This Land Belongs to [redacted] and [redacted]: An Analysis of Overseas Companies Property Ownership in London from 2008-2019 and Onwards

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0.1 Abstract

Within the United Kingdom, and specifically Greater London, the nature of land ownership and specifically overseas ownership has historically often been opaque and difficult to ascertain. While recent reforms have allowed for some data to be made accessible regarding this topic, the released data often lacks vital context, and meaningful data like owner Title is still paywalled or not accessible to the public. As a result, there is a relative paucity of scholarship as it relates to a quantitative analysis of foreign land ownership within Greater London. The primary research question of this dissertation is to determine how the spatial distribution of overseas land owners within Greater London has changed over time, how may it change in the future, and can it be predicted? The secondary research questions of this dissertation compare these patterns in London to New York City, and also examine overseas ownership at the borough level in London It is hoped that by conducting this analysis, there is a better understanding of where foreign land ownership occurs and how it can perhaps be anticipated by local officials and journalists when conducting analyses of land ownership within Greater London.

0.2 Statement of Work and Ethics Statement

0.2.1 Statement of Work

I, Matthew Klovski, confirm that the work presented in this dissertation is my own. Where information has been derived from other sources, I confirm that this has been indicated within this dissertation. The word count of 11,037 words in length was derived using a LaTeX word counter.

0.2.2 Ethics Statement

For this dissertation it was determined, after discussion with the advisor Dr. Duncan Smith, that ethics approval was not necessary for the information or analysis contained within this dissertation. All information used is publically accessible information, provided by government open data portals, or other similar means of distribution. For the individual land owning entities contained within the Overseas Companies Ownership dataset, all are company or LLC names, and as such do not contain any personal information. Individual identity is not possible to be determined after conducting the various methods of analysis within this dissertation as well.

Contents

List of Figures

List of Tables

0.3 Acknowledgements

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I am very grateful to all the inhabitants of the robust open-source geospatial community as this dissertation relies on various tools and programs on which countless people have worked and contributed towards. When at all possible, these individuals and organizations have been cited accordingly within this

dissertation.

I would like to thank my parents and family for their continued support in my hopes, dreams, and aspirations throughout my entire life and for the countless sacrifices that they have made to allow me to be in this position in the first place.

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0.4 Literature Review

0.4.1 Introduction

Within the United Kingdom, the format in which land ownership is documented has long been unique from forms of documentation commonly seen in other countries (Grover, 2008). While a full overview of land ownership peculiarities within the United Kingdom is well beyond the scope of this dissertation, the two most relevant factors in this regard are the unique use of a freehold/leasehold system, and the lack of a public cadastral reference (Grover, 2008). The dual freehold/leasehold land ownership system, in which one individual can fully own a building, but still be obligated to pay rent to the owner of the land beneath the building, allows for division of land ownership between multiple entities on a single plot (Grover, 2008). This complex form land acquisition makes it difficult to ascertain the true ownership of a property, while the lack of a public cadaster and ownership record makes it difficult to even investigate a property in the first place by a member of the general public. A cadaster or cadastral system refers to the spatial representation of land ownership boundaries across a geographic area.

Historically these sorts of features have benefited the aristocratic class that is estimated to currently hold roughly 30% of all land in the UK (Shrubsole, 2019). Indeed, within Greater London the Dukes of Westminster hold a 9.5-billion-pound fortune, much of it based on wealth accumulated from freehold lease ownership of the Grosvenor Estate, which owns over 300 acres of Central London, in and around Hyde Park and Knightsbridge (Garside, 2017).

More recent beneficiaries of land ownership regulations within the United Kingdom however, have been foreign owners from various locations. While this phenomenon occurs throughout the United Kingdom, London contains about one-third of the roughly 90,000 foreign owned properties within the United Kingdom, a greater proportion of foreign owned properties than the percentage (13%) of people in the UK who live within the bounds of Greater London (HM Land Registry, 2019) (Trust for London, 2019). Within Greater London, there is still yet a spatial divide in terms of where these properties are located. While only 8% percent of all homes purchased in 2017 were purchased by foreign buyers in Greater London, in the central boroughs of the City of London, Westminster, and Kensington & Chelsea, that proportion is 36% (Wilson & Barton, 2017).

There are many complex reasons as to why London in particular is such an attractive destination for foreign land besides simply secrecy, ranging from land investment in London seen as a kind of insurance if the investor's home country is less than stable (Badarinza & Ramadorai, 2018) to it being seen as a form of status, with many properties purchased being located near Buckingham Palace (Smirnova, 2016). Regardless of the causes however, in the last 40-50 years, this phenomenon has increased substantially (Shrubsole, 2019). This increase can be linked to the concurrent rise of "tax-haven" entities during this time, as many tax havens are former British Empire territories and have historically close links to the United Kingdom and London (Palan, 2009). These former or current members of the United Kingdom's overseas possessions like the UK Virgin Islands or Jersey can be simply defined as

"...typically small, well-governed states that impose low or zero tax rates on foreign investors" (Dharmapala & Hines, 2009).

While this type of property acquisition and company registration is fully legal within the United Kingdom, many advocacy groups and various politicians allege that due to the lack of transparency, it is relatively easy to use laundered money to purchase property using an anonymous LLC headquartered in one of the tax havens (Smirnova, 2016). For individuals who may not have acquired the money used to purchase property through non-illicit means, this form of property ownership and it's accompanying ability to avoid scrutiny are highly attractive (Butler and Lees, 2006).

Attempts at Documentation

Up until recently, ascertaining the ownership of these properties would have been a futile task for a member of the public. Land ownership records were not digitized, not publicly accessible, and often did not even have a geographical representation of the property boundaries, leaving an individual to decipher the metes and bounds written in the document to determine the geographic extent of the property (Shrubsole, 2019). There have been multiple campaigns through recent British history to make this data more accessible and open to the public, but most did not meet with success, as the entrenched aristocracy helped ensure that these reforms, such as those attempted after the creation of The Return of Owners of Land Act in 1872, failed (Shrubsole, 2017) (Bryant, 2017).

Recently however, there have been key developments that have opened data previously inaccessible to the public. In 2018, the INSPIRE polygons for the United Kingdom were made publicly available for the first time. INSPIRE polygons are the geometric boundaries of land ownership, standardized to the INSPIRE directive from the European Union (HM Land Registry, 2019). The Corporate and Commercial and Overseas Companies Ownership datasets were also released in 2014 as well (HM Land Registry, 2019), which was also previously publicly unavailable.

While this has allowed for previously impossible analysis, there is still a great degree of opacity in these datasets, as none of the three datasets link geographic boundaries to land owner records in an individual manner. The INSPIRE polygons contain only a polygon ID field which is different from the owner ID also maintained by the Land Registry. Technically, this information is available from The Land Registry, as a Title for an individual property can be obtained from The Land Registry for three pounds a Title, with all ownership information contained within (HM Land Registry, 2019). However, in order to conduct any sort of analysis on a larger scale, this rapidly becomes financially infeasible. To just determine the true owners of the roughly 90,000 overseas company owned properties in the United Kingdom would cost roughly 270,000 pounds.

The information provided within the company ownership datasets also does not necessarily provide a fully accurate picture of land ownership within the United Kingdom. In both datasets, anonymized land holding LLCs are the listed owners of the land in question many times, with many headquartered in locations like the U.K Virgin Islands, the Isle of Man, and the American state of Delaware (HM Land Registry, 2019). While there is work currently undertaken by organizations like Private Eye and Transparency International investigating the true owners behind these shell companies (Brooks & Eriksson, 2016), tracing the true nature of ownership remains difficult. A particularly arcane example is the case of two flats within Whitehall Court, which are both owned by Sova Real Estate LLC, a Russian real estate company that obtained the lease from a British Virgin Islands company two years prior, that itself had obtained a lease from the Crown Estate (Brooks & Eriksson, 2016). The ownership of Sova Real Estate LLC was traced to Russian Deputy Prime Minister Igor Shuvalov. As his official salary is roughly 112,000 pounds, and the cost of the two apartments were 11.44 million pounds, this has led to questions of how they were obtained in the first place (Transparency International, 2018). This is just a small example of hurdles currently posed by the current system of land ownership registration.

Comparison to New York City

While the focus of this dissertation is primarily within Greater London, it would be remiss to not mention the fact that while this pattern of land ownership is highly prevalent within London, it is by no means unique to London. A particularly notable example is the Canadian city of Vancouver which is currently dealing with similar issues of foreign shell investment (Ley, 2015). However, the city perhaps most like London in terms of foreign investment, and the secondary focus of this dissertation is New York City, as both act as the primary locations of land investment by foreign buyers (Fernandez et al. 2016). According to a 2014 investigation by New York magazine, from 2008 to 2014, 30% of condominiums in Manhattan real estate developments were bought by foreign buyers (Rice, 2014).

A key difference between New York and London, especially in the context of this dissertation, is that while London land ownership is difficult to obtain, New York City has publicly downloadable cadastral information for all five boroughs in the city (NYC Department of City Planning, 2019). This dataset, referred to as the PLUTO (Property Land Use Tax Lot Output) dataset, contains more than 857,374 records as of 2019 (NYC Department of City Planning, 2019), and historical versions are downloadable dating back to 2002. These polygons, in addition to having a unique "parcel id", owner, and address, also contain detailed assessment information like square footage, number of rooms, and other assessor fields. However, the main drawback of this information as it relates to this dissertation is that foreign land ownership or corporate land ownership is not specifically denoted as such. To roughly approximate where these properties are located, properties owned by Limited Liability Companies are used as a proxy. While this ownership type does not automatically mean that a property is owned by a foreign owner, the use of LLCs is strongly associated with this type of ownership (Rice, 2014).

In both New York City and London, one of the consequences of foreign land ownership of this nature is the idea of "super-gentrification" (Lees, 2003). This can be defined as when a neighborhood changes from what could be considered a typical format of gentrification, in which well-off urbanites supplant existing residents, to one where the aforementioned urbanites are themselves replaced by empty residential units used as shell investment (Butler & Lees, 2006). This phenomenon has also led to large-scale public protests this type of investment, with a focus on when socially-owned housing is transitioned to the private market, with the potential to then be purchased by foreign investment (Townsend & Kelly, 2015).

0.4.2 Methods Review

Introduction

As the core data used within this dissertation was only released relatively recently in 2017, there is a relative lack of scholastic work focused on this dataset or work specifically focused on examining the spatial spread of foreign land ownership through a city. However, a robust body of work does exist on the similar topic of gentrification, with most relevant literature and methodology utilized in this dissertation derived from work that examines the spatial patterns of gentrification. The use of gentrification as an analogue when examining other academic practices, rather than other forms of modeled urban phenomena like crime or poverty, is that one of the hypotheses of this paper is that patterns of foreign investment, often themselves linked to causing gentrification (Glucksberg, 2016), follow the patterns of gentrification themselves. While traditionally gentrification was tracked using a traditional sociological framework involving personal interviews, ethnographies, and other qualitative methods (Reades et. al, 2018), the papers examined here attempt to examine the phenomenon of gentrification problems through a more quantitative and model-based approach.

For the purposes of this paper, quantitative analysis may be more effective in determining the exact extent of foreign investment and how it spreads through a city. Prior work examining the behavior of foreign land ownership sometimes focuses on interpersonal interviews with subjects involved within the actual foreign investment process within London, as well as anecdotal evidence of new condominium buildings being constructed in neighborhoods, with the new owners never actually occupying the property (Glucksberg, 2016). However, identification of foreign ownership is not directly possible by visual inspection due to the complexity of legal ownership structure. The single largest factor however, is that most research into this topic, at least within London seems to have been conducted prior to the release of the Overseas Companies Ownership dataset by HM Land Registry in 2017. As a result, this is a topic ripe for further investigation.

Early Warning Systems for Gentrification

Perhaps the most widely used method of gentrification prediction, are so called "neighborhood early warning systems" (Chapple, 2016). Primarily concentrated and first developed within the United States, these systems were developed by various governmental and non-governmental groups attempting to predict if a neighborhood will undergo gentrification or not both within the immediate and distant future (Chapple, 2016). These systems are often focused on individual cities, and generally attempted to combine various potential factors of gentrification into a scaled index, which is then used to determine the relative state of gentrification for a neighborhood. While many different cities have attempted to create these systems, from Chicago to San Francisco to Philadelphia, few have been used in a sustained manner, or undergone a systematic evaluation of their accuracy (Chapple, 2016). An exception to this is the model constructed by the Houston branch of the Local Initiatives Support Organization, a national community development organization. Using the model of gentrification constructed by Dr. Karen Chapple in a 2009 examination of gentrification in San Francisco (Chapple, 2009), as well as Binary Logistic Regression, the model was able to predict successfully 86% of census tracts within Houston that underwent gentrification in the prior four years (Winston & Walker, 2012). This would appear to indicate that there is yet room for predictive quantitative models within this area of study.

A 2017 examination by Steif et al. used machine learning, specifically random forest classification, to examine patterns of gentrification within so-called "legacy cities", a synonym for post-industrial cities generally located in the North and Northeast of the United States, from 1990 to 2000 (Steiff et al. 2017). This paper used the machine learning algorithm of Random Forest classification to again, determine the main variables that lead to gentrification within a neighborhood, and then use those characteristics to determine where gentrification will occur next. While the model generally underpredicted the spread and scale of gentrification, it predicted with a general scale of accuracy the spatial location of gentrification. An example of this is located in Figure 1, illustrating the predicted locations of gentrification within the City of Chicago in 2010.

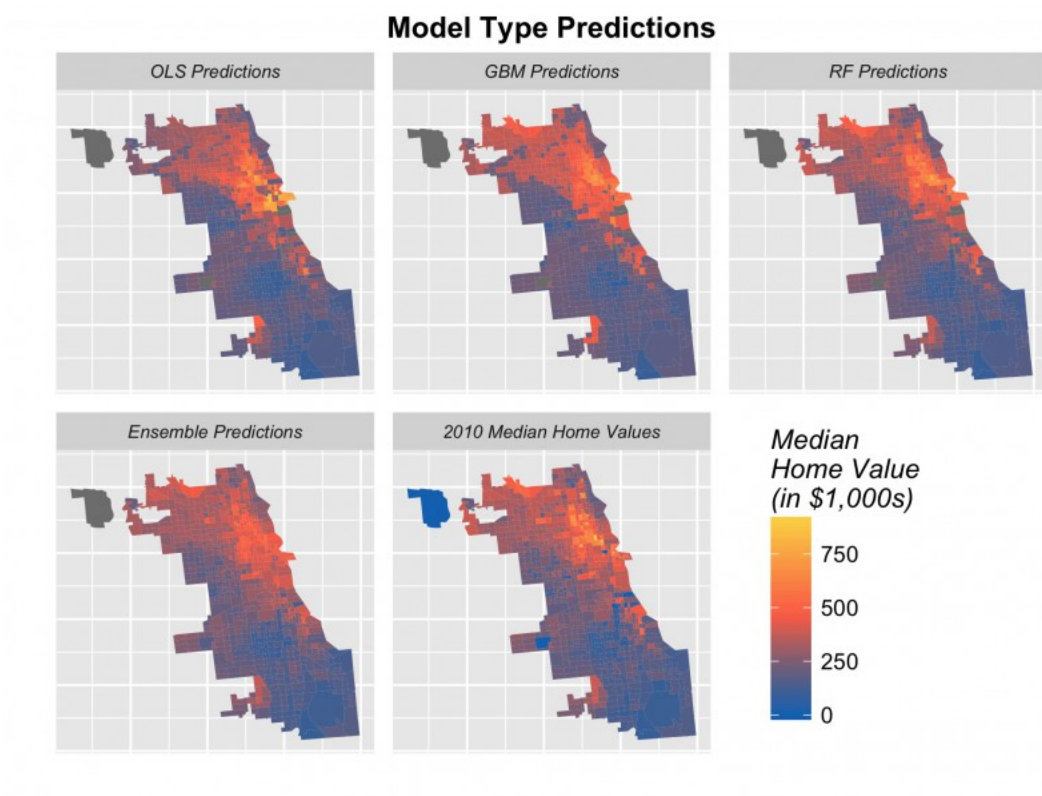

Figure 1: Example of Gentrification Classification within Chicago (Steiff et al. 2017)

As visible from the above figure, the northern Chicago neighborhoods predicted by the model to undergo gentrification, in fact, generally do. This type of model holds promise for use within the context of this dissertation in that this dissertation is not generally concerned with the magnitude of investment within an area (i.e., what was the sale price of a property to an overseas owner), but strictly the spatial clustering of the ownership.

Gentrification Prediction in the United Kingdom and Foreign Ownership Investigation

Continuing the idea of using machine learning to model these types of behavior but focusing on London specifically, a 2017 paper *Understanding urban gentrification through machine learning*, written by Dr. Reades as well as Jordan De Souza and Phil Hubbard (Reades et. al, 2018) attempts to do so using Random Forest Classification. This type of predictive machine learning technique is used to analyze over 160 different 2001 and 2011 Census data attributes for individual LSOAs within London. The model then attempts to use this data to predict gentrification patterns within London LSOAs at the time of the next census in 2021 using the metrics of "uplift" or "downlift", uplift being synonymous in this instance with gentrification.

Within this paper, the authors use a relatively small set of variables (Median Household Income, Median Property Sales Value, Occupational Share, and Qualifications) as the measure of gentrification within a neighborhood, with these variables selected based on other research into the root causes of gentrification. These four values are compressed into a single metric that the paper refers to as 'socioeconomic status'. To predict the outcomes of these four variables, 166 different predictor variables were used, all linked to the 2011 Census Data (Reades, 2019).

The report found that there are two general spatial axes of gentrification within London. The first is a western axis extending through Westminster, Kensington & Chelsea, and Hammersmith. The second is an axis heading north-north west from west-central London to Hampstead. The main gentrification prediction from the paper is that currently rising prices in East London, notably around Tower Hamlets, will continue, with this phenomenon spreading to Outer London boroughs in the east as well.

Something noteworthy about this paper is that it does not attempt to create a unique definition of gentrification, or determine which variables are most predictive of gentrification. The premise put forth by the paper is that there is already a substantial body of work that has determine which variables and factors have the largest effects on gentrification, in this case, the aforementioned four variables above. Instead of re-quantifying these variables, the variables are used pro-actively, rather than retroactively applying the label of gentrification to a phenomena that has already occurred or is occurring by "re-inventing the wheel".

As mentioned before, due to the relatively recent availability of the necessary data to conduct analysis of foreign land ownership within the UK, there is a relative paucity of scholarship for this topic. However, a 2017 report from the University of York Centre for Housing Policy attempted to measure a relative proportion of foreign residential new build ownership within London (Wallace et al. 2017). The scope of this investigation was from April 1st, 2014 to March 31st, 2016, with all information obtained from the Land Registry Price Paid Data (the dataset of Titles wherein each Title costs three pounds to obtain). The Title was purchased for 8,000 properties from a potential sample pool of 28,026 properties split across the four groupings of London boroughs, with those groupings displayed in the following Figure 2.

Prime London - City of London, City of Westminster, Kensington & Chelsea.

New Growth - Camden, Greenwich, Lambeth, Newham, Southwark, Tower Hamlets, Wandsworth

Inner London - Hackney, Islington, Lewisham, Hammersmith & Fulham.

Outer London - Barking & Dagenham, Barnet, Bexley, Brent, Bromley, Croydon, Ealing, Enfield, Haringey, Harrow, Havering, Hillingdon, Hounslow, Kingston upon Thames, Merton, Redbridge, Richmond upon Thames, Sutton, Waltham Forest.

Figure 2: Centre for Housing Policy Report London Borough Groups (Wallace et al. 2017

The investigation discovered that, of this 8,000-home sample split roughly equally between these four borough groupings, 57.5% of the sampled properties were occupied by the same individual who owned the home. However, this figure dropped to just 34.3% within "Prime London", defined within this paper as the boroughs of Westminster, Kensington & Chelsea, and the City of London (Wallace et al. 2017). The other unique category of borough utilized by this report is "New London", which contains the boroughs of Camden, Greenwich, Lambeth, Newham, Southwark, Tower Hamlets, and Wandsworth. All other remaining Inner London properties and Outer London properties are classified as such respectively. In total, 13 percent of all new build homes were purchased by foreign buyers. The foreign buyers were also relatively concentrated, with buyers from Hong Kong, Singapore, Malaysia, and China making up 61% of all foreign owners. Hong Kong and Singapore in particular are dominant in some metrics of overseas ownership, constituting over half of all mortgaged purchases and the majority of new builds (Wallace et al. 2017).

This report also attempts to assess the occupancy status of foreign owned properties. Using Census and Read demographic match data, it was determined that roughly 42.3% of foreign owned residential properties meet a definition of "under-used", as opposed to the 5.6% of properties owned by UK residents that meet this definition. Despite being only 13% of all new-build home owners, in absolute count, there is roughly the same number of under-used homes owned by foreign owners as UK owners. Regardless of domestic or foreign owner status, the boroughs constituting "Prime London", as well as the most expensive category of home purchase, have the highest rates of "under-used" residential properties.

While the broad scope of the University of York investigation is similar to this dissertation, this dissertation seeks to examine the spatial distribution of these properties at a more granular scale than borough alone, in contrast to the University of York. While certain boroughs like Kensington and Chelsea are known for foreign investment, there exist stark socioeconomic differences between areas within this borough (MacLeod, 2018), which could lead to uneven spatial distribution of foreign owned properties in that borough.

The key issue with the report from the Centre for Housing Policy, is not with the work conducted by researchers involved in the creation of the report, but rather the prohibitive cost of the data needed to conduct the research in the first place. The estimated 24,000 pounds sterling needed by the Centre for the purposes of obtaining Title is a somewhat prohibitive cost for most private individuals, and perhaps many institutional academics and entities as well. Despite the relative well funding of this investigation in comparison to other examinations of land ownership, the Title selection process required care in order to provide a semi-representative survey of foreign property ownership within the United Kingdom (Wallace et al. 2017). The fact that this information even needed to be obtained at a cost for two public institutions is in of itself problematic. It is difficult to imagine a robust body of scholastic work taking place on this topic in the future if the most relevant dataset to any investigation of land ownership within the United Kingdom continues to be paywalled away.

0.5 Methodology

0.5.1 Introduction

To conduct the analyses necessary to answer the reseach questions posed by this dissertation, various methods were used to join geographic boundaries to the Overseas Companies Ownership dataset, with further analysis like Random Forest regression conducted on the newly geographically-referenced dataset. This dataset was then compared to the New York City PLUTO dataset for 2019, along with examining various trends and patterns in spatial distribution and ownership location for the Overseas Companies Owner dataset.

Something that was considered while designing the methodology for this investigation is what to do for properties that are sold from one foreign owner to another. While the ownership has changed and perhaps the country of ownership too, the property is then also double counted when considering the total number of properties within London. To avoid this issue when looking at summary statistics, for the table of current properties, if there were any duplicate properties contained within, the one with the most recent acquisition date was kept. For other statistical investigations, such as examining the number of properties acquired within a borough in a given year, these properties were kept, as a sale from a foreign owner to another foreign owner is still obviously a property acquired by a foreign owner. In this dissertation, the original full table from November 2017 was used as the base dataset, with every month after only joining new property information (or updating the new foreign owners of a property). The most recent dataset used within this dissertation is from June 2019.

0.5.2 Datasets

Land Registry Information

The core dataset that is within this dissertation is the Overseas Companies Ownership dataset provided by HM Land Registry. This is a dataset that has been released monthly since Winter 2017 by the Land Registry as publicly available data, albeit only available from a Kahootz page. This data contains a variety of information about properties owned by overseas owners within London. This dataset does not include individuals who are registered as owning property under their names, due to privacy concerns (Land Registry, 2019). However, all other forms of overseas ownership are included. For a fuller overview of the dataset, Figure 1 is a list of the included columns within the dataset, as well as a description of each field, obtained from the Land Registry. It is important to note that while the dataset only includes corporate overseas ownership, many of the LLCs contained within may or may not be held by private individuals. There are secondary, tertiary, and quaternary proprietor name, company registration numbeer, proprietorship category, country incorporated, and proprietor address columns that for purposes of brevity are not included in the following table.

Field name	Mandatory?	Description
Title number	Yes	Unique Register Number
Tenure	Yes	Freehold or Leasehold.
Property Address	Yes	Property Address
District	Yes	District Name
County	Yes	County
Region	Yes	Region Name
Postcode	No	Postcode
Multiple address Indicator	Yes	Multiple Addresses
Price Paid	No	Transfer Deed Sale Price
Proprietor name (1)	Yes	Non-Private Individual Name
Company Registration No. (1)	No	Company Registration Number
Proprietorship Category (1)	Yes	Proprietor Type
Country Incorporated (1)	Yes	Country of Incorporation Name
Proprietor (1) address (1)	Yes	Register Address
Proprietor (1) address (2)	No	Register Address
Proprietor (1) address (3)	No	Register Address
Date Proprietor added	No	Date Registered
Additional Proprietor Indicator	Yes	Indicates Other Non-Overseas Proprietors

Table 1: Overseas Owner Dataset Field Descriptions

While there are a variety of fields included within this dataset, there is no geometry column or other spatial data allowing the properties to be mapped, other than the address or postcode. While these datasets consist of specific properties or addresses owned by companies, the only geographically usable information included within the datasets are postcodes. While the dataset was only made public in 2017, and has been updated monthly since that time, the dataset is still useful for historical analysis, as a sale date is provided for every property in the table, including those acquired by an overseas owner before 2017. This is used throughout the dissertation to provide a general timeline of property purchase within Greater London.

Postcodes

As mentioned in the above section, the Overseas Ownership dataset does not include any geographically referenced information but does come equipped with a postcode column. In order to map the property points, postcode polygons were obtained for the whole of Greater London from MasterMap, the online geospatial repository operated by the University of Edinburgh (University of Edinburgh, 2019). When downloaded, the postcodes initially came in many separate folders, each separated by postcode prefix, as well as if the postcode contained one or two characters in the first section of the postcode name. For general ease of analysis, each of these individual shapefiles were joined into a single postcode shapefile for the entirety of Greater London using the MMQGIS plugin for QGIS, which allowed for multiple layers to be merged at once rather than having to sequentially join the layers as would be necessary without MMQGIS. As the selection area of postcodes was done manually in MasterMap, the resulting layer then needed to be trimmed to the actual outline of Greater London. After doing so, the postcode polygons were then exported to PostgreSQL.

PLUTO Data

Used to compare common owners between London and New York City, as well as comparing the spatial patterns of overseas land ownership, PLUTO data is created by the City of New York Department of Planning to hold the city's assessment parcel information. Since the NYC PLUTO data is only used for the comparison of common owners between New York City and London in 2019, only the most recent PLUTO dataset, the tax roll for 2018, was used for the purposes of this dissertation. In comparison to the Overseas Ownership dataset for London, the PLUTO dataset is more field rich, but lacking in information regarding the provenance of ownership, with no column or information indicating if an owner is overseas or not. However, Limited Liability Companies, business entities that allow individuals to anonymously own land and conduct other business transactions, are a popular choice of land ownership vessel for individuals within New York City (Rice, 2014). While it is an imperfect measurement as some percentage of LLCs within New York City are held by entities that are domestic owners, it is the most specific metric currently available for this topic. It is also worth noting that there is a risk of domestic ownership being included within the Overseas Ownership dataset for London, as the true owner of a property behind however-so-many LLCs or companies could in fact be British.

Auxiliary Data

Besides these three fundamental datasets used, other datasets were used in more rudimentary contexts. A London borough boundary shapefile obtained from the London Datastore (London Datastore, 2019) was used to trim the postcode polygons to the shape of Greater London. Additionally, a boundary file for the outline of New York City's boroughs was obtained from the NYC Department of City Planning (NYC Department of City Planning, 2019) for the same purpose within New York City

0.5.3 Data Cleaning

Throughout this dissertation, the primary data cleaning and data manipulation tool used was a PostgreSQL database equipped with PostGIS (PostGIS, 2019). PostGIS is an add-on library to PostgreSQL that allows for SQL-based spatial queries on geometric objects. As PostGIS allows PostgreSQL to make sense of spatial objects, the database used can be linked to QGIS, an open source GIS program (QGIS, 2019), allowing easy import and export of data, as well as allowing for easier previews of the data.

London Data Cleaning and Joining

To combine the twenty different Overseas Ownership tables obtained per the previously outlined method, all tables were imported into PostgreSQL. The tables were then trimmed to just include properties within the "County" of

Greater London.

After doing so, each subsequent table was appended to the prior table that included the previously joined tables. To provide geographic context for the properties, an empty geometry column was created in the newly joined Overseas Ownership dataset. Since the Overseas Ownership dataset does not include a geometry column, the geometry column from the postcodes table was joined to a newly created geometry column within the Overseas Ownership dataset. Using the postcode column from the Overseas Ownership dataset, the geometry of a postcode was joined to each respective overseas-owned property. After conducting this join, it was discovered that within this dataset roughly 13% of all properties within the area of Greater London had blank values for the associated postcode. This should not be technically possible, due to the UK postcode system covering every physical inch of the country. For the purposes of this analysis, these properties were removed, as it is impossible to link any spatial information to them without the presence of a postcode. To avoid the issue of having duplicate postcodes layered on top of one another for each property record, a new geometry column was created for each property record, with the geometry populated as a random point within the postcode in question for a property. While this adds some degree of obfuscation to the geographic location of the property record, this was deemed to be the best way to visualize multiple records within a postcode area. This was accomplished using the `ST_GeneratePoints` function from PostGIS.

After generating these individual points for records within postcodes, the previous geometry column was deleted, and replaced with the new point-based geometry column.

The next step in data cleaning was to add an acquisition year column to the combined dataset. While the dataset already included a sale date column, as the planned scope of investigation for this dissertation encompasses the time from 2008 to present day, a column containing just the registry year was created using a regex statement on the Proprietor Date column.

PLUTO Data Cleaning

Similarly, to the Overseas Ownership dataset, the 2018 PLUTO tax parcel dataset was uploaded into PostgreSQL. As the PLUTO dataset includes all owners, not just foreign owners, a foreign ownership dataset was roughly approximated by removing all parcel records where the owner name does not include the text “LLC“ within the owner name column. Where a property owner’s name was just defined as ’LLC’ (a definition that applied to 55,177 properties within New York City), these were removed from the table, as these cannot be used for the purposes of matching to London ownership. For the purposes of comparing owners from the PLUTO dataset to the London data, the string ‘LLC’ within owner names were renamed to “LIMITED“ to match the way that LLC names are formatted within the London data.

0.5.4 Summary Statistics

Most summary statistics for the dataset were created using various PostGIS and PostgreSQL queries. The charts and graphs indicating the number of properties associated with a specific borough or owners or similar were created using Python. To create these within Python, the results of various queries from PostgreSQL were saved as CSVs and then imported into Python as DataFrames using the `pandas` library (McKinney, 2007). Once imported as DataFrames, the `matplotlib` (Hunter, 2007) and `seaborn` libraries (Waskom et. Al., 2017) were used to create the various figures.

0.5.5 Grid Map Creation

In order to show the progression of foreign land ownership patterns over time in London, all properties up to a given year between 2008 to 2019 were placed into individual tables for each year within the dataset. These tables were then exported to QGIS and re-projected from WGS 84 to British National Grid so meter measurements could be used in subsequent spatial analyses. Using a London Boroughs shapefile obtained from the Greater London Authority (London Datastore, 2019), the "Vector grid" tool in QGIS was used to create a vector grid over the extent of Greater London, with the extent of each square in the grid set to 500 by 500 meters. After creating this grid, each GeoJSON file with the total number of properties present in that file's given year was joined to this grid by using the "Count points in polygon" tool in

QGIS, with the number of points per square added as a new column. This was repeated for each year from 2008 to 2019. In order to visualize the relative number of points per square in the grid, the data was broken into five categories based on the Jenks Breaks for the initial 2008 dataset and assigned a graduated color scheme using the 2008 dataset as the baseline for classification to allow for meaningful comparisons across years.

This same process using the boundaries of New York City's boroughs was used for the PLUTO Dataset in 2019. Since the PLUTO data came formatted as individual polygons for each property, the geometry for the PLUTO dataset was converted to a point format within PostGIS so it could be mapped in the same way as the London information. As the borough shapefile came projected in the `NAD_1983_StatePlane_New_York_Long_Island_FIPS_3104_Feet` projection, the grid sides had to be set to 1,640.42 feet instead of 500 meters so that the format would match for both cities. The classification was based on the five Jenks Breaks categories derived from the 2008 table of Overseas Owned London properties so that both cities could be compared on the same spatial scale.

0.5.6 World Region Classification

To provide context into the countries of origin for owners, or at least the countries of registration, are congregated within London, a new copy of the combined London dataset was created. A column entitled "world region" within this new table was then manually populated with a world region based on the country of origin. The world region categories created are as follows.

"world_region"
AFRICA
ASIA
CARIBBEAN
CENTRAL AMERICA
EUROPE OTHER
EUROPEAN UNION
MIDDLE EAST
NORTH AMERICA
OCEANIA
SOUTH AMERICA
UK TERRITORY

Table 2: World Region Categories

0.5.7 PLUTO and Overseas Ownership Cross-Referencing

After the cleaning processes for all London and New York datasets are completed, an index is created on owner name for both the 2019 PLUTO and combined London Overseas Owner datasets. A new empty table named is also created, using all columns from both tables. If an overseas corporation name is a match to an owner within the NYC PLUTO database, the columns derived from the NYC datasets are populated with the matching LLC information, with the same process repeated for the London data using SQL join statements. The goal of doing so is to examine if and how owners of property in both cities differ from the general trends in foreign land ownership in the two cities.

0.5.8 Model Preparation

During preliminary investigation of this analysis, the originally planned method involved construction of a hedonic model incorporating property information about purchased properties and surrounding properties to see if there were characteristics that attracted foreign ownership to a neighborhood that may not currently be obvious. A potential example of this analysis could be a finding indicating that the most important variable attracting overseas ownership to a neighborhood is the number of flats with gold-plated toilets within a 500-meter radius of an LSOA. However, because of the opaque nature of London land information, information that could be used for a potential hedonic model of foreign and corporate and investment in London could not be obtained. Instead, a Random Forest classification algorithm was decided upon for two main reasons. The first reason was the ease of parameter tuning within the model, and the second being that after undertaking the model training, the actual predictive time of the model would be relatively quick. Considering that the model needed to predict five separate years, this was not an insubstantial concern.

The type of random forest model method used within this dissertation specifically is random forest regression, with the type of parameters determined to be the best for each prediction set determined when the `regressor.fit` function was run. To construct this model, the Random Forest Regression model provided by the `scikit-learn` library (Pedregosa et al, 2011) was used for all modeling. The `pandas` (McKinney, 2007) and `numpy` (Oliphant, 2007) libraries were used as well to handle the various data format conversions required for the Random Forest regression model.

The workflow process of the model utilized the total counts of Overseas Owned properties within the neighboring squares of a square (up to nine squares in total) as the primary predictor of the number of properties within a square, in addition to the property count within the given square. To calculate the number of “neighboring properties“, a Python script (Gandhi, 2019) was used to calculate neighboring polygons in a polygon table, as well as the sum of a common variable across those neighbors to create an additional measure of prediction for the future count of an individual square. For each grid map, a new column was created in QGIS named with the “id“ column converted from an integer to text type to allow it to be used as the unique identifier within each square for the Python script. When running the script, the chosen field to sum by the counts of neighbors was the number of points within each square. The maximum number of neighbors for any given square is nine, with the largest number of neighboring properties for any given square in 2019 being 2195. This process was repeated for each grid map.

In order to prepare the model to predict the location and number of foreign owned properties in the future, multiple different testing scenarios were used to assess the accuracy of the predictions. These testing and training scenarios are listed as following

- 1) All counts per grid square from 2008-2017 used to predict grid square counts in 2018
- 2) All counts per grid square from 2008-2016 used to predict grid square counts in 2017
- 3) All counts per grid square from 2008-2013 used to predict grid square counts in 2014
- 4) All counts per grid square from 2008-2010 used to predict grid square counts in 2011
- 5) All counts per grid square for any square with more than zero properties in all years from 2008-2017 used to predict grid square counts in 2018 for squares with more than zero properties.

After running these training and testing models, the following years were predicted by lagging the years included within the model as part of the prediction, as random-forest regression is a form of autoregressive model. As an example, to predict the year 2022, the years 2018, 2019, and 2020 were used to predict the existing “2021“, with the existing “2021“ column used as the `y` variable in the regression model. This process was repeated until predicted variables for the year 2025 were obtained.

Grid Map Statistics

For all created grid maps, Moran's I and Geary's C statistics were calculated to determine the relative level of spatial auto-correlation within each map. These statistics were calculated within `R` (R Core Team, 2018), using the `geojsonio` (Chamberlain & Teucher, 2018), `spdep` and `sp` libraries (Bivand et al, 2013). These two different measures were used to account for any potential variance in auto-correlation by just using a single metric.

Model and Prediction Qualifiers

Something important to note about the predictive model constructed within this dissertation, as well as these types of predictive analyses, is the inherent difficulty in attempting to predict the future, especially with phenomenon as complex as these. There a multitude of various events and influences that could influence the appearance and behavior of foreign land-owning capital within Greater London in the future. However, there is still potential utility in this predictive model to determine if there are at least any geographic behaviors and trends that can be at least partially predicted in foreign land-owning capital.

Another key qualifier for the model predictions is that it relies on incomplete data for the year of 2019. As half of 2019 was included within this dataset, a rough approximation of 2019 was constructed by taking the existing six months of values and doubling them.

As each future year prior to the final year of 2025 is predicted individually (rather than directly generating 2025 based on the existing data from 2008 to 2017), there is naturally an element of increasing linearity to the model as each subsequent prediction “flattens“ any year to year irregularities. While this is less than ideal, this was somewhat unavoidable given the nature of the predictive analysis. After predicting each year, the results were saved to individual CSV files for each year and exported to QGIS. Once imported to QGIS, they were joined to the existing grid map template in the same method as the “actual“ years were to create the grid maps, using the same Jenks breaks and classifications, with this step culminating the process of analysis for this dissertation.

All Python scripts used to create the Random Forest model, as well as other tools used during the process of methodology creation, are visible at `https://github.com/klovskim/my_dissertation`.

0.6 Results

The results of the various analyses of the Overseas Ownership and PLUTO datasets can be divided into three parts. The first consists of various summary statistics, examining things like total numbers of Overseas Owned Properties per borough, what countries have large numbers of associated properties, and if there is any spatial distribution of properties associated with specific countries or regions. The second set of results examines the spatial extent of LLC ownership within New York City and examining which Overseas Owners within London in 2019 also hold property within the City of New York. The third and final set of analysis is using a random forest regression model to predict the future geographic extent of Overseas Ownership within Greater London from 2020 to 2025.

0.6.1 Summary Statistics

As of 2019, there are 30,775 Overseas Owned Properties within the whole of Greater London. The following Table 3 indicates the number of properties associated with each individual borough in Greater London.

"district"	borough_count
CITY OF WESTMINSTER	5243
KENSINGTON AND CHELSEA	3882
CAMDEN	1352
LAMBETH	1235
WANDSWORTH	891
HAMMERSMITH AND FULHAM	867
BARNET	827
TOWER HAMLETS	781
ISLINGTON	627
SOUTHWARK	552
HACKNEY	485
CITY OF LONDON	484
BRENT	459
EALING	433
CROYDON	401
HOUNSLOW	395
HARINGEY	363
NEWHAM	343
LEWISHAM	327
MERTON	317
HARROW	317
HILLINGDON	299
RICHMOND UPON THAMES	288
ENFIELD	232
KINGSTON UPON THAMES	232
BROMLEY	205
GREENWICH	170
WALTHAM FOREST	143
SUTTON	131
REDBRIDGE	118
HAVERING	108
BEXLEY	97
BARKING AND DAGENHAM	69

Table 3: Number of Overseas Owned Properties Per Borough

The following Figure 3 indicates the total number of overseas owned properties per borough in chart form.

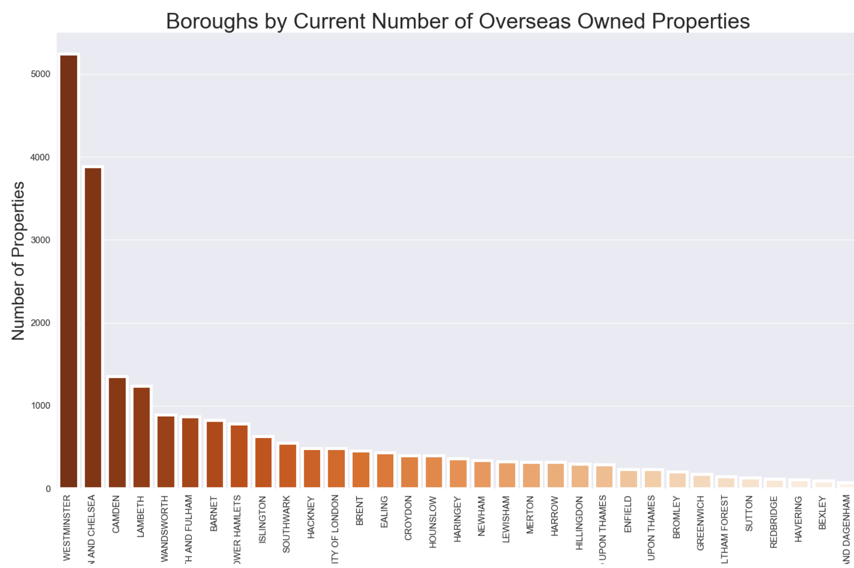

Figure 3: Number of Overseas Owned Properties Per Borough

Per borough there is an average number of 932.58 properties however, as visible from the above table, there is a high degree of spatial concentration within specific boroughs. Within the four boroughs of Westminster, Kensington & Chelsea, Camden, and Lambeth there are 11,712 properties. These four boroughs have more foreign-owned properties than there are in the rest of London, which has only 10,961 foreign owned properties in total. Additionally, while the median number of properties per borough in a given year is 31, the average number of properties purchased per borough in a given year is 62.46. This ranges from 612 properties purchased in 2013 by Overseas buyers in Westminster, to a single property purchased in Bexley in 2009. This speaks as well to the unequal distribution of foreign investment within the city.

This pattern seems to align with the findings from the 2016 paper *A view from the top* by Dr. Luna Glucksberg, wherein by anecdotal evidence and interpersonal interviews this spatial concentration is alluded to (Glucksberg, 2016). However, these statistics do not provide any information as to how this spatial concentration has changed and grown over time, or for how long it has existed. To answer these questions, the following Figure 4 shows the number of properties associated with each borough. The horizontal axis is determined by using the acquisition year for each property.

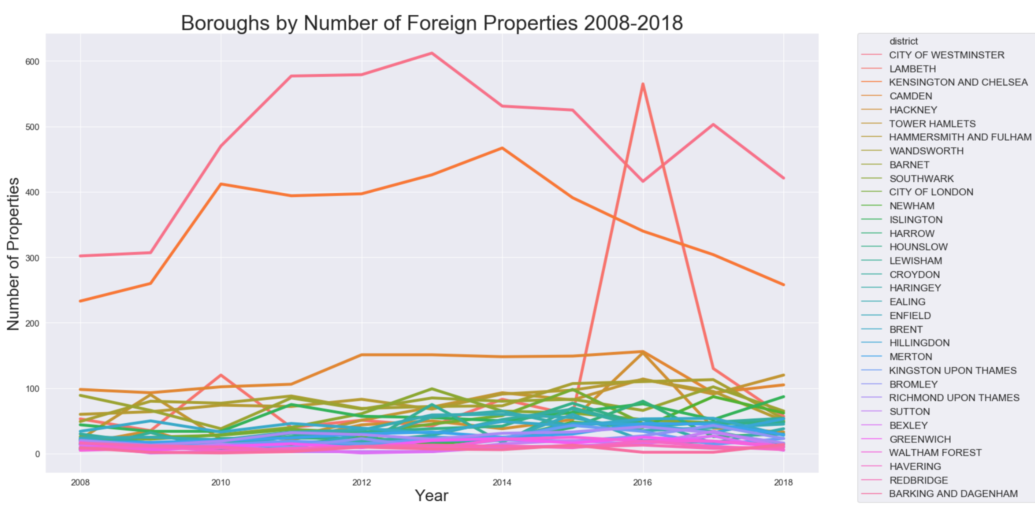

Figure 4: Boroughs by Number of Properties Acquired by Overseas Owners 2008-2018

The spatial concentration of foreign ownership in London outlined in the previous table holds true looking at property acquisition over time as well. Over the scope of time investigated by this dissertation, there is not a single year in which Westminster does not have, by a substantial portion, the highest concentration of foreign ownership within Greater London. Compared to the four boroughs with many foreign owned properties, most of the other boroughs are barely distinguishable at the scale needed to visualize the numbers for Westminster accurately. However, across most boroughs, especially ones with large numbers of foreign owned properties, the number of properties acquired by foreign buyers has decreased within recent years. The following Figure 5 is intended to provide some visual clarity for the top five boroughs according to this metric.

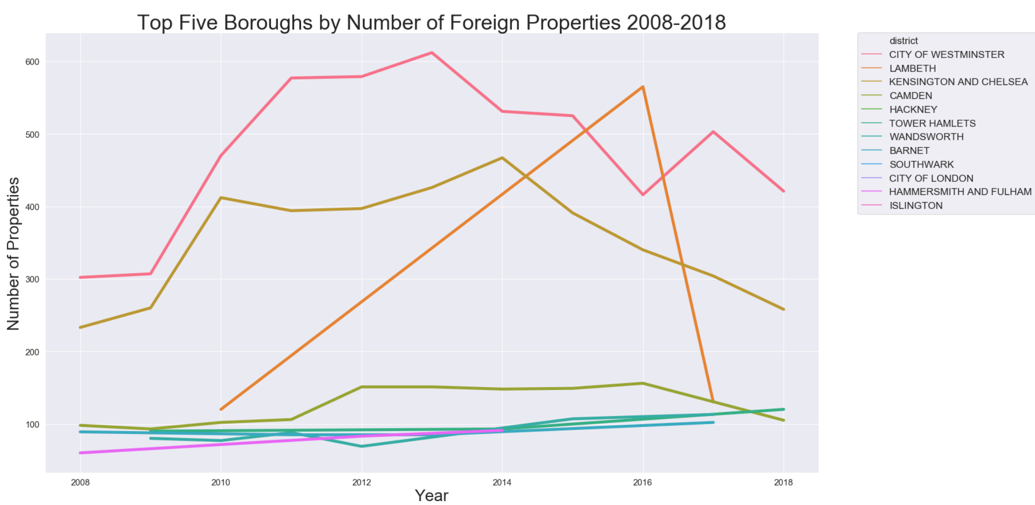

Figure 5: Top Five Boroughs by Number of Properties Acquired by Overseas Owners 2008-2018

Something unusual about this plot is the degree of linearity in number of foreign owned properties acquired each year within the borough of Lambeth. It is highly unusual that this degree of linearity exists within Lambeth, when it does not exist nearly to the same extent in other boroughs.

Foreign Owners by Country

The next investigation step is to examine the number of properties associated with a given country. While the column is meant to only included country-level governmental authorities, there are various subnational units included within this category, notably the U.S State of Delaware. While it was considered to combine these records into a single listing by changing all individual state name entries to “U.S.A”, it was deemed appropriate to keep them separate, as it illustrates the gap between entities in a single country that allow for opacity in ownership. Table 4 indicates the total number of properties associated with the top twenty-five land-holding countries or territories as of June 2019.

country_incorporated_1	count
BRITISH VIRGIN ISLANDS	10626
JERSEY	4514
ISLE OF MAN	2974
GUERNSEY	2725
PANAMA	869
NETHERLANDS	783
CYPRUS	642
SEYCHELLES	623
GIBRALTAR	604
BAHAMAS	588
HONG KONG	458
LUXEMBOURG	399
IRELAND	361
CAYMAN ISLANDS	347
MAURITIUS	262
LIBERIA	260
LIECHTENSTEIN	184
GERMANY	184
SWITZERLAND	177
ITALY	176
BELIZE	172
SINGAPORE	160
JAPAN	145
DELAWARE, U.S.A.	140
MARSHALL ISLANDS	140

Table 4: Overseas Owner Country Counts 2019

Within the dataset there is a high concentration of ownership headquartered within the British Virgin Islands, as well as Jersey, the Isle of Man, and Guernsey. Of all foreign owned properties, roughly two thirds are owned by entities headquartered in these places. These four offshore territories have a history, roughly since the 1970s, of allowing tax havens and shelters to headquarter themselves within these places (Pegg & Garside, 2019). However, this may change soon, as Guernsey, Jersey, and The Isle of Man have announced that they will open their LLC ownership records, which may dissuade entities from using these three places to incorporate for the purposes of property ownership (Pegg & Garside, 2019). Another area of ownership to note is the presence of the U.S state of Delaware. With 140 entities headquartered there, this is a higher number than the number of properties registered in other U.S states, as well as those just registered as being in the United States itself. The reason for this is that Delaware has some of the loosest regulations of LLCs and company registration in the United States (Wayne, 2012), and as such is a popular choice for business headquarters that might otherwise register in a place like the U.K Virgin Islands.

Similarly, to the borough-level investigation, line plots were created to show the change in foreign land ownership over time. As there were over 100 different countries and governmental units listed as countries of origin within the dataset, only the top 20 were used to construct these plots due to limits of legibility. To examine how the location of incorporation has changed over time in London since 2008, the following two charts each illustrate the change in "rank", or that is, number of properties acquired in a given year associated with the top five and next five countries of incorporation by quantity. While 2019 is included within the dataset, it is excluded from this and other bar graphs since the counts for 2019 are incomplete as the year is not yet over at the time of writing.

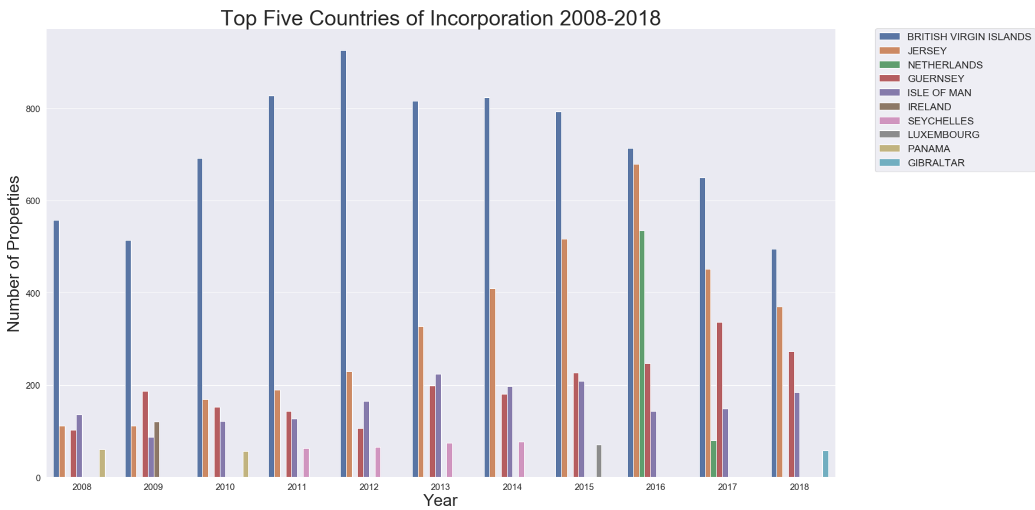

Figure 6: Top Five Countries by Number of Properties Acquired by Overseas Owners 2008-2018

Much like the Borough of Westminster, the U.K Virgin Islands and other UK Territories similarly dominate this chart compared to all other places of origin. Similarly, to the line plots of properties purchased in each borough, this plot indicates a decrease over the last few years in foreign ownership acquisition. To provide more visual clarity to the subsequent countries, a second figure, Figure 7, was created showing the next five countries by number of registered properties.

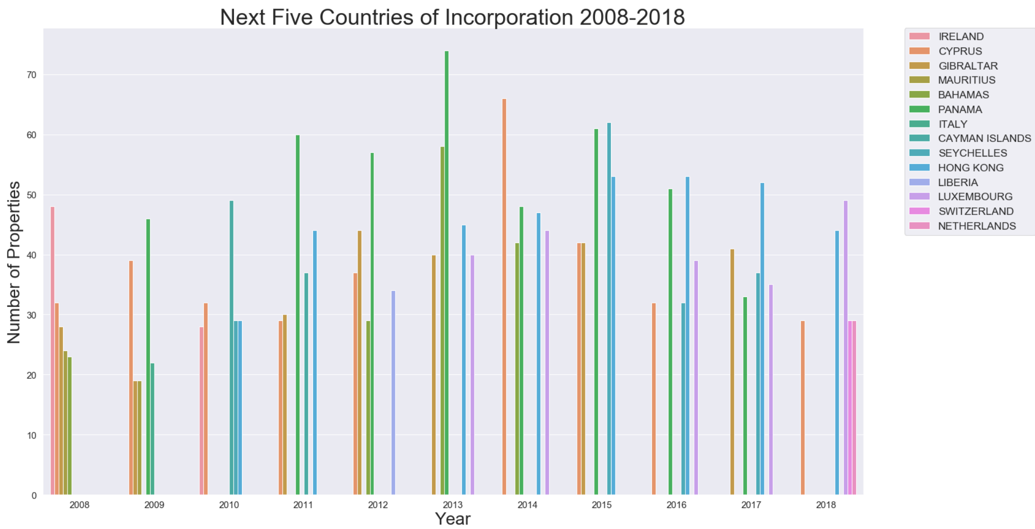

Figure 7: Next Five Countries by Number of Properties Acquired by Overseas Owners 2008-2018

The next five owners provide insight into countries that have large amounts of overseas ownership outside of the UK Territories which dominate the first chart. Many countries on this chart are either European Union entities, or other countries within Europe.

0.6.2 Spatial Distribution by Postcode

When examining the data at the more granular postcode level, the spatial concentration of properties even within boroughs becomes much starker. While the median and average number of properties per postcode is 1 and 2.21 respectively, there are six postcodes that each contain more than 50 properties owned by foreign owners, with the two postcodes of SE1 7UT and SW7 1RH containing 625 and 132 properties each respectively, the two highest numbers of properties within Greater London. The following Figure 8 indicates the geographic location of these two postcodes.

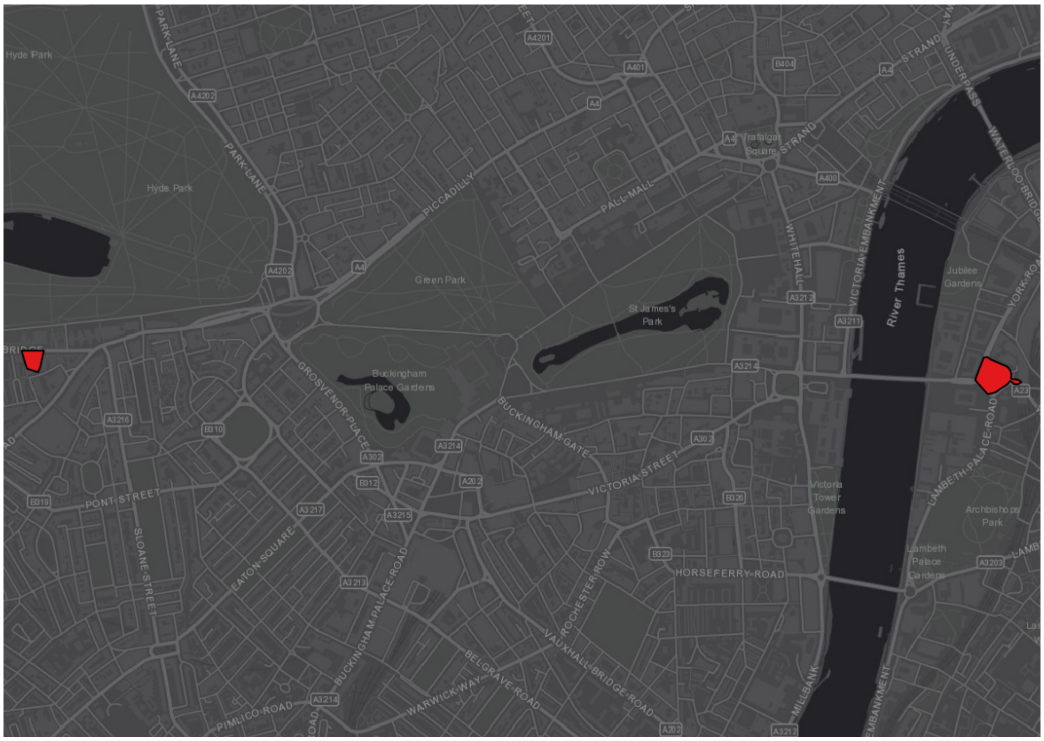

Figure 8: SE1 7UT *left* and SW7 1RH *right* Postcode Locations

Of the 625 properties associated with SE1 7UT, every single one is an apartment located within the Park Plaza building, located on Westminster Bridge Road. As of 2019, these apartments account for more than half of all foreign properties within the borough of Lambeth. However, most of these are held by the same owner, as 509 of these apartments are owned by an entity named “WESTMINSTER BRIDGE LONDON (REAL ESTATE) B.V.“, a company registered at “Claude Debussylaan 14, Vinoly Tower, 1082 MD, Amsterdam, Netherlands“. As the building in question is a Park Plaza Hotel, these separate apartments appear to possibly be hotel rooms in an attempt to split the ownership of the building, despite almost all held by the same entity.

In the postcode of SW7 1RH, the ownership pattern is slightly different in that while most of the Overseas Owners are concentrated within one building, in this case 199 Knightsbridge, it is not the same owner for most properties. Within this postcode, no one owner sees to dominate the holdings. However, curiously there are a few properties held by an LLC named “ANAKONDA HOLDING LIMITED“ that claim to be registered within the U.K Virgin Islands. However, the associated proprietor address for this LLC is not located within the British Virgin Islands but is in fact located in 199 Knightsbridge as the owned properties. Despite ownership appearing to consist entirely of LLC entities, 199 Knightsbridge nonetheless received the 'Residential Development of the Year' award in 2006 at the Property Awards according to the website of Multiplex, the developer of the property (Multiplex, 2019).

199 Knightsbridge is also notable for being the subject of investigation in 2018, as multiple properties within the building were suspected of being used for money laundering and real estate fraud by Ukrainian Mafia members, as uncovered by the BBC's Paradise Papers investigation division (British Broadcasting Service, 2019). A similar investigation of other units within this building has the potential to perhaps uncover other interesting results.

0.6.3 Missing Proprietor Addresses

After finding empty proprietor addresses within the SE1 7UT and SW7 1RH postcodes, other property records were investigated to see if they also had missing proprietary addresses. A new table was created consisting of all properties within London in 2019 where the property address is the same as the first proprietor address. Buildings that did not have “null“ secondary or tertiary addresses were omitted in order to avoid properties that may have the foreign address located in the second or third line. All properties within the newly created table have only a London address of the property owned by a foreign entity as the point of reference for the foreign entity's address. This is despite the foreign entity's address being in London, which does not appear to match the definition of foreign ownership.

Within this table there were 1,519 properties in Greater London, or roughly 4.94% of all foreign owned properties within London. Table 9 is a map of where these properties are located within Greater London in grid map format.

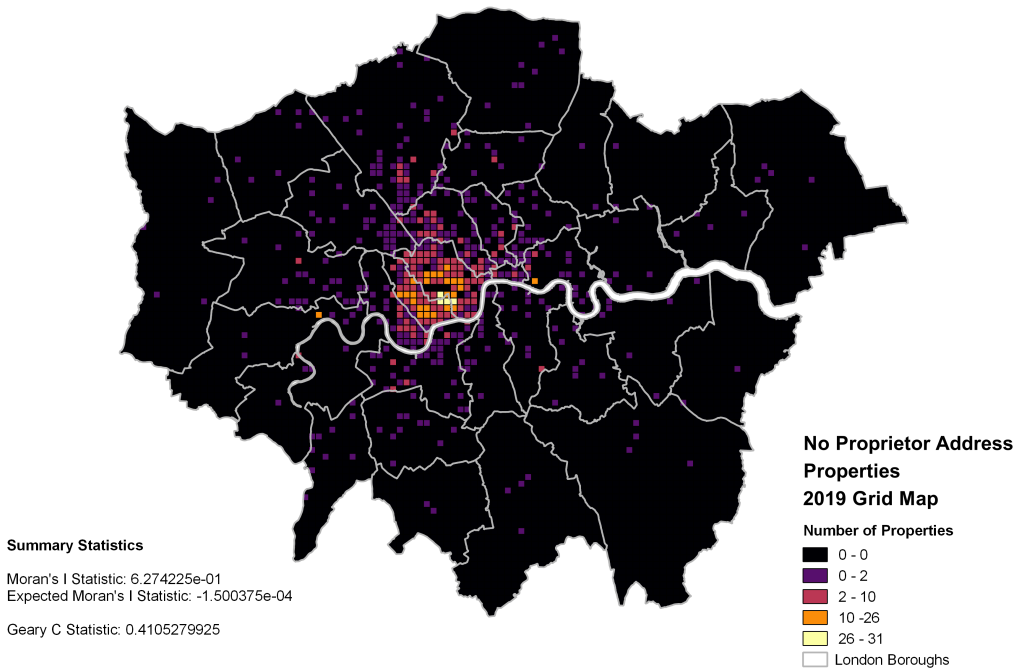

Figure 9: 2019 Grid Map of Properties with Missing Proprietor Addresses

As visible from the above grid map, there is a high concentration of these property types within Knightsbridge and along the South-Eastern edge of Hyde Park (the dark three squares in the middle of west-central London). Table 5 indicates the top ten owners of these type of missing proprietor address properties.

"proprietor_name_1"	count
W2 WESTBOURNE INVESTMENTS LIMITED	12
SAPCOTE INVESTMENTS LIMITED	8
SULLIVAN & CROMWELL LLP	6
HAAB DEVELOPMENT LIMITED	5
BELLBLUE LIMITED	5
SUMMERFIELD TRADING MANAGEMENT LIMITED	4
GREAT BEAR LIMITED	4
RATHMOY (CENTURION HOUSE) LIMITED	4
BIRWARI LIMITED	4
DUSK ASSOCIATES LIMITED	4

Table 5: Top Ten Owners of Properties with Missing Proprietor Addresses

In future investigations of land ownership within Greater London, examining the ownership habits of the above entities could be a potential priority for local officials or investigative journalists in determining potential ownership.

0.6.4 Spatial Distribution of Foreign Ownership by UK Territory or Not

As roughly two thirds of all Overseas Owned properties within Greater London are associated with a owner registered in a UK Territory, these properties and Overseas Owned properties not registered in UK Territories were compared to see if there was any substantial spatial difference between the two. The following figures show the number of properties associated with UK Territories and all other entities respectively.

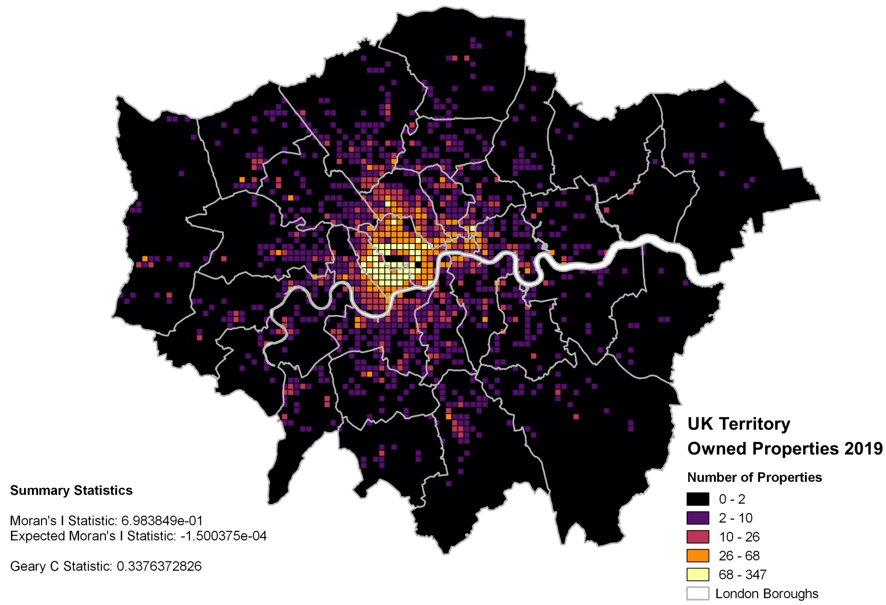

Figure 10: 2019 Grid Map of Properties Registered in UK Overseas Territories

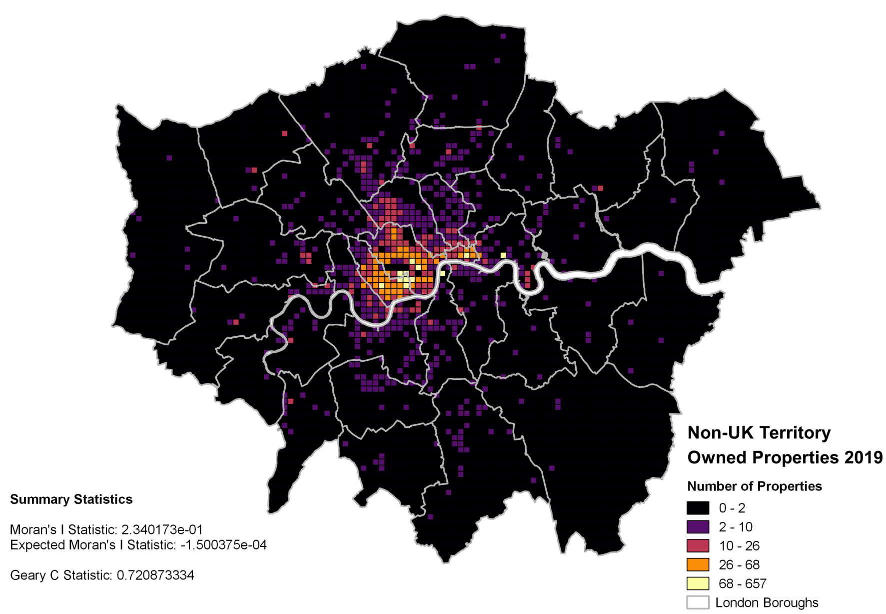

Figure 11: 2019 Grid Map of Properties Not Registered in UK Overseas Territories

The difference in number of properties between the two categories is plainly visible in the two figures, despite both being relatively centrally concentrated. There is also not a substantial difference between the two in terms of distribution between Outer and Inner London, as roughly 25% of properties in each category are in Outer London, using the definitions of Outer and Inner London as defined by London Councils (London Councils, 2019).

Foreign Ownership by World Region

The next step of analysis was to compare world regions by total count per region, as well as to map them in the same grid format as the other maps. Table 6 is a table of property counts per region.

”world_region”
AFRICA
ASIA
CARIBBEAN
CENTRAL AMERICA
EUROPE OTHER
EUROPEAN UNION
MIDDLE EAST
NORTH AMERICA
OCEANIA
SOUTH AMERICA
UK TERRITORY

Table 6: Property Counts Per World Region, 2019

These tables were then converted to grid maps in the same process outlined for the other grid maps created. These categories were then mapped separately in the same grid format as the other maps. While five Jenks breaks categories were used per other grid maps, since these maps have fewer properties than the yearly grid maps, the first color classification was adjusted to be just grid square with zero properties, rather than squares with zero to two properties. the results are visible in the following sequence of Figures 12-21.

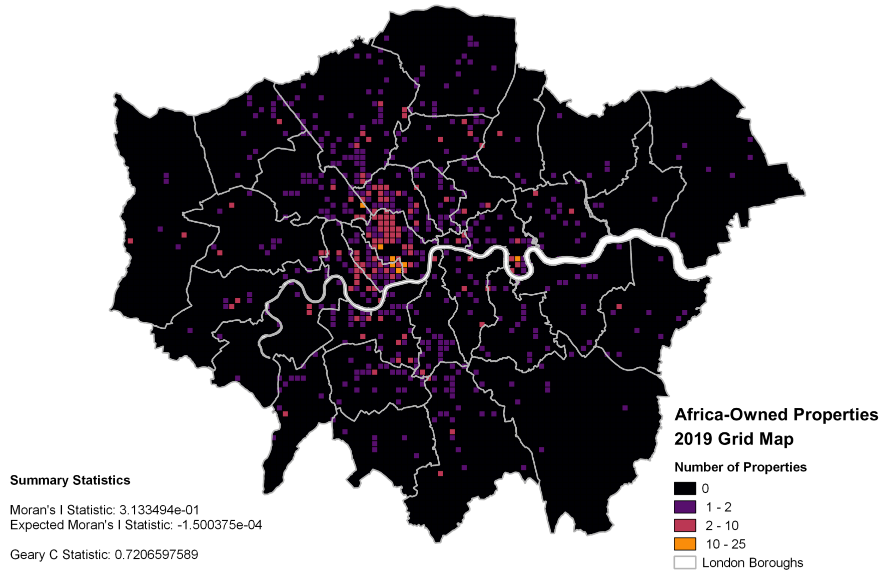

Figure 12: 2019 Grid Map of Properties Registered in Africa

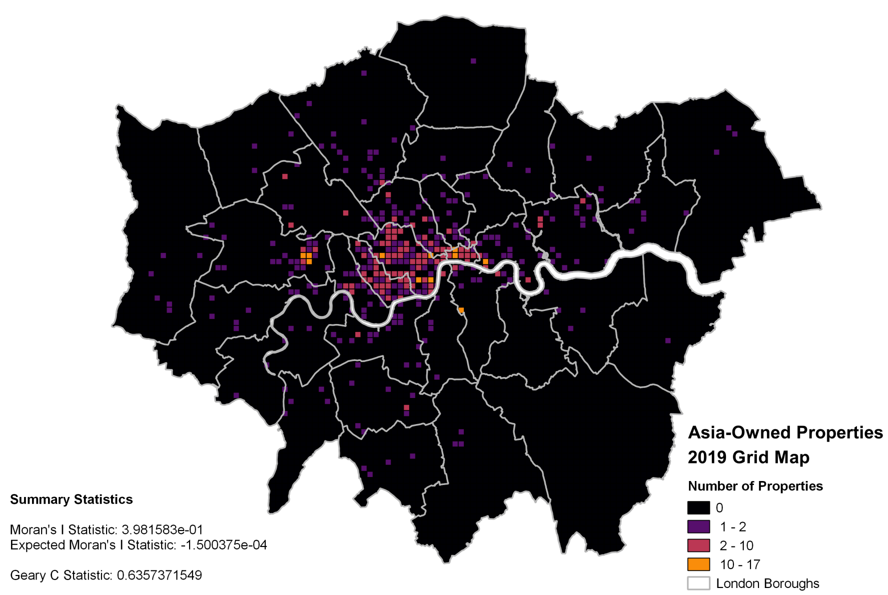

Figure 13: 2019 Grid Map of Properties Registered in Asia

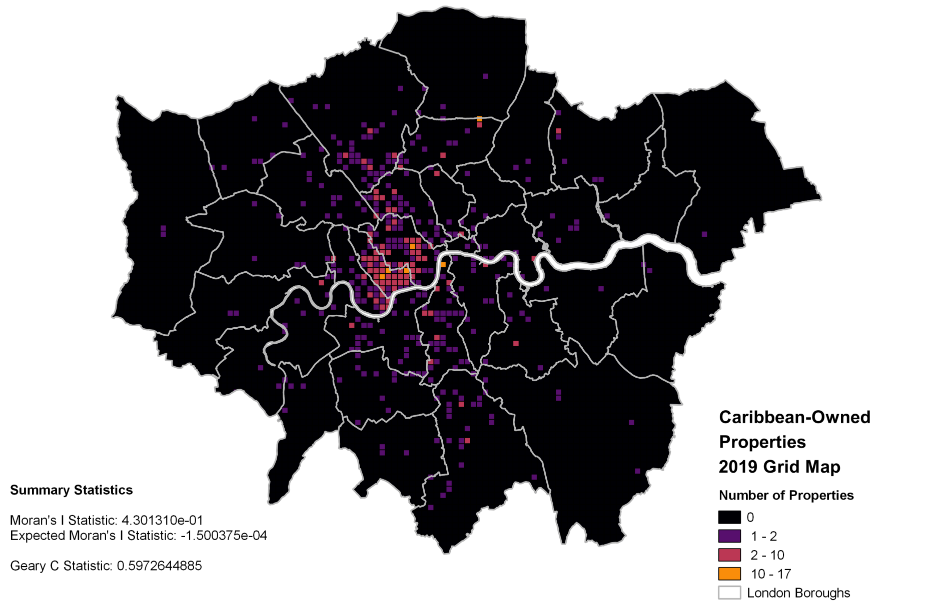

Figure 14: 2019 Grid Map of Properties Registered in The Caribbean

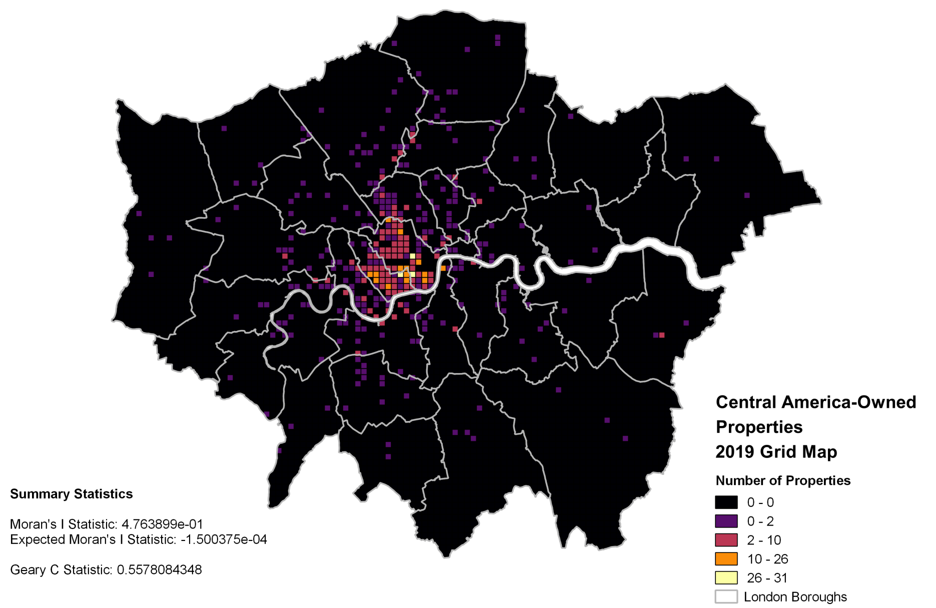

Figure 15: 2019 Grid Map of Properties Registered in Central America

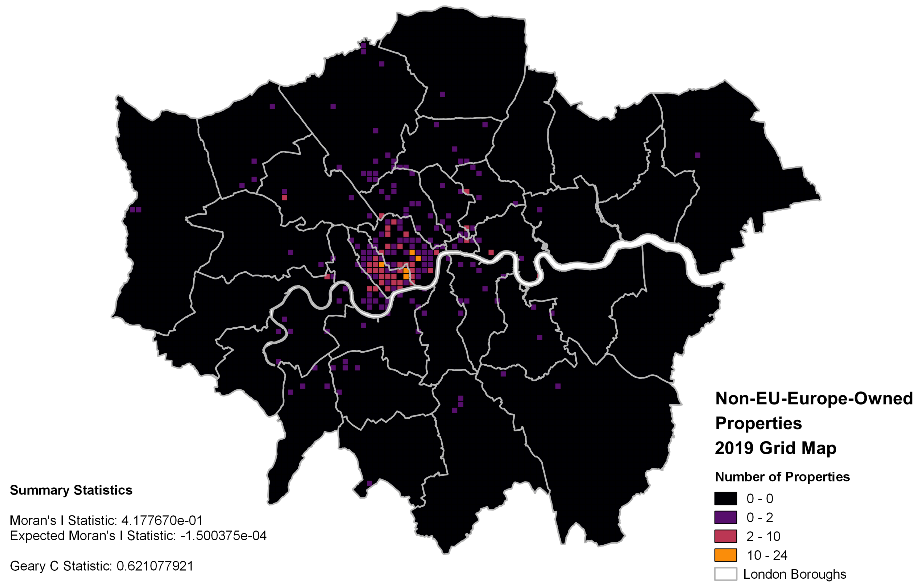

Figure 16: 2019 Grid Map of Properties Registered in Non-European-Union Europe

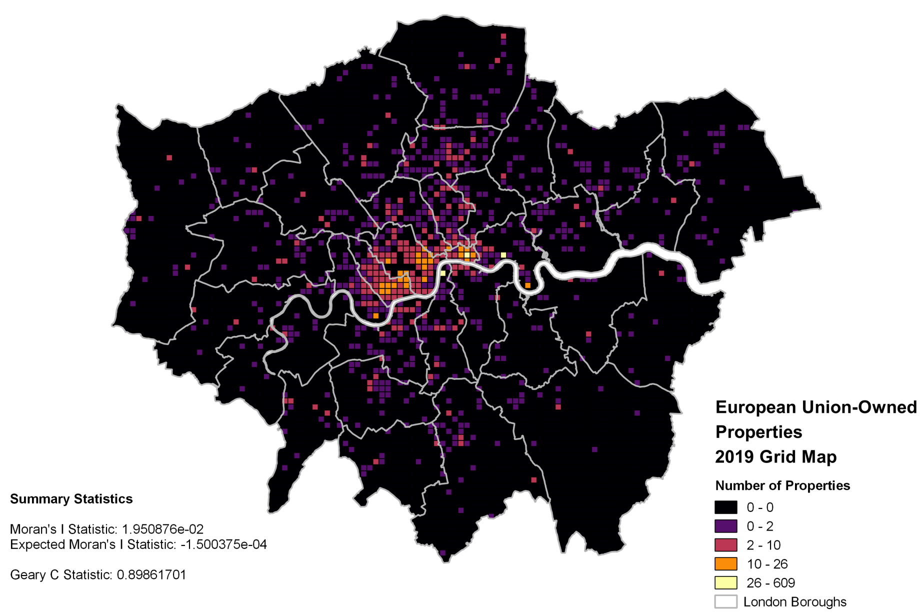

Figure 17: 2019 Grid Map of Properties Registered in The European-Union

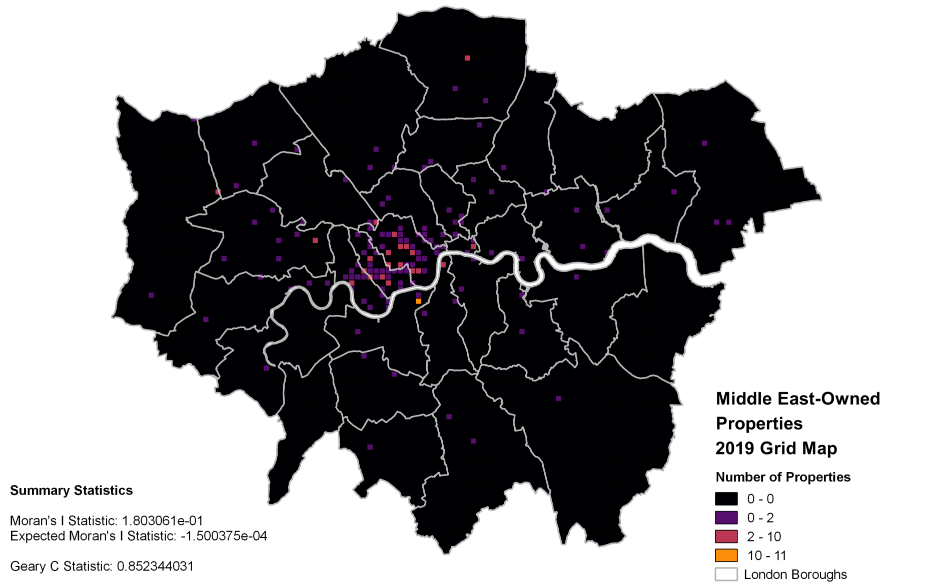

Figure 18: 2019 Grid Map of Properties Registered in The Middle East

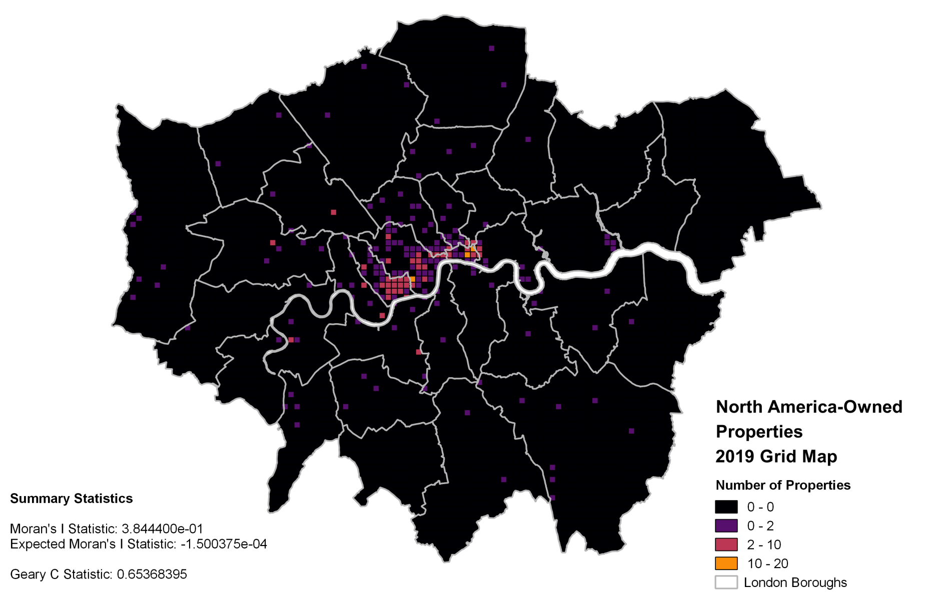

Figure 19: 2019 Grid Map of Properties Registered in North America

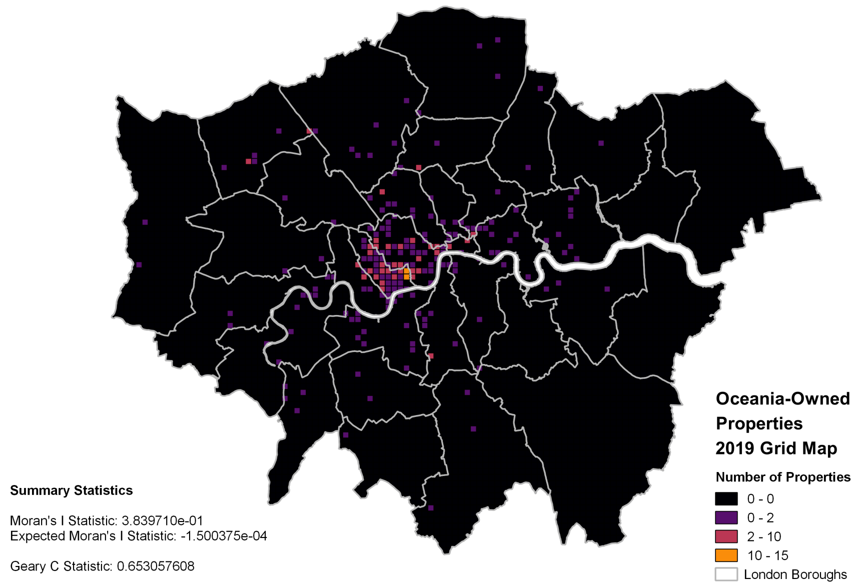

Figure 20: 2019 Grid Map of Properties Registered in Oceania

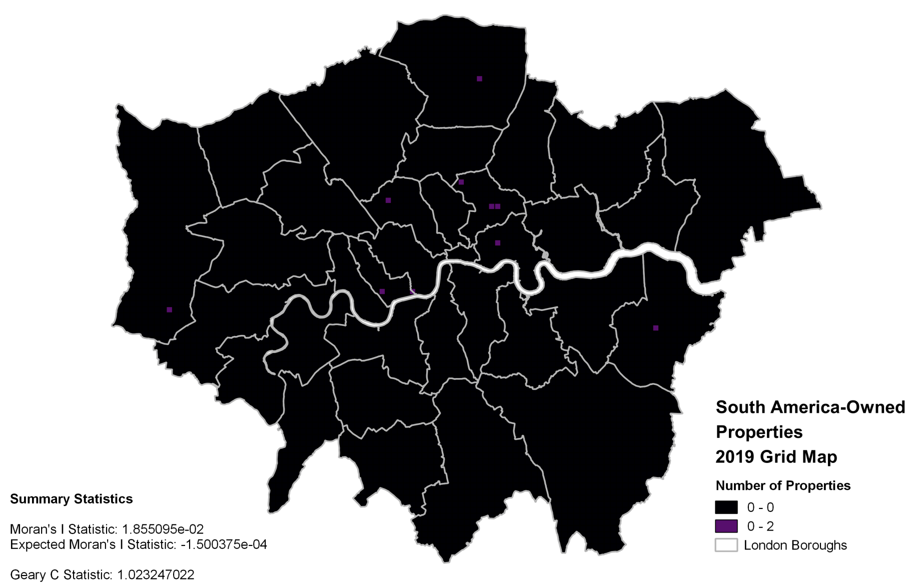

Figure 21: 2019 Grid Map of Properties Registered in South America

As visible in the above charts, there is a clear inequity between different regions in terms of the total number of properties, with South America most notably barely visible on the map. Other regions, like Central America or The Caribbean are well represented due to a subsection of countries within those regions like Panama that have historically acted as tax havens and locations for anonymous business registration (Warf, 2002).

There are also spatial patterns visible within certain regional clusters of owners. For overseas entities registered in Asia, there is a notable concentration of ownership around Southall in the borough of Ealing, due west of Central London. This is perhaps linked to the large concentration of South Asian population within this area of Ealing (Chaudhary, 2018). For properties owned by companies within the European Union, there is many properties located within the City of London. Of the properties registered to companies within Europe, but no located within the European Union, most of these properties are registered in Russia, and are clustered around Knightsbridge and Chelsea.

0.6.5 Grid Map Results

The following sequence of Figures 23-33 visualize all properties located within Greater London as of the given year for each map.

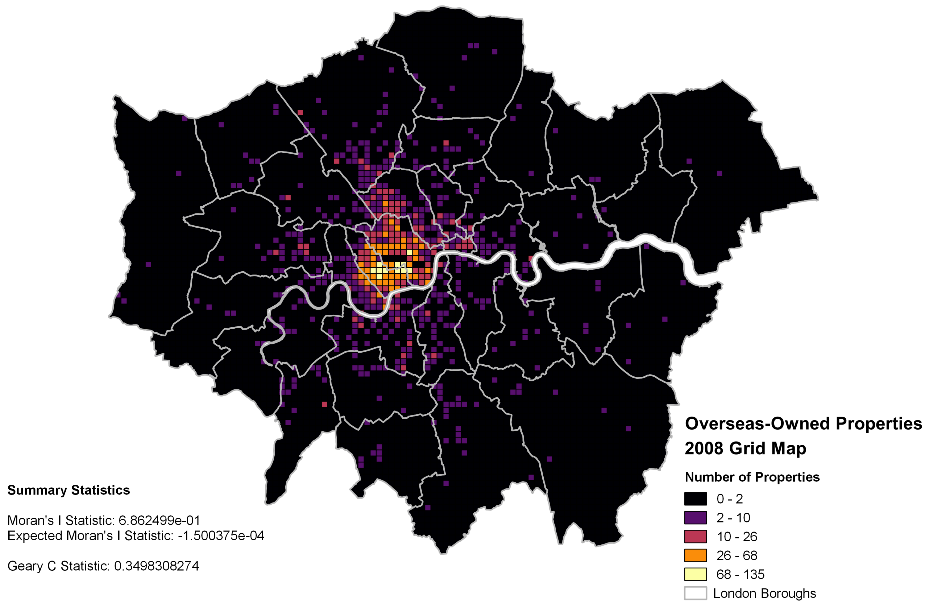

Figure 22: Grid Map of Overseas Owned Properties in 2008

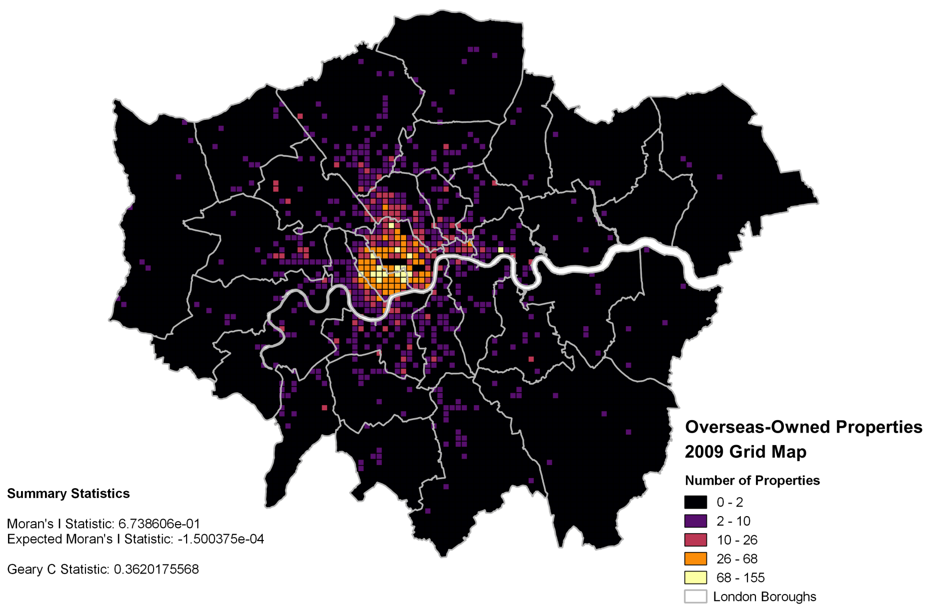

Figure 23: Grid Map of Overseas Owned Properties in 2009

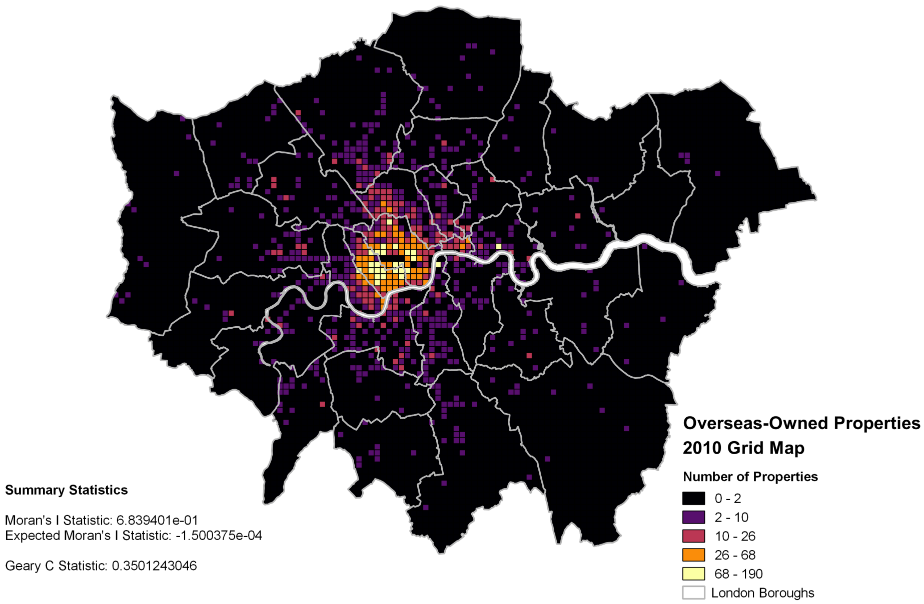

Figure 24: Grid Map of Overseas Owned Properties in 2010

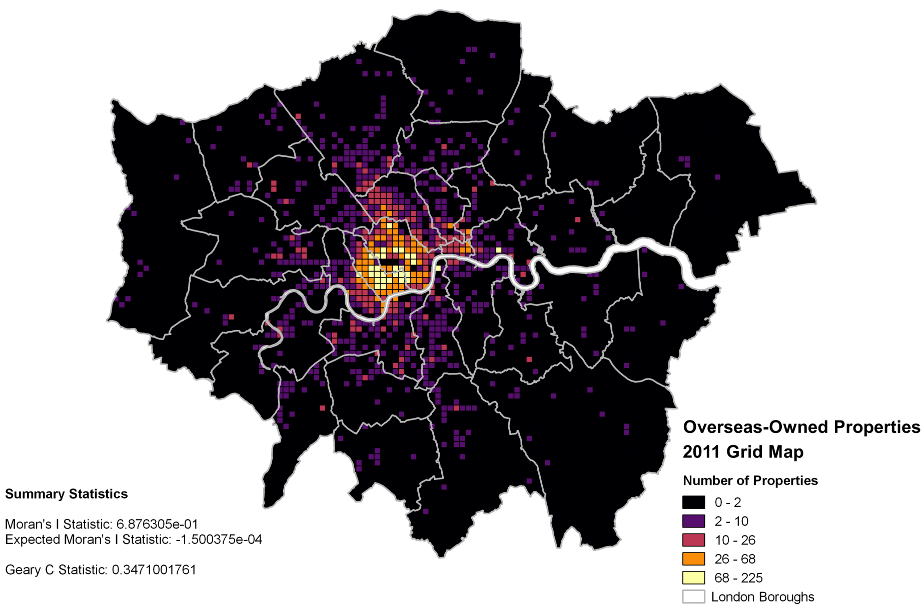

Figure 25: Grid Map of Overseas Owned Properties in 2011

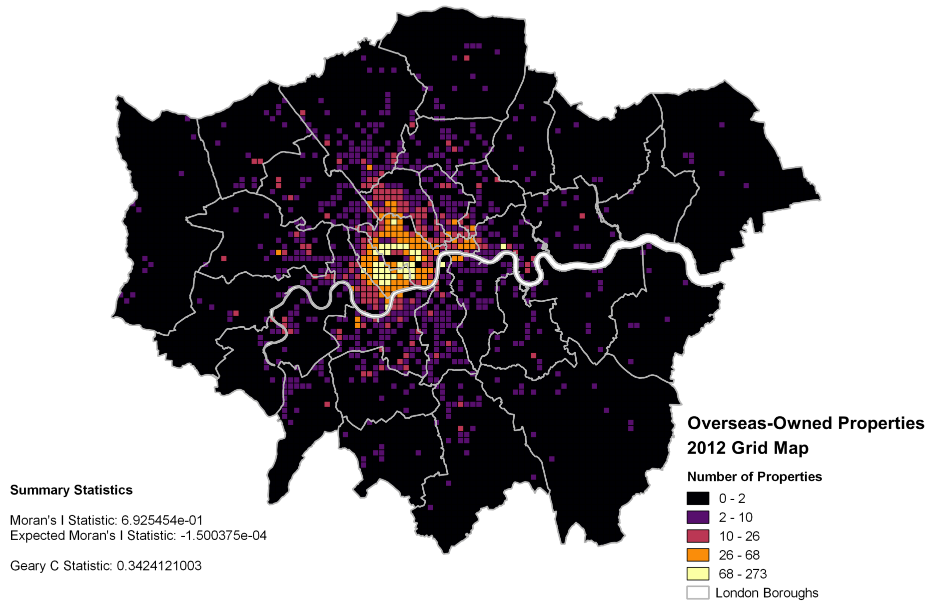

Figure 26: Grid Map of Overseas Owned Properties in 2012

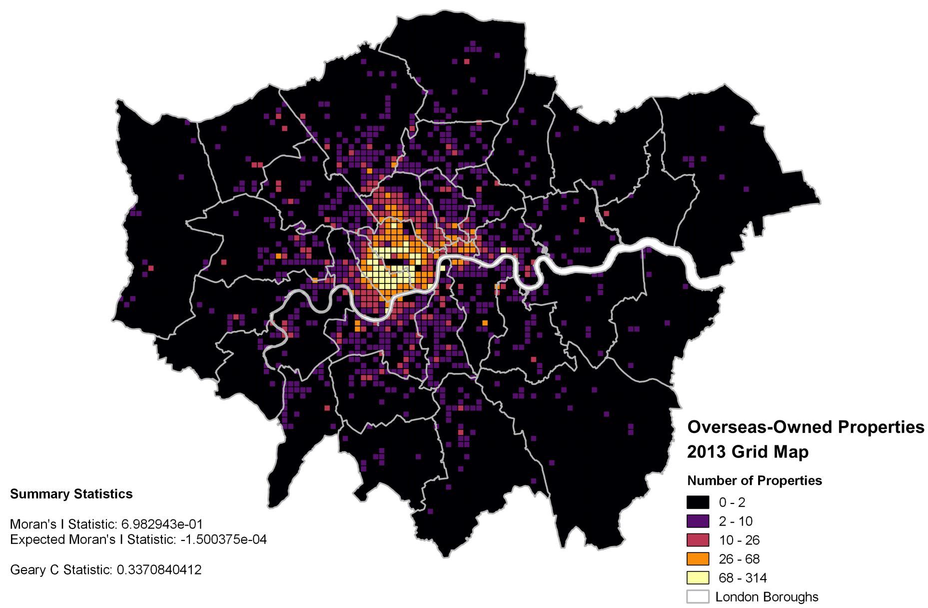

Figure 27: Grid Map of Overseas Owned Properties in 2013

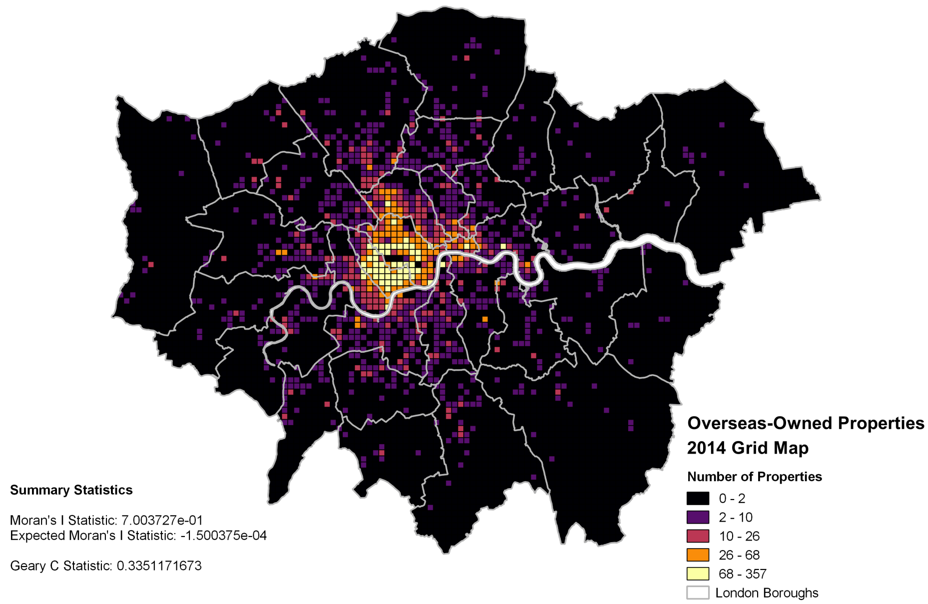

Figure 28: Grid Map of Overseas Owned Properties in 2014

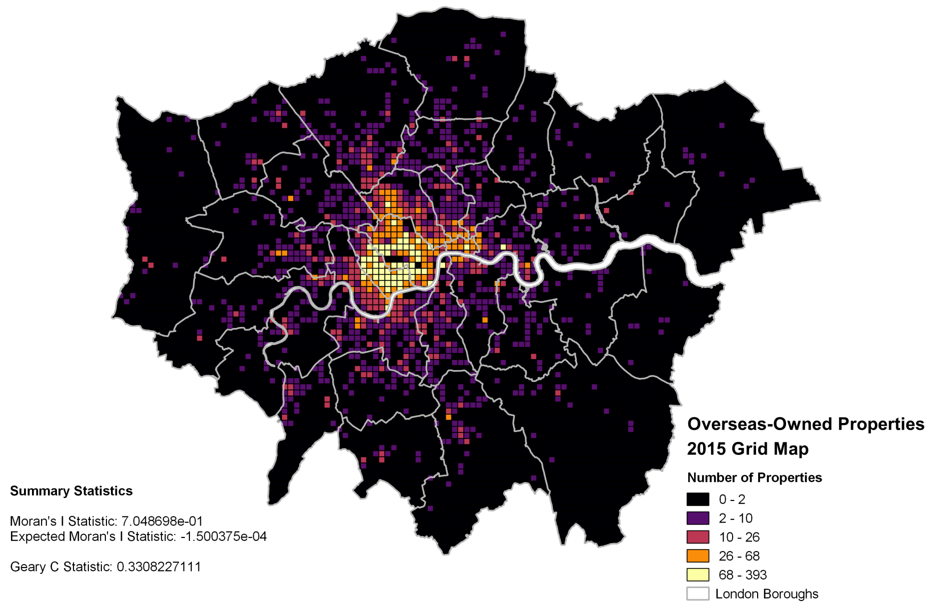

Figure 29: Grid Map of Overseas Owned Properties in 2015

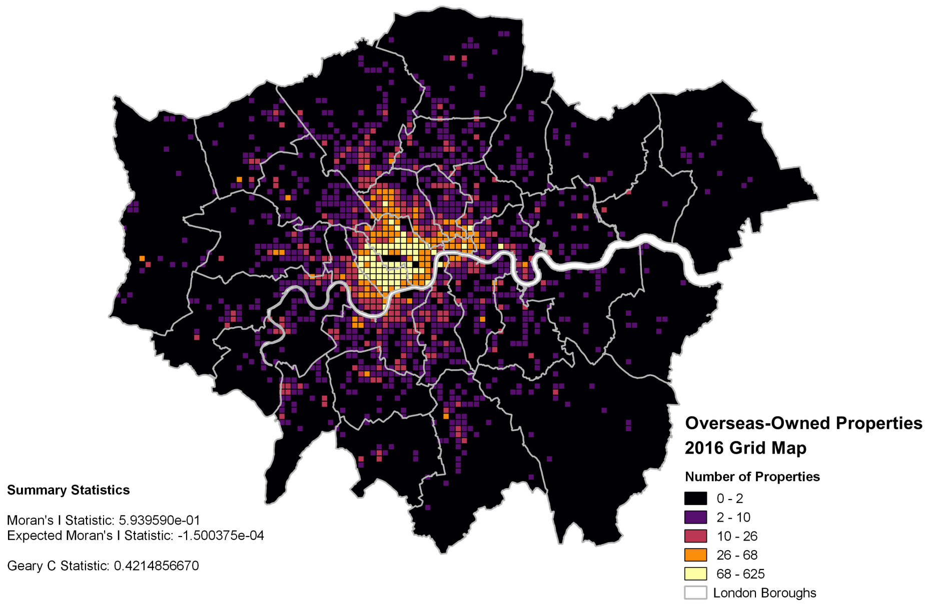

Figure 30: Grid Map of Overseas Owned Properties in 2016

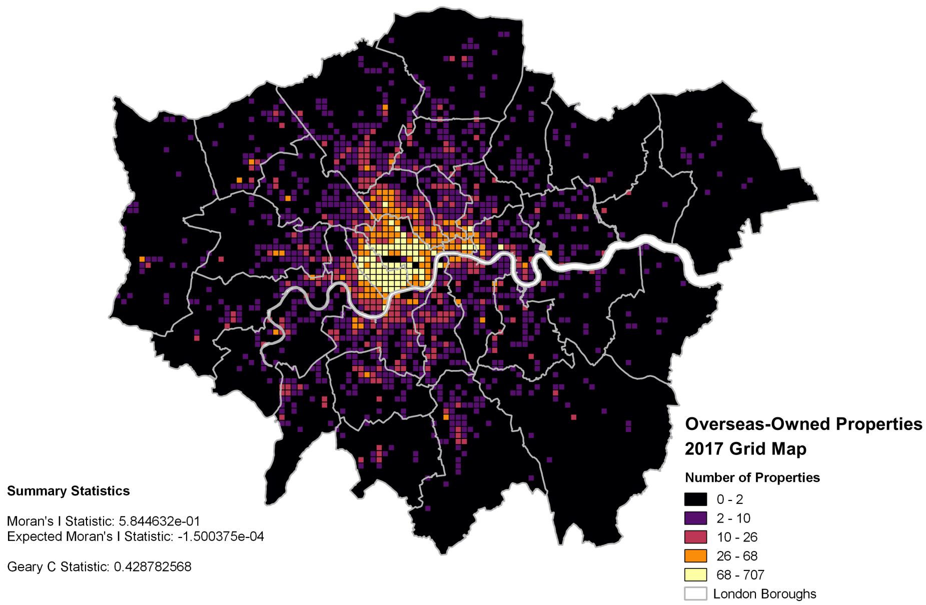

Figure 31: Grid Map of Overseas Owned Properties in 2017

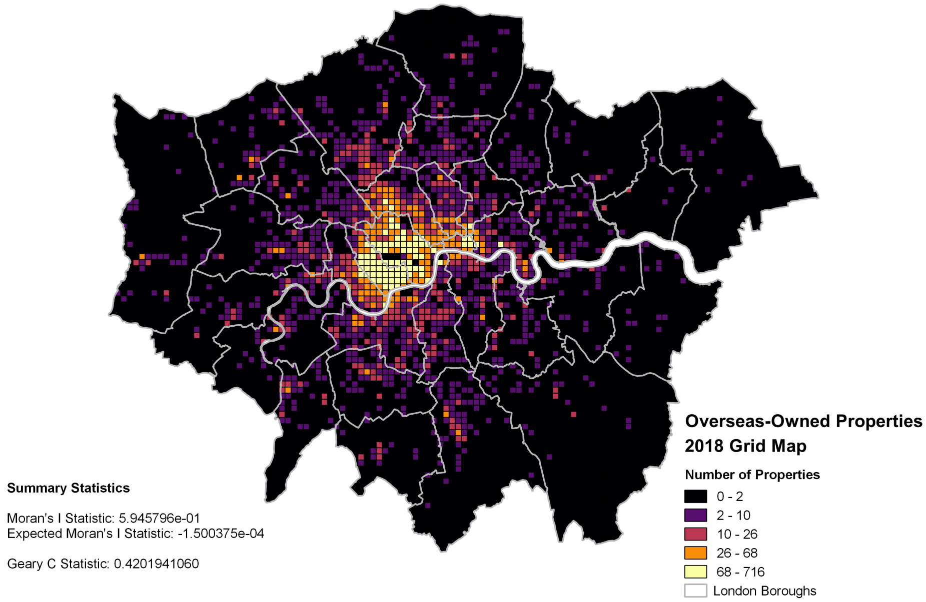

Figure 32: Grid Map of Overseas Owned Properties in 2018

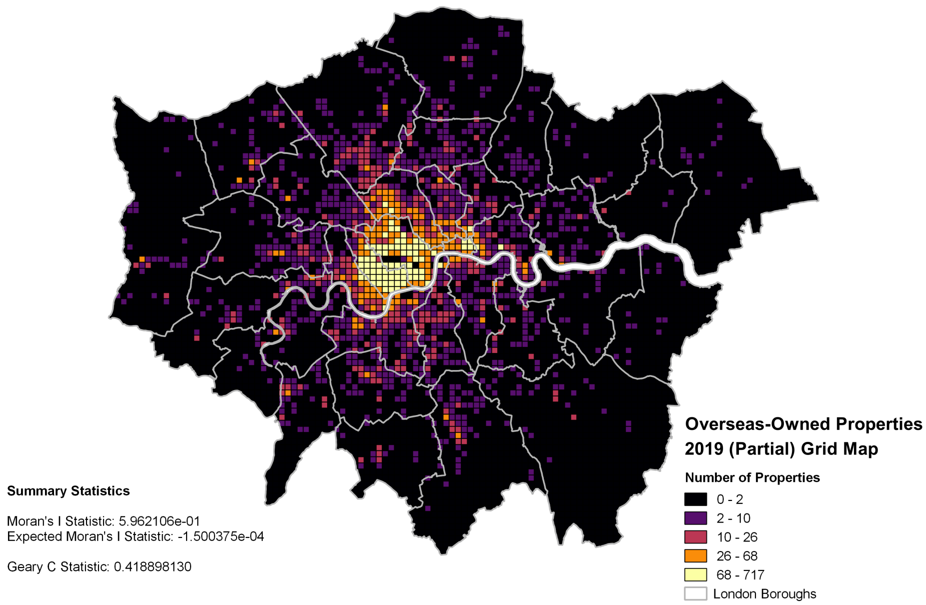

Figure 33: Grid Map of Overseas Owned Properties in 2019

As visible from the above maps, there is a consistent pattern of expansion, both in terms of total number of properties, as well as spatial extent, of foreign owned properties within London. The main avenues of spatial expansion in London appear to be a North-Northwest axis extending up from Westminster to Hampstead, a Western axis extending towards Heathrow through Southall, and a Southern axis with a concentration in Croydon extending from Westminster. Despite the abstraction of the grid format, details in spatial extent are still visible, with Hyde Park visible as the sequence of three black squares in the middle of Westminster. In mild contrast to the findings from the University of York Housing Policy Centre Report, there does not seen to be as much of a cluster in the eastern boroughs of London as that report found (Wallace et al. 2017).

To measure the relative concentration of the properties as time goes on, Moran's I and Geary's C measures of centrality were used for each iteration of the grid maps. The spatial concentration of the properties does not vary by large amounts over time, as visible in the following table.

Year	Moran's I Test Result	Geary C Result
2008	6.86	0.35
2009	6.74	0.36
2010	6.84	0.35
2011	6.88	0.35
2012	6.93	0.34
2013	6.98	0.34
2014	7	0.34
2015	7.05	0.33
2016	5.94	0.42
2017	5.84	0.43
2018	5.95	0.42
2019	5.96	0.42

Table 7: Moran's I and Geary's C Test Results for 2008-2019 Grid Maps

An important caveat to consider, as mentioned earlier in the methodology, is the fact that sales transactions between foreign owners, as well as overseas owners selling off properties to domestic owners are not included in the data prior to November 2017, which probably accounts for the more rapid increase in properties between 2016 and 2017.

0.6.6 NYC Grid Map and Comparison to London

Figure 34 is a map of all LLC owned properties located within the five boroughs of New York City, as of the most recent PLUTO dataset created at the end of 2018. The grid map for London as of 2019 is also provided in Figure 35, to allow for close visual comparison.

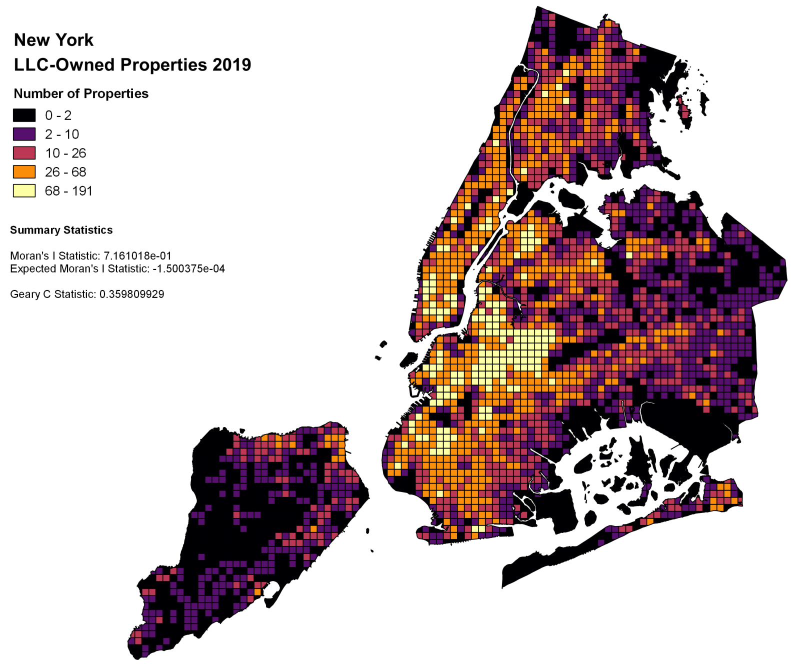

Figure 34: New York City LLC-Owned Properties 2019

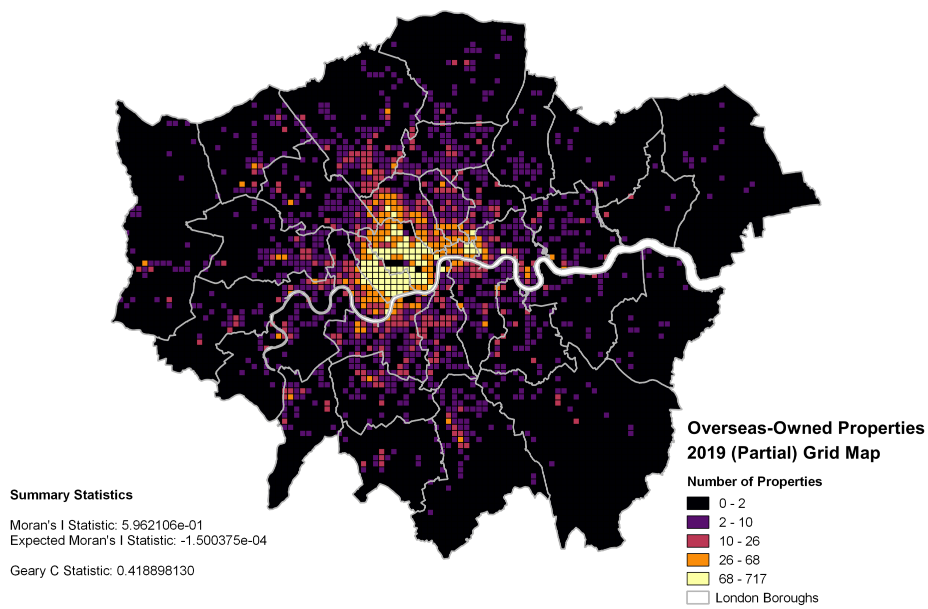

Figure 35: Grid Map of Overseas Owned Properties in 2019

In comparison to London, there is less spatial concentration within New York City than there is in London, at least according to the metric of Moran's I and Geary's C. The necessary caveat to this map, as mentioned before, is that using LLCs to measure Overseas Ownership within New York City, contains the risk of containing properties that, while registered as LLCs, are not necessarily owned by overseas entities. As a result, the 55,177 included LLC properties within New York City dwarfs the 30,775 Overseas Owned properties within London. However, according to this map there appears to be a concentration of properties within the northern portion of Brooklyn, extending into a portion of southern Queens. This seems to correspond with research conducted by on the phenomenon of "super-gentrification" that have occurred within portions of Brooklyn (Lees, 2003).

0.6.7 Common Owners Between London and New York City

There are 73 distinct owners that own properties in both cities, with 61 unique properties held by these owners within London, and 32 distinct properties held by these owners within New York City, and with a total number of 93 unique properties held by these 73 owners. The reason that this section was included, despite apparently appearing to be unrelated to the main question of examining change within London, is to illustrate the point that this even though the effects of this behavior are highly local, the actual processes that lead to concentrations in foreign ownership appear to behave in similar ways despite being different cities and countries. In contrast to studies of gentrification, there exists a much smaller body of work that examines how foreign ownership behaves within cities. While a larger examination of foreign ownership across multiple cities is beyond the scope of this dissertation, it is hoped that future analysis will examine and compare other types and groups of cities where this information is available to determine if there is a broader pattern of foreign investment. The following Figures 36 and 37 depict properties within New York City and London that both share common owners, visualized using the grid map format.

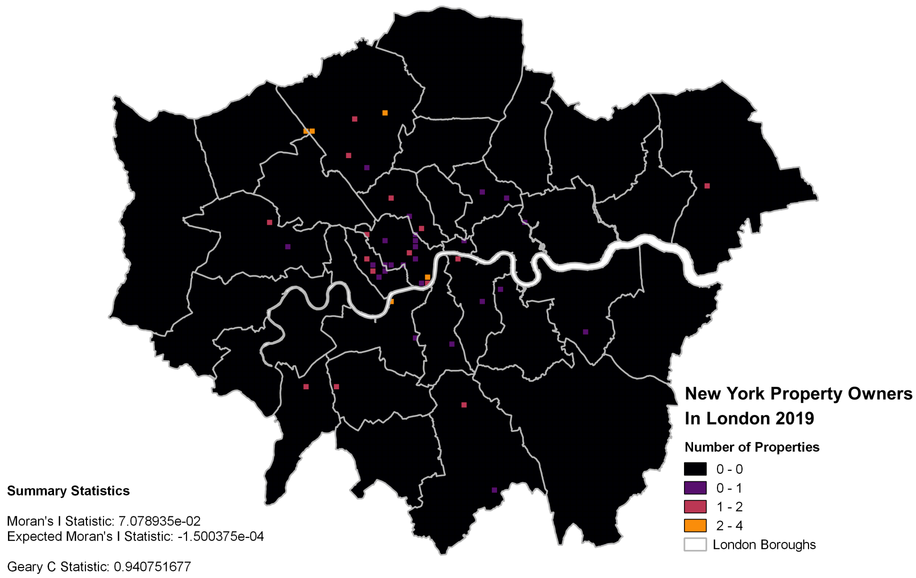

Figure 36: New York Property Owners in London 2019

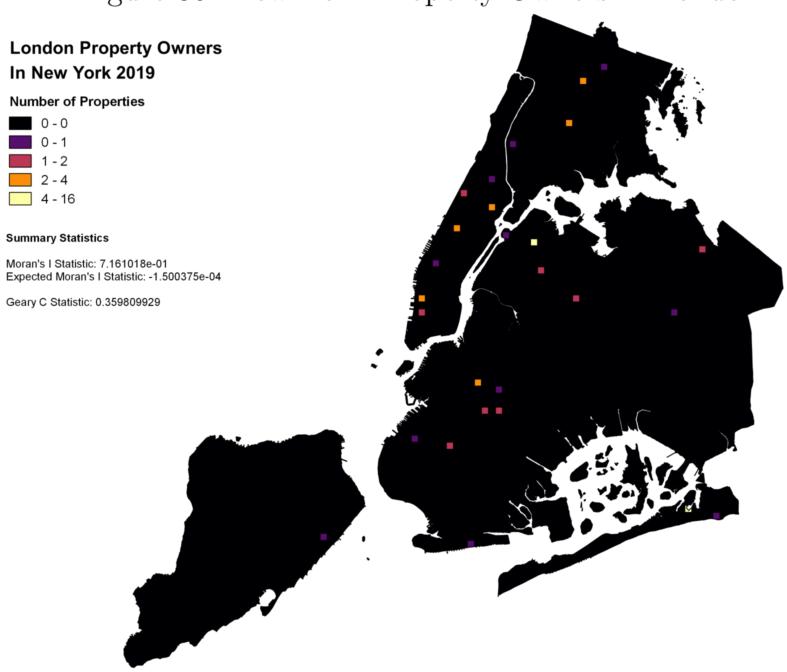

Figure 37: London Property Owners in New York 2019

0.6.8 Predictive Model Testing in London

When each future year to 2025 was predicted using the random forest regression model, a test was run for each year, determining the ideal number of parameter estimators to be used for the regression. The ideal number of parameter estimators was determined using the mean test time and score of each parameter setting After running the test model using the suggested parameters as well as the regression score, mean absolute error, mean squared error, root mean squared error, and the r-squared value. The results of these parameter tests for each predicted year from 2020-2025 are located in Table 8.

Years Used	Year Predicted	Number of Parameter Estimators	Regressor Score	Mean Absolute Error	Mean Squared Error	Root Mean Squared Error	R Squared
2008-2017	2018	200	-0.054	-0.059	0.054	0.23	0.99
2008-2016	2017	200	-0.088	0.069	0.088	0.3	0.99
2008-2013	2014	200	-0.026	0.064	0.026	0.16	0.995
2008-2010	2011	400	-0.029	0.046	1.15	0.17	0.99
2008-2017 (Without Zeros)	2018 (Without Zeros)	600	-0.46	0.17	0.46	0.68	0.98

Table 8: Random Forest Regression Model Testing Scenario Statistics

Perhaps the most notable metric from Table 8 is the consistently high regression score. While normally this would be considered the sign of a particularly accurate model, this statistic is somewhat misleading within the context of this model as many grid squares contain zero overseas owned properties in any of the existing year datasets. As a result, these are consistently easy for the model to predict and throw off the score of the model as a result. To compensate for this, the final test used extracted all grid squares where values were not zero in all years from 2008 to 2017 to predict 2018. In this test scenario, the test metrics become slightly more typical as a result of removing the grid squares with zero properties within them. While the R Score is still quite high, possibly due to the number of grid squares that may remain static from one year to the next, it is lower than the other testing iterations. There is also a higher level of error within the other four measures of error, which indicates that the model had a bit more difficulty in determining grid squares that already had a certain number of properties within them.

While the summed number of properties within neighboring squares was included as a potential predictor variable, it did not display any variable importance in any of the testing scenarios. The most significant predictor for all testing scenarios was the number of points for a square in the previous year, with a typical significance between 0.7 and 0.8. Below is a typical chart of variable importance, taken from the scenario using the 2008-2016 data to predict 2017.

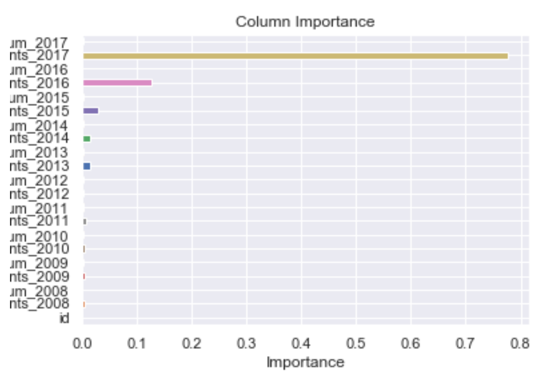

Figure 38: Column Importance From the 2008-2016 Predicting 2017 Scenario

After conducting these tests, the same process was applied, but to all existing years, in order to generate a prediction of Overseas Owned property distribution in from 2020 to 2025. After each future year was generated, the number of points for each square was appended as a new column to the base dataset, and the process repeated for the following year. The results of the regression statistics for each of these predicted years are located in the following Table 9.

Year Predicted	Number of Parameter Estimators	Regressor Score	Mean Absolute Error	Mean Squared Error	Root Mean Squared Error	R Squared
2020	200	-16.02	0.15	16.02	4	0.99
2021	200	-6.67	0.075	6.67	2.58	0.99
2022	200	-3.36	0.046	3.36	1.83	0.99
2023	200	-1.55	0.033	1.55	1.24	0.99
2024	200	-0.86	0.033	0.86	0.93	0.99
2025	200	-0.32	0.042	0.32	0.57	0.99

Table 9: Regression Statistics for Predicted Years

As with the testing scenarios, the most important variable typically was the number of points within a square in the previous year, with the sum of properties in neighboring squares again exhibiting zero importance. However, due to increasing auto-correlation and linearity within the model over time, in iterations of the model from 2023 and onwards, prior years became more equal in their influence on the predicted year, with a chart of column importance for the predicted year of 2024 included below.

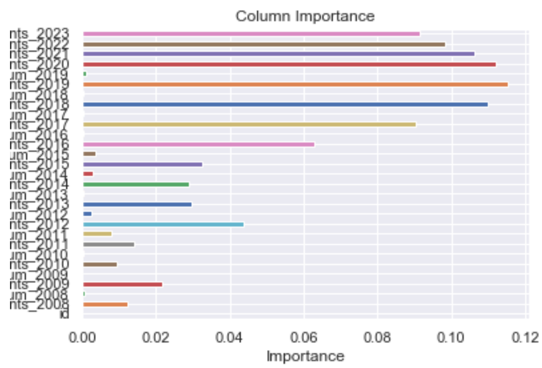

Figure 39: Column Importance of Columns Predicting 2024

After generating the predicted counts of properties in each grid square, each of the years was then appended to the London grid map template and mapped in the same way as other grid maps, with the resulting sequence of figures as a result.

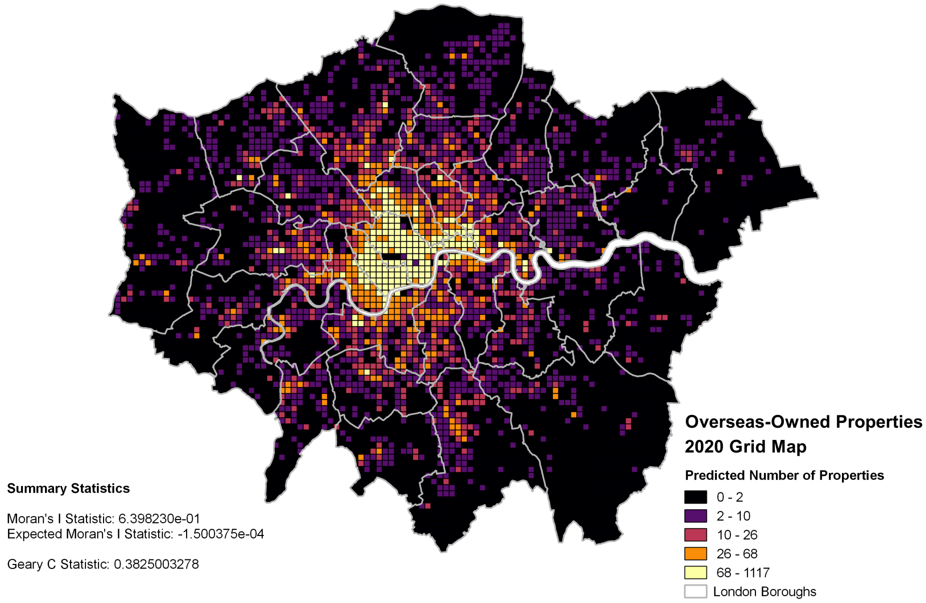

Figure 40: Grid Map of Predicted Overseas Owned Properties Counts in 2020

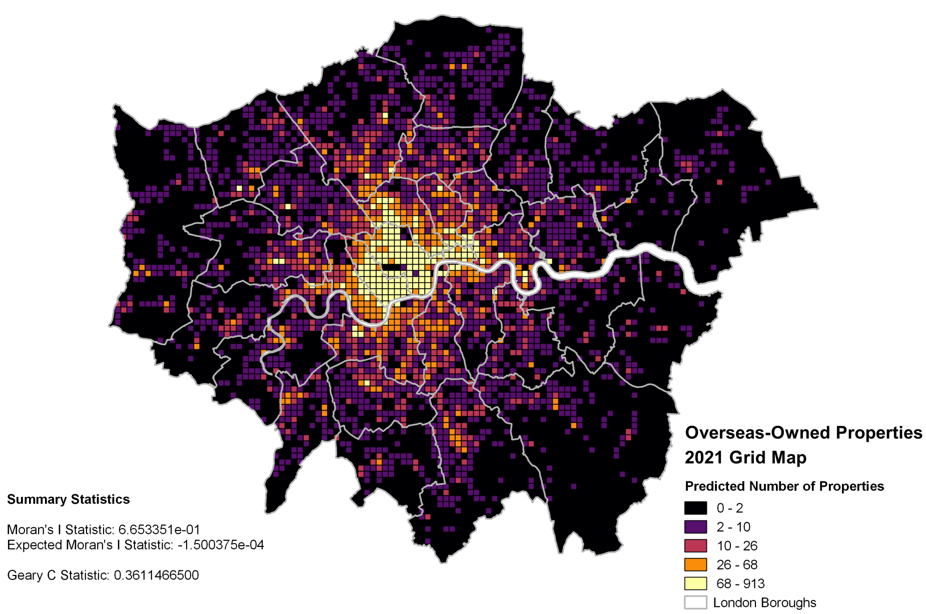

Figure 41: Grid Map of Overseas Owned Properties in 2021

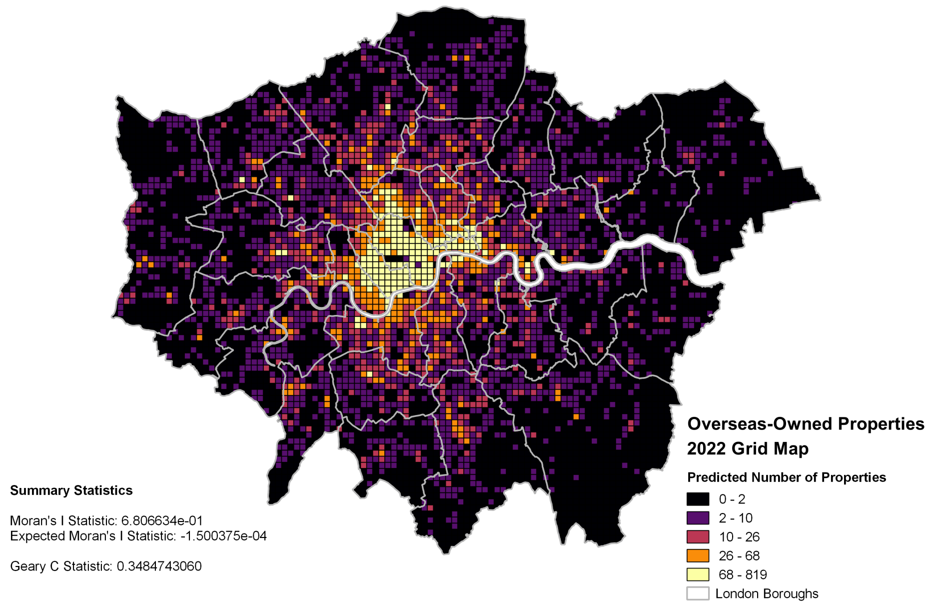

Figure 42: Grid Map of Predicted Overseas Owned Properties Counts in 2022

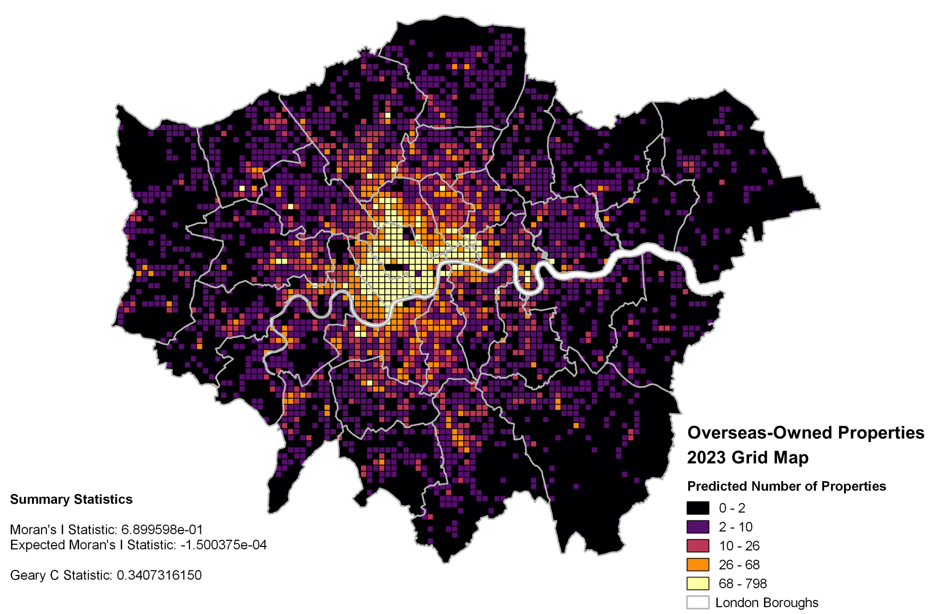

Figure 43: Grid Map of Overseas Owned Properties in 2023

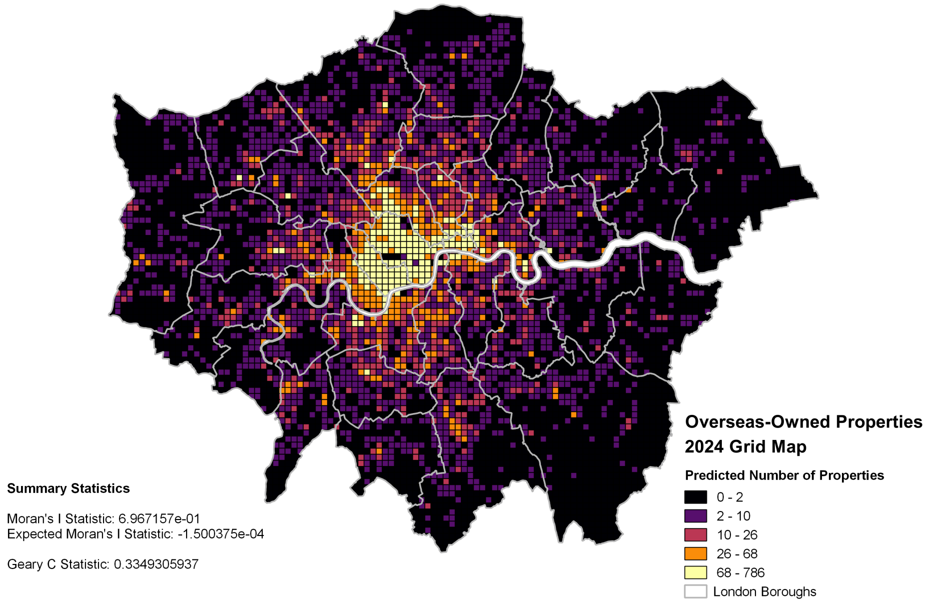

Figure 44: Grid Map of Predicted Overseas Owned Properties Counts in 2024

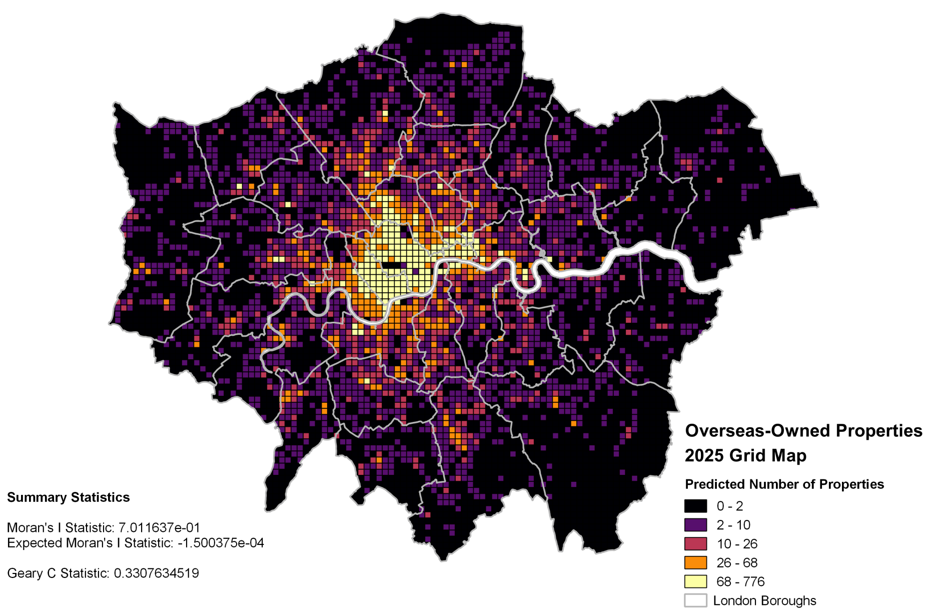

Figure 45: Grid Map of Overseas Owned Properties in 2025

As visible from above, from visual inspection it appears that the predicted property maps seem to roughly follow the same spatial patterns as the existing years, aside from the relatively large increase in properties for 2020. The Moran's I and Geary's C results seem to align with existing years as well.

Perhaps the most noteworthy pattern from the predicted distributions is that while the overall number of properties increases in 2020, it then decreases in every subsequent year. However, while this occurs, the spatial distribution of properties becomes more widespread, with a larger number of grid squares included in the highest level of properties - "68 or more". This seems to suggest future avenues of investigation to determine reasons for this pattern, as well as if this pattern has occurred in other cities around the world that contain large amounts of foreign land investment and ownership.

An important caveat for this is that the number of properties predicted for each grid square needed to be rounded after generation by the random forest regression model, as all results outputted by the random forest regression model are in decimal form, which is misleading considering that it is not currently possible, future tax evasion methods asides, to have fractional numbers of properties owned by a single entity.

0.7 Conclusion

At the beginning of the process for this dissertation, the initial goal of the work undertaken was to determine the relative extent of foreign owned properties within London, as well as predicting the potential spatial distribution of properties within London into the future. While these goals were met, perhaps the most notable lesson from this dissertation is realizing the extent of obfuscation and secrecy pertaining to land ownership information that provides a true insight into the nature of land ownership, foreign or otherwise, within Greater London. While not the most relevant in terms of spatial analyses, the fact that around 1,500 properties within Greater London owned by overseas entities do not have associated proprietor addresses is concerning.

The fundamental issue with all work conducted within this dissertation, as well as almost any attempt currently undertaken to determine the nature of land ownership anywhere within the United Kingdom, is the ability to nest LLC ownership of a given property through multiple LLC owners, all potentially registered within a different country. The ability to do so prevents any sort of meaningful ownership analysis on a large scale to be undertaken within the United Kingdom. As a result, if there was any potential policy recommendation from this paper to be undertaken, it would be to reform the means of land ownership by shell companies. Initiatives to open rolls of land ownership, like those currently undertaken by the Isle of Man and Jersey, while useful in providing owner information for properties at the second level of land ownership previously not available, this still does not necessarily entail that those names and companies are the “final level“ of land ownership.

For future investigation, the most substantial suggested change in methodology would be to incorporate as many census variables as possible to see if it is possible to create a hedonic model of overseas owner location. While this dissertation focuses on where and how overseas ownership spatially spreads over time, future investigations could focus on *why* overseas ownership spreads over time. Other models could potentially be used to predict owner changes over time. Additionally, the spatial extent of domestic corporate ownership could be investigated using the Commercial and Corporate Ownership dataset, potentially in conjunction with the Overseas Companies Ownership dataset.

The other main policy recommendation from this paper is to provide geographically referenced information for the Overseas Ownership dataset provided by HM Land Registry. While the dataset includes postcode and address as columns within the dataset, the postcode polygons that needed to be joined to the dataset to provide geographic context are currently only accessible to academics and other non-public entities. This limits the ability of those in the general public to examine this facet of Overseas Ownership. Until the Land Registry releases names associated with all properties, overseas owner or otherwise, a substantial investigation of land ownership within the United Kingdom will remain stymied.

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