10	254,561	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Kandahar	Afghanistan	3	3,333,080	10.46	318,592	Southern Asia
Prediction	Sheikhupura	Pakistan	3	3,329,538	9.79	340,256	Southern Asia
Prediction	Bandar Abbas	Iran (Islamic Republic of)	3	3,300,390	14.15	233,321	Southern Asia
Prediction	Shillong	India	3	3,299,193	9.89	333,520	Southern Asia
Prediction	Siliguri	India	3	3,292,822	9.69	339900.2777	Southern Asia
Prediction	Thanjavur	India	3	3,266,580	15.29	213,697	Southern Asia
Prediction	Belgaum	India	3	3,213,626	9.29	345,824	Southern Asia
Prediction	Ichalakaranji	India	3	3,203,508	10.30	311084.6333	Southern Asia
Prediction	Mathura	India	3	3,202,696	14.06	227,814	Southern Asia
Prediction	Korba	India	3	3,168,652	9.50	333644.8973	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Bijapur	India	3	3,160,438	11.84	267027.7766	Southern Asia
Prediction	Bokaro Steel City	India	3	3,144,658	9.17	342,948	Southern Asia
Prediction	Kottayam	India	3	3,142,779	9.07	346,397	Southern Asia
Prediction	Ranipet	India	3	3,119,088	14.69	212,356	Southern Asia
Prediction	Gujrat	Pakistan	2	3,112,576	9.93	313317.7237	Southern Asia
Prediction	Davangere	India	2	3,103,158	9.43	329,001	Southern Asia
Prediction	Tumkur	India	2	3,087,019	14.64	210831.1073	Southern Asia
Prediction	Okara	Pakistan	2	3,071,152	10.08	304,603	Southern Asia
Prediction	Bathinda	India	2	3,054,044	10.71	285,044	Southern Asia
Prediction	Bhagalpur	India	2	2,975,234	21.07	141,186	Southern Asia
Prediction	Kadapa	India	2	2,903,395	9.65	300,790	Southern Asia
Prediction	Kasur	Pakistan	2	2,890,811	12.08	239307.4038	Southern Asia
Prediction	Palakkad	India	2	2,881,640	13.51	213,244	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Roorkee	India	2	2,845,514	10.63	267808.5028	Southern Asia
Prediction	Navsari	India	2	2,811,197	16.37	171,709	Southern Asia
Prediction	Karimnagar	India	2	2,804,158	9.50	295309.2573	Southern Asia
Prediction	English Bazar	India	2	2,801,088	27.58	101,561	Southern Asia
Prediction	Junagadh	India	1	2,775,631	11.85	234,242	Southern Asia
Prediction	Latur	India	1	2,774,070	10.50	264,277	Southern Asia
Prediction	Tirunelveli	India	1	2,766,919	9.54	290,002	Southern Asia
Prediction	Jalna	India	1	2,750,270	11.84	232259.7435	Southern Asia
Prediction	Thoothukkudi (Tuticorin)	India	1	2,744,241	12.50	219,561	Southern Asia
Prediction	Chandrapur	India	1	2,733,524	12.33	221,665	Southern Asia
Prediction	Sagar	India	1	2,733,348	14.56	187,739	Southern Asia
Prediction	Maunath Bhanjan	India	1	2,721,417	11.05	246,301	Southern Asia
Prediction	Purnia	India	1	2,713,224	11.07	245,141	Southern Asia

Table 6.17: Southern Asia

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Dindigul	India	1	2,702,820	13.28	203,467	Southern Asia
Prediction	Aizawl	India	1	2,702,500	15.17	178,169	Southern Asia
Prediction	Nawabshah	Pakistan	1	2,697,808	18.74	143,940	Southern Asia
Prediction	Farrukhabad	India	1	2,696,163	13.30	202,692	Southern Asia
Prediction	Barddhaman	India	1	2,692,024	18.01	149,459	Southern Asia
Prediction	Habra	India	1	2,688,474	17.40	154537.5556	Southern Asia
Prediction	Parbhani	India	1	2,686,131	10.48	256314.7029	Southern Asia
Prediction	Bihar Sharif	India	1	2,659,801	10.21	260,476	Southern Asia

Table 6.18: Southern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Madrid	Spain	20	226,039,999	34.74	6507502	Southern Europe
Calibration/Validation	Milan	Italy	20	180,506,001	44.45	4,060,624	Southern Europe
Calibration/Validation	Rome	Italy	20	142,054,001	35.44	4008095	Southern Europe
Calibration/Validation	Athens	Greece	20	122,799,999	34.46	3563607	Southern Europe
Calibration/Validation	Barcelona	Spain	20	117,650,000	32.01	3,675,206	Southern Europe
Calibration/Validation	Lisbon	Portugal	20	86,121,000	30.78	2,797,612	Southern Europe
Calibration/Validation	Naples	Italy	20	61,820,000	17.40	3,552,568	Southern Europe
Calibration/Validation	Turin	Italy	20	54,538,000	31.21	1,747,614	Southern Europe
Calibration/Validation	Valencia	Spain	20	39,475,000	25.14	1570517	Southern Europe
Calibration/Validation	Bilbao	Spain	19	33,450,000	33.54	997,311	Southern Europe
Calibration/Validation	Seville	Spain	19	30,053,000	21.15	1,421,045	Southern Europe
Calibration/Validation	Bologna	Italy	19	28,942,000	38.84	745,255	Southern Europe
Calibration/Validation	Porto	Portugal	19	27,101,000	20.84	1,300,285	Southern Europe

Table 6.18: Southern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Florence	Italy	19	24,889,000	34.42	723,164	Southern Europe
Calibration/Validation	Zaragoza	Spain	19	24,381,000	29.52	825,838	Southern Europe
Calibration/Validation	Genova	Italy	19	22,110,000	30.87	716,159	Southern Europe
Calibration/Validation	Ljubljana	Slovenia	18	19,775,000	34.87	567098	Southern Europe
Calibration/Validation	Malaga	Spain	18	18,586,000	22.28	834,023	Southern Europe
Calibration/Validation	Thessalonica	Greece	18	18,551,000	19.37	957946	Southern Europe
Calibration/Validation	Palermo	Italy	18	18,492,000	19.76	935,921	Southern Europe
Calibration/Validation	Venice	Italy	18	17,098,000	31.55	541,969	Southern Europe
Calibration/Validation	Las Palmas	Spain	18	15,769,000	23.93	658,958	Southern Europe
Calibration/Validation	Bari	Italy	17	12,167,000	21.05	577,899	Southern Europe
Calibration/Validation	Catania	Italy	17	11,190,000	17.94	623,610	Southern Europe
Prediction	Beograd (Belgrade)	Serbia	13	7,554,605	8.57	881165.3149	Southern Europe
Prediction	Murcia	Spain	10	4,886,763	9.80	498880.3222	Southern Europe

Table 6.18: Southern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Palma	Spain	9	4,619,488	10.06	459,098	Southern Europe
Prediction	Zagreb	Croatia	9	4,527,789	10.38	436097.5457	Southern Europe
Prediction	Alicante	Spain	9	4,484,249	10.43	429,732	Southern Europe
Prediction	Valladolid	Spain	7	4,213,938	11.76	358,275	Southern Europe
Prediction	Barletta	Italy	7	4,157,718	43.77	94,986	Southern Europe
Prediction	Brescia	Italy	6	3,809,848	11.52	330,706	Southern Europe
Prediction	Cordoba	Spain	6	3,772,305	14.15	266,611	Southern Europe
Prediction	Padova	Italy	6	3,731,408	12.05	309673.6697	Southern Europe
Prediction	Pescara	Italy	5	3,669,379	19.80	185,278	Southern Europe
Prediction	Skopje	TFYR Macedonia	5	3,595,469	13.84	259,861	Southern Europe
Prediction	Salerno	Italy	5	3,585,574	27.39	130,916	Southern Europe
Prediction	Verona	Italy	5	3,567,709	13.45	265,169	Southern Europe

Table 6.18: Southern Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Parma	Italy	5	3,556,020	22.86	155,552	Southern Europe
Prediction	Latina	Italy	5	3,531,853	41.41	85,294	Southern Europe
Prediction	Taranto	Italy	4	3,522,163	19.12	184256.7907	Southern Europe
Prediction	Modena	Italy	4	3,513,842	21.52	163,295	Southern Europe
Prediction	Reggio Emilia	Italy	4	3,478,377	26.11	133,231	Southern Europe
Prediction	Cagliari	Italy	4	3,455,940	12.61	274,050	Southern Europe
Prediction	Sarajevo	Bosnia and Herzegovina	3	3,326,069	10.94	304,145	Southern Europe
Prediction	Treviso	Italy	2	3,040,302	13.37	227,376	Southern Europe
Prediction	Vicenza	Italy	2	3,007,595	17.13	175620.0454	Southern Europe

Table 6.19: Sub-Saharan Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Luanda	Angola	16	10,306,738	1.54	6,691,566	Sub-Saharan Africa
Prediction	Lagos Ikorodu	Nigeria	16	10,084,651	0.81	12,397,810	Sub-Saharan Africa
Prediction	Kaduna	Nigeria	16	9,935,328	7.97	1,247,316	Sub-Saharan Africa
Prediction	Nairobi	Kenya	16	9,844,305	2.24	4,393,681	Sub-Saharan Africa
Prediction	Abomey-Calavi Cotonou	Benin	16	9,773,449	5.97	1,637,427	Sub-Saharan Africa
Prediction	Kigali	Rwanda	16	9,346,958	9.66	967240.3306	Sub-Saharan Africa
Prediction	Kumasi	Ghana	16	9,265,063	3.00	3090695.075	Sub-Saharan Africa
Prediction	Port Harcourt	Nigeria	15	8,964,732	7.82	1,146,346	Sub-Saharan Africa
Prediction	Kinshasa Brazzaville	Democratic Republic of the Congo	15	8,949,996	1.21	7,385,796	Sub-Saharan Africa

Table 6.19: Sub-Saharan Africa predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Kano	Nigeria	15	8,748,673	2.35	3,727,788	Sub-Saharan Africa
Prediction	Bamako	Mali	15	8,673,688	2.81	3087434.348	Sub-Saharan Africa
Prediction	Dar es Salaam	United Republic of Tanzania	15	8,637,919	1.91	4,529,511	Sub-Saharan Africa
Prediction	Accra	Ghana	15	8,444,372	2.10	4,012,944	Sub-Saharan Africa
Prediction	Addis Ababa	Ethiopia	15	8,429,419	2.62	3,220,578	Sub-Saharan Africa
Prediction	Dakar	Senegal	15	8,337,225	2.82	2959308.584	Sub-Saharan Africa
Prediction	Johannesburg	South Africa	14	8,216,642	1.53	5370157.857	Sub-Saharan Africa
Prediction	Douala	Cameroon	14	8,207,777	4.55	1,802,645	Sub-Saharan Africa
Prediction	Maputo Matola	Mozambique	14	8,169,435	3.54	2,305,992	Sub-Saharan Africa
Prediction	Cape Town	South Africa	14	8,114,225	2.44	3,327,148	Sub-Saharan Africa

Table 6.19: Sub-Saharan Africa predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Prediction	Pretoria Soshanguve	South Africa	14	8,073,666	2.99	2699690.449	Sub-Saharan Africa
Prediction	Ouagadougou	Burkina Faso	14	8,061,254	2.96	2,724,739	Sub-Saharan Africa
Prediction	Lusaka	Zambia	14	7,976,324	3.62	2203952.121	Sub-Saharan Africa
Prediction	Maiduguri	Nigeria	14	7,969,130	9.75	817,284	Sub-Saharan Africa
Prediction	Durban	South Africa	14	7,966,986	2.84	2,801,578	Sub-Saharan Africa
Prediction	Lubumbashi	Democratic Republic of the Congo	14	7,966,049	3.92	2,033,628	Sub-Saharan Africa
Prediction	Harare	Zimbabwe	14	7,952,063	6.20	1,281,824	Sub-Saharan Africa
Prediction	Kampala	Uganda	14	7,916,340	2.76	2,867,997	Sub-Saharan Africa
Prediction	Abuja	Nigeria	13	7,734,394	6.60	1,172,506	Sub-Saharan Africa
Prediction	Antananarivo	Madagascar	13	7,710,307	4.63	1,664,641	Sub-Saharan Africa

Table 6.19: Sub-Saharan Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Benin City	Nigeria	13	7,511,317	6.58	1,141,873	Sub-Saharan Africa
Prediction	Mombasa	Kenya	13	7,506,841	7.38	1,016,502	Sub-Saharan Africa
Prediction	Nouakchott	Mauritania	13	7,483,369	7.12	1051054.164	Sub-Saharan Africa
Prediction	Aba	Nigeria	13	7,432,226	7.41	1002950.433	Sub-Saharan Africa
Prediction	Onitsha	Nigeria	13	7,411,541	6.56	1130148.789	Sub-Saharan Africa
Prediction	Lilongwe	Malawi	13	7,409,640	7.31	1013177.296	Sub-Saharan Africa
Prediction	Niamey	Niger	13	7,387,722	7.78	949,266	Sub-Saharan Africa
Prediction	Conakry	Guinea	13	7,344,889	5.01	1,466,191	Sub-Saharan Africa
Prediction	Monrovia	Liberia	13	7,233,813	5.79	1,249,879	Sub-Saharan Africa
Prediction	Bujumbura Uvira	Burundi	13	7,101,733	7.81	909675.5192	Sub-Saharan Africa
Prediction	Freetown	Sierra Leone	12	7,042,907	6.46	1090912.497	Sub-Saharan Africa
Prediction	Ilorin	Nigeria	12	6,834,208	8.12	842099.9122	Sub-Saharan Africa

Table 6.19: Sub-Saharan Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Bangui	Central African Republic	12	6,670,348	7.89	844,962	Sub-Saharan Africa
Prediction	Blantyre-Limbe	Malawi	12	6,283,792	7.70	815,563	Sub-Saharan Africa
Prediction	Port Elizabeth	South Africa	12	6,161,061	8.23	748271.574	Sub-Saharan Africa
Prediction	Libreville	Gabon	12	6,000,875	9.04	664,094	Sub-Saharan Africa
Prediction	Sekondi Takoradi	Ghana	11	5,305,679	8.27	641,711	Sub-Saharan Africa
Prediction	Banjul	Gambia	10	5,138,604	7.00	734321.6722	Sub-Saharan Africa
Prediction	Warri	Nigeria	10	4,979,231	9.02	551,731	Sub-Saharan Africa
Prediction	Nampula	Mozambique	9	4,701,427	9.16	513,137	Sub-Saharan Africa
Prediction	Katsina	Nigeria	9	4,694,186	11.04	425,099	Sub-Saharan Africa
Prediction	Owerri	Nigeria	9	4,667,929	12.95	360,456	Sub-Saharan Africa
Prediction	Bloemfontein	South Africa	9	4,618,568	9.37	492,789	Sub-Saharan Africa

Table 6.19: Sub-Saharan Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Enugu	Nigeria	9	4,529,049	6.72	674,450	Sub-Saharan Africa
Prediction	Sokoto	Nigeria	9	4,525,722	6.55	691,441	Sub-Saharan Africa
Prediction	Zaria	Nigeria	9	4,481,627	6.71	668,087	Sub-Saharan Africa
Prediction	Oshogbo	Nigeria	9	4,478,160	6.45	693,983	Sub-Saharan Africa
Prediction	Zanzibar	United Republic of Tanzania	8	4,406,386	6.77	650,522	Sub-Saharan Africa
Prediction	Jos	Nigeria	8	4,376,727	6.95	630085.383	Sub-Saharan Africa
Prediction	Minna	Nigeria	8	4,299,050	12.25	350,882	Sub-Saharan Africa
Prediction	Mwanza	United Republic of Tanzania	8	4,251,300	6.82	622963.8335	Sub-Saharan Africa
Prediction	Bulawayo	Zimbabwe	7	4,215,978	8.14	518,090	Sub-Saharan Africa

Table 6.19: Sub-Saharan Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Uyo	Nigeria	7	4,208,063	8.15	516,339	Sub-Saharan Africa
Prediction	Djibouti	Djibouti	7	4,185,189	8.62	485,513	Sub-Saharan Africa
Prediction	Pietermaritzburg	South Africa	7	4,164,411	8.41	494989.1117	Sub-Saharan Africa
Prediction	Arusha	United Republic of Tanzania	7	4,140,751	7.38	561,192	Sub-Saharan Africa
Prediction	Windhoek	Namibia	7	4,137,897	11.10	372,677	Sub-Saharan Africa
Prediction	Kitwe	Zambia	7	4,071,900	8.78	463943.1832	Sub-Saharan Africa
Prediction	Abeokuta	Nigeria	7	3,981,444	8.07	493221.3665	Sub-Saharan Africa
Prediction	Akure	Nigeria	6	3,857,703	8.34	462,523	Sub-Saharan Africa
Prediction	Bissau	Guinea-Bissau	6	3,783,353	8.93	423,589	Sub-Saharan Africa
Prediction	Nakuru	Kenya	6	3,771,678	8.45	446,166	Sub-Saharan Africa

Table 6.19: Sub-Saharan Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Vereeniging	South Africa	6	3,737,276	10.72	348,692	Sub-Saharan Africa
Prediction	Chitungwiza	Zimbabwe	5	3,665,735	9.08	403,630	Sub-Saharan Africa
Prediction	Kisangani	Democratic Republic of the Congo	5	3,617,822	10.00	361,884	Sub-Saharan Africa
Prediction	Kolwezi	Democratic Republic of the Congo	5	3,574,430	32.92	108,585	Sub-Saharan Africa
Prediction	Tamale	Ghana	4	3,411,395	12.74	267850.845	Sub-Saharan Africa
Prediction	Zinder	Niger	3	3,247,511	16.42	197,816	Sub-Saharan Africa
Prediction	Lubango	Angola	3	3,234,684	11.70	276,523	Sub-Saharan Africa
Prediction	Ndola	Zambia	3	3,217,589	9.25	347,712	Sub-Saharan Africa
Prediction	Witbank	South Africa	3	3,214,241	9.43	341,016	Sub-Saharan Africa

Table 6.19: Sub-Saharan Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Pointe-Noire	Congo	3	3,214,130	9.23	348,233	Sub-Saharan Africa
Prediction	Bobo-Dioulasso	Burkina Faso	3	3,168,970	9.60	330,117	Sub-Saharan Africa
Prediction	Beira	Mozambique	3	3,119,051	10.23	304769.6038	Sub-Saharan Africa
Prediction	East London	South Africa	3	3,117,763	10.88	286,634	Sub-Saharan Africa
Prediction	Likasi	Democratic Republic of the Congo	2	3,052,601	8.99	339,735	Sub-Saharan Africa
Prediction	Huambo	Angola	2	3,011,754	13.09	230,061	Sub-Saharan Africa
Prediction	Umuahia	Nigeria	2	2,907,867	9.31	312,330	Sub-Saharan Africa
Prediction	Matadi	Democratic Republic of the Congo	1	2,795,467	19.04	146,822	Sub-Saharan Africa
Prediction	Asmara	Eritrea	1	2,784,611	10.76	258,911	Sub-Saharan Africa

Table 6.19: Sub-Saharan Africa predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Rustenburg	South Africa	1	2,754,126	16.01	172,055	Sub-Saharan Africa
Prediction	Calabar	Nigeria	1	2,740,852	9.51	288145.2134	Sub-Saharan Africa
Prediction	Hargeysa	Somalia	1	2,705,668	50.31	53,785	Sub-Saharan Africa
Prediction	Ado-Ekiti	Nigeria	1	2,702,284	9.81	275,565	Sub-Saharan Africa
Prediction	Makurdi	Nigeria	1	2,688,461	11.01	244,073	Sub-Saharan Africa
Prediction	Lokoja	Nigeria	1	2,667,096	39.56	67413.17624	Sub-Saharan Africa
Prediction	Gombe	Nigeria	1	2,661,983	14.33	185,794	Sub-Saharan Africa
Prediction	Mekele	Ethiopia	1	2,659,932	24.02	110,728	Sub-Saharan Africa
Prediction	Bauchi	Nigeria	1	2,654,792	10.90	243629.6773	Sub-Saharan Africa
Prediction	Ife	Nigeria	1	2,575,056	10.10	255,032	Sub-Saharan Africa

Table 6.20: Western Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**GMP per capita**	**Sub-region**
Prediction	Istanbul Gebze	Turkey	18	15,762,995	1.24	12,739,837	Western Asia
Prediction	Baghdad	Iraq	17	12,019,683	2.65	4,530,842	Western Asia
Prediction	Yerevan	Armenia	17	10,722,038	10.09	1,062,693	Western Asia
Prediction	Ankara	Turkey	16	10,295,461	2.79	3,684,676	Western Asia
Prediction	Dubayy (Dubai) Sharjah Ajman	United Arab Emirates	16	10,236,506	5.48	1,867,223	Western Asia
Prediction	Bayrut (Beirut)	Lebanon	16	10,141,228	3.16	3214058.059	Western Asia
Prediction	Amman Zarqa Ar-Rusayfah	Jordan	16	10,051,886	3.19	3,151,703	Western Asia
Prediction	Dimashq (Damascus)	Syrian Arab Republic	16	10,011,055	3.02	3,315,214	Western Asia

Table 6.20: Western Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**GMP per capita**	**Sub-region**
Prediction	Ar-Riyadh (Riyadh)	Saudi Arabia	16	9,325,638	2.60	3580564.977	Western Asia
Prediction	Baku Sumquayit	Azerbaijan	16	9,302,242	3.71	2507163.339	Western Asia
Prediction	Tel Aviv-Yafo (Tel Aviv-Jaffa)	Israel	16	9,283,744	3.53	2,626,707	Western Asia
Prediction	Al Kuwayt (Kuwait City)	Kuwait	16	9,146,366	4.17	2,193,943	Western Asia
Prediction	Izmir	Turkey	16	9,050,364	3.82	2,371,900	Western Asia

Table 6.20: Western Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	GMP per capita	Sub-region
Prediction	Ad-Dawhah (Doha) Ad-Dawhah (Doha) Ar-Rayyan	Qatar	15	8,929,732	3.06	2,914,554	Western Asia
Prediction	Jerusalem	Israel	15	8,929,563	5.98	1,494,435	Western Asia
Prediction	Bursa	Turkey	15	8,509,680	5.40	1,574,982	Western Asia
Prediction	Halab (Aleppo)	Syrian Arab Republic	15	8,482,556	4.66	1,822,216	Western Asia
Prediction	Tbilisi	Georgia	15	8,292,737	7.91	1,047,828	Western Asia
Prediction	Jiddah	Saudi Arabia	15	8,250,716	4.92	1,678,241	Western Asia
Prediction	Al-Manamah (Manama)	Bahrain	14	8,079,483	4.74	1,702,891	Western Asia
Prediction	Sana'a'	Yemen	14	8,046,014	3.44	2,335,651	Western Asia
Prediction	Gaziantep	Turkey	14	7,972,216	6.87	1160674.551	Western Asia

Table 6.20: Western Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	GMP per capita	Sub-region
Prediction	Ad-Dammam	Saudi Arabia	13	7,760,923	8.02	967,283	Western Asia
Prediction	Mersin	Turkey	12	6,714,699	8.24	815,099	Western Asia
Prediction	Antalya	Turkey	12	6,318,663	8.47	746,268	Western Asia
Prediction	Ta'izz	Yemen	12	6,288,730	7.86	799,685	Western Asia
Prediction	Al-Basrah (Basra)	Iraq	11	5,753,775	8.87	648827.0165	Western Asia
Prediction	Kayseri	Turkey	11	5,531,449	8.09	683,538	Western Asia
Prediction	Adana	Turkey	11	5,530,198	8.18	676423.8649	Western Asia
Prediction	Izmit	Turkey	11	5,318,733	8.28	642,533	Western Asia
Prediction	Samsun	Turkey	11	5,238,385	14.81	353,605	Western Asia
Prediction	Konya	Turkey	10	5,139,001	8.07	636,532	Western Asia
Prediction	Irbil (Erbil)	Iraq	10	5,018,410	24.14	207,859	Western Asia
Prediction	Hims (Homs)	Syrian Arab Republic	10	4,974,382	8.85	562018.9212	Western Asia
Prediction	Adan (Aden)	Yemen	10	4,957,840	8.94	554,743	Western Asia

Table 6.20: Western Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**GMP per capita**	**Sub-region**
Prediction	Eskisehir	Turkey	10	4,767,164	9.86	483335.0093	Western Asia
Prediction	Al-Madinah (Medina)	Saudi Arabia	9	4,717,785	11.91	396254.1208	Western Asia
Prediction	Kirkuk	Iraq	9	4,680,524	15.81	296,115	Western Asia
Prediction	Van	Turkey	9	4,598,024	12.32	373,245	Western Asia
Prediction	Denizli	Turkey	9	4,533,627	9.84	460522.3497	Western Asia
Prediction	Sanliurfa	Turkey	8	4,436,247	10.45	424,672	Western Asia
Prediction	Diyarbakir	Turkey	8	4,354,763	10.41	418,265	Western Asia
Prediction	Irbid	Jordan	8	4,348,123	10.54	412,682	Western Asia
Prediction	Lattakia	Syrian Arab Republic	8	4,309,253	11.81	364946.1545	Western Asia
Prediction	Hefa (Haifa)	Israel	8	4,297,973	10.80	397884.947	Western Asia
Prediction	Al-Hudaydah	Yemen	7	4,216,469	10.49	401,787	Western Asia

Table 6.20: Western Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**GMP per capita**	**Sub-region**
Prediction	Makkah (Mecca)	Saudi Arabia	7	4,201,396	10.53	398,848	Western Asia
Prediction	Abu Zaby (Abu Dhabi)	United Arab Emirates	7	4,093,905	11.70	349,859	Western Asia
Prediction	Karbala	Iraq	6	3,880,327	11.34	342,206	Western Asia
Prediction	Al-Mukalla	Yemen	6	3,873,038	32.45	119360.1212	Western Asia
Prediction	Kahramanmaras	Turkey	6	3,773,857	11.33	333177.5558	Western Asia
Prediction	Ibb	Yemen	6	3,772,068	9.39	401,853	Western Asia
Prediction	Najaf	Iraq	6	3,713,245	12.17	305,083	Western Asia
Prediction	Batman	Turkey	6	3,713,029	11.63	319,219	Western Asia
Prediction	Sulaimaniya	Iraq	6	3,708,972	12.08	307,056	Western Asia
Prediction	Amara	Iraq	5	3,669,079	25.17	145782.2177	Western Asia
Prediction	Al-Mawsil (Mosul)	Iraq	5	3,631,322	14.64	248,058	Western Asia

Table 6.20: Western Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	GMP per capita	Sub-region
Prediction	Sivas	Turkey	5	3,624,121	15.36	235,969	Western Asia
Prediction	Manisa	Turkey	5	3,586,319	12.04	297,940	Western Asia
Prediction	Nasiriyah	Iraq	5	3,548,885	15.13	234,528	Western Asia
Prediction	Erzurum	Turkey	5	3,541,851	28.28	125,227	Western Asia
Prediction	Hamah	Syrian Arab Republic	5	3,529,531	14.95	236,077	Western Asia
Prediction	Hillah	Iraq	5	3,529,253	24.35	144,921	Western Asia
Prediction	Al-Raqqa	Syrian Arab Republic	5	3,522,340	26.19	134,471	Western Asia
Prediction	Diwaniyah	Iraq	4	3,515,640	30.32	115,959	Western Asia
Prediction	Kut	Iraq	4	3,515,289	27.80	126456.2652	Western Asia
Prediction	Elazig	Turkey	4	3,512,866	13.92	252,373	Western Asia
Prediction	Masqat (Muscat)	Oman	4	3,507,241	11.22	312,492	Western Asia
Prediction	Tartus	Syrian Arab Republic	4	3,501,349	27.51	127,298	Western Asia
Prediction	Malatya	Turkey	4	3,494,484	12.13	288,186	Western Asia

Table 6.20: Western Asia predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	GMP per capita	Sub-region
Prediction	Be'er Sheva	Israel	4	3,486,169	22.47	155149.4038	Western Asia
Prediction	Deir El-Zor (Deir ez-Zor)	Syrian Arab Republic	4	3,484,190	27.94	124,692	Western Asia
Prediction	Al-Kamishli	Syrian Arab Republic	4	3,476,488	18.76	185,280	Western Asia
Prediction	Sakarya	Turkey	4	3,466,883	17.32	200154.4535	Western Asia
Prediction	Al-Hasakah	Syrian Arab Republic	4	3,441,417	21.66	158,849	Western Asia
Prediction	Buraydah	Saudi Arabia	4	3,367,819	50.00	67,352	Western Asia
Prediction	Tabuk	Saudi Arabia	4	3,366,214	40.64	82,839	Western Asia
Prediction	Hafar al-Batin	Saudi Arabia	4	3,360,648	53.81	62451.75789	Western Asia
Prediction	Hufuf-Mubarraz	Saudi Arabia	3	3,350,133	17.30	193,666	Western Asia
Prediction	Ha'il	Saudi Arabia	3	3,344,772	66.46	50330.45527	Western Asia
Prediction	Al-Ain	United Arab Emirates	3	3,333,506	19.36	172,165	Western Asia
Prediction	Jubayl	Saudi Arabia	3	3,314,051	23.09	143,499	Western Asia

Table 6.20: Western Asia predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**GMP per capita**	**Sub-region**
Prediction	Taif	Saudi Arabia	3	3,313,772	31.67	104649.3944	Western Asia
Prediction	Najran	Saudi Arabia	3	3,307,229	20.05	164,924	Western Asia
Prediction	Khamis Mushayt	Saudi Arabia	3	3,281,379	16.46	199350.7467	Western Asia
Prediction	Faloojah	Iraq	3	3,205,124	56.71	56520.64818	Western Asia
Prediction	Ramadi	Iraq	3	3,120,597	27.16	114,914	Western Asia
Prediction	Baaqoobah	Iraq	2	3,041,761	43.63	69,717	Western Asia

Table 6.21: Western Europe predictions

Data set	City Name	Country	Ventile	GMP	GMP per capita	Population	Sub-region
Calibration/Validation	Paris	France	20	578,790,002	49.50	11693218	Western Europe
Calibration/Validation	Munich	Germany	20	146,077,000	51.35	2,844,749	Western Europe
Calibration/Validation	Hamburg	Germany	20	134,128,000	44.93	2984966	Western Europe
Calibration/Validation	Berlin	Germany	20	131,116,000	29.97	4,374,708	Western Europe
Calibration/Validation	Frankfurt	Germany	20	122,873,000	48.80	2,517,805	Western Europe
Calibration/Validation	Brussels	Belgium	20	113,709,000	45.75	2,485,480	Western Europe
Calibration/Validation	Vienna	Austria	20	107,616,000	40.11	2,683,251	Western Europe
Calibration/Validation	Amsterdam	Netherlands	20	93,485,000	39.60	2,360,958	Western Europe
Calibration/Validation	Stuttgart	Germany	20	83,849,000	42.89	1,954,756	Western Europe
Calibration/Validation	Cologne	Germany	20	72,699,000	38.20	1,903,154	Western Europe
Calibration/Validation	Lyon	France	20	69,117,000	36.47	1,894,945	Western Europe
Calibration/Validation	Zurich	Switzerland	20	58,058,000	48.13	1206312	Western Europe
Calibration/Validation	Dusseldorf	Germany	20	56,420,000	39.51	1,428,162	Western Europe

Table 6.21: Western Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Rotterdam	Netherlands	20	55,002,000	37.04	1,484,830	Western Europe
Calibration/Validation	Marseille	France	20	51,930,000	30.15	1722236	Western Europe
Calibration/Validation	Mannheim	Germany	20	45,297,000	36.50	1,240,964	Western Europe
Calibration/Validation	Nuremberg	Germany	20	44,985,000	38.55	1,166,976	Western Europe
Calibration/Validation	Hanover	Germany	20	44,420,000	36.33	1,222,773	Western Europe
Calibration/Validation	Antwerp	Belgium	19	39,332,000	37.33	1,053,725	Western Europe
Calibration/Validation	Toulouse	France	19	38,680,000	31.77	1217316	Western Europe
Calibration/Validation	Bremen	Germany	19	37,363,000	36.43	1,025,580	Western Europe
Calibration/Validation	Lille	France	19	33,968,000	25.18	1,349,194	Western Europe
Calibration/Validation	Bordeaux	France	19	32,757,000	29.20	1,121,983	Western Europe
Calibration/Validation	Geneva	Switzerland	19	31,432,000	40.04	785022	Western Europe
Calibration/Validation	The Hague	Netherlands	19	30,678,000	35.17	872289	Western Europe
Calibration/Validation	Utrecht	Netherlands	19	30,142,000	42.06	716648	Western Europe

Table 6.21: Western Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Duisburg	Germany	19	29,820,000	36.79	810,525	Western Europe
Calibration/Validation	Basel	Switzerland	19	29,618,000	38.63	766,619	Western Europe
Calibration/Validation	Bonn	Germany	19	29,304,000	39.28	746,013	Western Europe
Calibration/Validation	Karlsruhe	Germany	19	27,683,000	40.30	686,938	Western Europe
Calibration/Validation	Nantes	France	19	25,763,000	29.61	870,046	Western Europe
Calibration/Validation	Essen	Germany	19	25,717,000	33.97	757,019	Western Europe
Calibration/Validation	Dortmund	Germany	19	25,551,000	31.04	823,139	Western Europe
Calibration/Validation	Nice	France	19	25,521,000	30.20	845,186	Western Europe
Calibration/Validation	Eindhoven	Netherlands	19	25,313,000	36.74	689018	Western Europe
Calibration/Validation	Linz	Austria	19	23,044,000	37.99	606514	Western Europe
Calibration/Validation	Strasbourg	France	19	22,553,000	29.72	758,724	Western Europe
Calibration/Validation	Leipzig	Germany	19	21,708,000	25.92	837,610	Western Europe
Calibration/Validation	Dresden	Germany	18	21,246,000	25.38	836,995	Western Europe

Table 6.21: Western Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Graz	Austria	18	20,867,000	34.30	608,420	Western Europe
Calibration/Validation	Augsburg	Germany	18	19,912,000	33.29	598,063	Western Europe
Calibration/Validation	Grenoble	France	18	19,424,000	29.92	649,285	Western Europe
Calibration/Validation	Bochum	Germany	18	19,197,000	29.72	646,036	Western Europe
Calibration/Validation	Saarbrucken	Germany	18	18,895,000	32.09	588,734	Western Europe
Calibration/Validation	Rennes	France	18	18,611,000	27.70	671,929	Western Europe
Calibration/Validation	Rouen	France	18	18,443,000	26.41	698,385	Western Europe
Calibration/Validation	Liege	Belgium	18	17,842,000	24.56	726,431	Western Europe
Calibration/Validation	Munster	Germany	18	17,396,000	31.92	544,962	Western Europe
Calibration/Validation	Freiburg im Breisgau	Germany	18	17,199,000	32.60	527,581	Western Europe
Calibration/Validation	Ghent	Belgium	18	16,933,000	29.38	576408	Western Europe
Calibration/Validation	Montpellier	France	18	16,583,000	26.08	635,897	Western Europe

Table 6.21: Western Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Calibration/Validation	Aachen	Germany	18	15,681,000	27.06	579,473	Western Europe
Calibration/Validation	Toulon	France	17	13,206,000	24.11	547703	Western Europe
Calibration/Validation	Saint-Etienne	France	17	12,963,000	24.90	520667	Western Europe
Prediction	Charleroi	Belgium	6	3,747,540	14.85	252,388	Western Europe
Prediction	Bern	Switzerland	5	3,598,531	16.41	219245.5489	Western Europe
Prediction	Avignon	France	5	3,591,704	21.63	166,047	Western Europe
Prediction	Lausanne	Switzerland	5	3,587,193	12.52	286,582	Western Europe
Prediction	Douai-Lens	France	5	3,561,991	35.73	99698.28106	Western Europe
Prediction	Bielefeld	Germany	4	3,506,625	20.81	168,510	Western Europe
Prediction	Tours	France	4	3,504,640	15.25	229847.3046	Western Europe
Prediction	Valenciennes	France	4	3,486,875	23.24	150,021	Western Europe
Prediction	Muenster (Westfalen)	Germany	2	3,081,170	15.10	203991.6295	Western Europe

Table 6.21: Western Europe predictions

Data set	**City Name**	**Country**	**Ventile**	**GMP**	**GMP per capita**	**Population**	**Sub-region**
Prediction	Wuppertal	Germany	2	3,076,597	16.02	192,014	Western Europe

Chapter 7

CONCLUSION AND DISCUSSION

7.1 Conclusion

This thesis sets out to find a method to reliably estimate metropolitan areas' gross economic output using publicly available data, ranging from Census data to satellite imagery. We utilized various raster images and cross-sectional data sets to create a feature vector for different statistical learning models. Random forest was chosen as the most accurate predictive model. The model was then trained on 409 observations and tested for 102 observations. Finally, we used this random forest for estimating 1298 cities' GMP and grouped the predictions into 20 groups, the first group showing the poorest city and the last group showing the wealthiest city.

We conclude that the combination of socioeconomic data, big data (in the form of satellite imagery, and statistical learning methods can provide us with the first set of useful predictions regarding the distribution of GMP across the globe.

7.2 Discussion

Chen and Nordhouse 2010 [8] is one of the pioneering research works that assesses the impact of nighttime satellite images in estimating economic growth. While this paper finds luminosity to be a poor predictor of growth especially in the developed world, we find this spatial data source to be quite a useful proxy. We were able to derive numerous explanatory variables that account for luminosity and urban form by using the satellite images and the city boundaries. The difference between the previously conducted research and the one at hand is also noteworthy.

The Chen and Nordhouse 2010 [8] and many other research studies, looks at one nighttime lights image only, with high probabilities of saturation, while we utilize three sources of luminosity that are designed to battle saturation in city centers and to capture urban form specifically.Chen and Nordhouse 2010 [8] and Henderson et al. 2012 [25] studies, are conducted over a panel data with countries as the study subject scale. However, we used longitudinal data for 2010 and set the metropolitan areas as the subject of this thesis. These two studies are also fundamentally different in their methodology for achieving estimations. This thesis utilizes a way more complex methodology than its predecessors in the field.

There were many challenges and limitations regarding this research. We address some of the limitations and recommend possible solutions aiming at future work in the following paragraphs.

Firstly, we decided to use the web projection that is widely used in online maps (EPSG:3857 - WGS 84 / Pseudo-Mercator) as our target coordinate reference system (CRS) for reprojecting raster images. While this reprojection converts map units from decimal degrees to meters, it contains distortions as we move away from the equator towards the North. Therefore, we suggest each raster be tiled according to the 60 UTM zones and reprojected based on each zones formula to remedy the distortions in the map.

Additionally, we have not fully utilized the theoretical significance of population as a predictor for the GMP. According to the urban scaling law theory [2], GMP exhibits a scaling relationship with each cities population within each country. Based on specific characteristics of an urban system, the scaling relationship is characterized by a scaling coefficient that ranges from 1 to 1.15. This range follows both theoretical and empirical studies. Consequently, we believe that a bootstrap method such as the one we applied for the downscaling technique will allow us in the future to introduce predictions that take into consideration urban scaling theory.

We also anticipate our future work to include self reported data and manufacturing sector of the GDP. There are various ways to collect insights into the urabn structure. Self reporting data can be a goof proxy of how well an urban areas is doing. Consequently, self reported data can be helpful in GMP estimation. In addition, the manufacturing portion of the GDP is especially significant in some of the developing world. As a result, we plan to include this metric in the downscaling process in our future work.

Finally, because the training and testing data include many developed countries' metropolitan areas, we cannot make lower predictions than the lowest observation in the training dataset. We included various GDP-based downscaled estimations of the GMP in order to account for different regions that were not included in the training/testing data. However, we suggest the inclusion of simulations made through a WGAN model in our machine learning models to represent data is not considered in the models. In addition, simulation data can be introduced to the model to increase the models' training spectrum and, thus, predictions.

Chapter 8

APPENDIX

Table 8.1: Urban form metrics' description [26]

Indicator	**Significance/Description**
Number of patches (Aggregation metric)	"where n_i is the number of patches. NP is an 'Aggregation metric'. It describes the fragmentation of a class, however, does not necessarily contain information about the configuration or composition of the class. Equals $NP = 1$ when only one patch is present and increases, without limit, as the number of patches increases"
Aggregation index (Aggregation metric)	"where g_{ii} is the number of like adjacencies based on the single-count method and $max - g_{ii}$ is the classwise maximum number of like adjacencies of class i. AI is an 'Aggregation metric'. It equals the number of like adjacencies divided by the theoretical maximum possible number of like adjacencies for that class. The metric is based on he adjacency matrix and the the single-count method".

Table 8.1: Urban form metrics' description [26]

Indicator	Significance/Description
Mean of patch area (Area and edge metric)	"where $AREA[patch_{ij}]$ is the area of each patch in hectares AREA_MN is an 'Area and Edge metric'. The metric summarises each class as the mean of all patch areas belonging to class i. The metric is a simple way to describe the composition of the landscape. Especially together with the total class area (lsm_c_ca), it can also give an an idea of patch structure (e.g. many small patches vs. few larges patches)".
Mean of core area index (Core area metric)	"where $CAI[patch_{ij}]$ is the core area index of each patch. CAI_{MN} is a 'Core area metric'. The metric summarises each class as the mean of the core area index of all patches belonging to class i. The core area index is the percentage of core area in relation to patch area. A cell is defined as core area if the cell has no neighbour with a different value than itself (rook's case)".

Table 8.1: Urban form metrics' description [26]

Indicator	Significance/Description
Clumpiness index (Aggregation metric)	"where g_{ii} is the number of like adjacencies, g_{ik} is the classwise number of all adjacencies including the focal class, minei is the minimum perimeter of the total class in terms of cell surfaces assuming total clumping and P_i is the proportion of landscape occupied by each class. CLUMPY is an 'Aggregation metric'. It equals the proportional deviation of the proportion of like adjacencies involving the corresponding class from that expected under a spatially random distribution. The metric is based on he adjacency matrix and the the double-count method."
Patch Cohesion Index (Aggregation metric)	"where p_{ij} is the perimeter in meters, aij is the area in square meters and Z is the number of cells. COHESION is an 'Aggregation metric'. It characterises the connectedness of patches belonging to class i. It can be used to asses if patches of the same class are located aggregated or rather isolated and thereby COHESION gives information about the configuration of the landscape."

Table 8.1: Urban form metrics' description [26]

Indicator	Significance/Description
Mean of Contiguity index (Shape metric)	"where $CONTIG[patch_{ij}]$ is the contiguity of each patch. $CONTIG\_MN$ is a 'Shape metric'. It summarises each class as the mean of each patch belonging to class i. CONTIG_MN asses the spatial connectedness (contiguity) of cells in patches. The metric coerces patch values to a value of 1 and the background to NA. A nine cell focal filter matrix is then used to weight orthogonally contiguous pixels more heavily than diagonally contiguous pixels. Therefore, larger and more connections between patch cells in the rookie case result in larger contiguity index values."

Table 8.1: Urban form metrics' description [26]

Indicator	Significance/Description
Disjunct core area density (core area metric)	"where n_{ij}^{core} is the number of disjunct core areas and A is the total landscape area in square meters. DCAD is a 'Core area metric'. It equals the number of disjunct core areas per 100 ha relative to the total area. A disjunct core area is a 'patch within the patch' containing only core cells. A cell is defined as core area if the cell has no neighbour with a different value than itself (rook's case). The metric is relative and therefore comparable among landscapes with different total areas."
Edge Density (Area and Edge metric)	"where e_{ij} is the total edge length in meters and A is the total landscape area in square meters. ED is an 'Area and Edge metric'. The edge density equals the sum of all edges of class i in relation to the landscape area. The boundary of the landscape is only included in the corresponding total class edge length if count_boundary = TRUE. The metric describes the configuration of the landscape, e.g. because an aggregation of the same class will result in a low edge density. The metric is standardized to the total landscape area, and therefore comparisons among landscapes with different total areas are possible."

Table 8.1: Urban form metrics' description [26]

Indicator	**Significance/Description**
Largest patch index (Area and Edge metric)	"where $\max(a_{ij})$ is the area of the patch in square meters and A is the total landscape area in square meters. The largest patch index is an 'Area and edge metric'. It is the percentage of the landscape covered by the corresponding largest patch of each class i. It is a simple measure of dominance."
Landscape shape index (Aggregation metric)	"where e_i is the total edge length in cell surfaces and $\min e_i$ is the minimum total edge length in cell surfaces. LSI is an 'Aggregation metric'. It is the ratio between the actual edge length of class i and the hypothetical minimum edge length of class i. The minimum edge length equals the edge length if class i would be maximally aggregated."

Table 8.1: Urban form metrics' description [26]

Indicator	Significance/Description
Patch density (Aggregation metric)	"where n_i is the number of patches and A is the total landscape area in square meters. PD is an 'Aggregation metric'. It describes the fragmentation of a class, however, does not necessarily contain information about the configuration or composition of the class. In contrast to lsm_c_np it is standardized to the area and comparisons among landscapes with different total area are possible."
Percentage of Like Adjacencies (Aggregation metric)	"where g_{ij} is the number of adjacencies between cells of class i and g_{ik} is the number of adjacencies between cells of class i and k. PLADJ is an 'Aggregation metric'. It calculates the frequency how often patches of different classes i (focal class) and k are next to each other, and following is a measure of class aggregation. The adjacencies are counted using the double-count method."

Table 8.1: Urban form metrics' description [26]

Indicator	Significance/Description
Percentage of landscape of class (Area and Edge metric)	"where a_{ij} is the area of each patch and A is the total landscape area. PLAND is an 'Area and edge metric'. It is the percentage of the landscape belonging to class i. It is a measure of composition and because of the relative character directly comparable among landscapes with different total areas."
Mean shape index (Shape metric)	"where $SHAPE[patch_{ij}]$ is the shape index of each patch. SHAPE_MN is a 'Shape metric'. Each class is summarised as the mean of each patch belonging to class i. SHAPE describes the ratio between the actual perimeter of the patch and the hypothetical minimum perimeter of the patch. The minimum perimeter equals the perimeter if the patch would be maximally compact."
Splitting index (Aggregation metric)	"where a_{ij} is the patch area in square meters and A is the total landscape area. SPLIT is an 'Aggregation metric'. It describes the number of patches if all patches of class i would be divided into equally sized patches."

Table 8.1: Urban form metrics' description [26]

Indicator	Significance/Description
Total (class) edge (Area and Edge metric)	"where e_{ik} is the edge lengths in meters. TE is an 'Area and edge metric'. Total (class) edge includes all edges between class i and all other classes k. It measures the configuration of the landscape because a highly fragmented landscape will have many edges. However, total edge is an absolute measure, making comparisons among landscapes with different total areas difficult. If cound_boundary = TRUE also edges to the landscape boundary are included."

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