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Dissertation:

Exploring the relationship between identified strategic housing capacity and housing delivery rates in London since 2013

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Abstract

London is projected to grow to almost 10 million people by 2031 and the consequent pressure on the housing market is greater than ever. In order to address the housing crisis, it is important to consider where potential housing capacity has been identified and could be identified in the future by understanding what truly influences residential development in London.

This study aims to understand relationship between identified strategic housing capacity and housing delivery rates in London since 2013. This is done by adopting a spatial approach comprised of a suitability analysis using multicriteria factors which could potentially influence housing capacity and delivery rates within London. The existing central government endorsed Strategic Housing Land Availability Assessment (SHLAA 2013) methodology is utilised, critiqued and adapted to add further insights towards understanding the suitability of potential sites for residential development. Another key objective is understanding which variables influence housing capacity and delivery rates within London.

Developing this understanding can allow city planners within London to understand the factors influencing housing capacity and delivery and where investment needs to be targeted and prioritised to enable future housing development to come forward.

Declaration of Authorship

I, Shivani Bhatnagar, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. The dissertation is 11865 words in length from the introduction to conclusion inclusive, excluding footnotes, tables and figures. Word count by Microsoft Word.

Signed: _____

Date: 30 August 2019

Table of contents

Abstract		**2**
Declaration of authorship		**3**
Table of contents		**4**
Table		**5**
Figures		**6**
Acronyms		**7**
Acknowledgement		**8**
1. Introduction		**9**
	1.1 Motivation	10
2. Research Objectives		**11**
	2.1 Scope of research	12
	2.2 Study structure	13
3. Literature Review		**15**
	3.1 Housing Supply and housing need in England	15
	3.2 London's housing crisis	17
	3.3 London SHLAA	18
	3.4 Limitations of SHLAA methodology	22
	3.5 Spatial regression modelling and Geographically Weighted Regression modelling	25
	3.6 Weighted overlay analysis for suitability studies	26
	3.7 Feature scaling of coefficients	27
	3.8 GIS tools	28
	3.9 Summary	29
4. Methodology		**30**
	4.1 Data collection	30
	Data sources table	31
	4.2 Data preparation	33

	4.3 Deviations from SHLAA 2013 methodology	43
	4.4 Defining capacity, delivery and delivery rate aggregation	45
	4.5 Defining 'residential capacity suitability'	48
	4.6 'Residential capacity' suitability classification	49
	4.7 Quantitative methods, spatial analysis and workflow	49
	Workflow diagram	50
	4.8 Weighted overlay analysis	53
	4.9 Rasterising layers	53
	4.10 Reclassifying the variables input	
	4.11 Assigning weights to variable inputs…	53
5. Results and analysis		
	5.1 – 5.4 Research questions	54 - 63
6. Evaluation		
	6.1 – 6.2 Remaining research questions	71-72
7. Conclusion		**73**
8. References		**75**
9. Appendix 1.1		**84**

Tables

Table 1 SHLAA 2013 Planning Policy constraints and impacts on probability 22
Table 2 SHLAA 2013 Strategic/ Environmental constraints and impacts on probability 22
Table 3 SHLAA 2013 Local constraints and impacts on probability 23
Table 4 Summary of data sources 34
Table 5 Residential suitability classification 50
Table 6 Model 1.3 absolute capacity density predicted by significant SHLAA constraints 65
Table 7 Model 1.4 ab_Cap_Den predicted by all SHLAA and additional datasets... 66
Table 8 model 3.2 delivery rate predicted by all significant variables 69
Table 9 Model 2.2 ab_Delivery_density predicted by all significant variables 69
Table 10 Weighted overlay analysis for only SHLAA constraints`` 71
Table 11 Absolute capacity density 71
Table 12 Weighted overlay analysis for all input variables 71

Figures

Figure 1 Housing supply in England compared with housing need (source: Tackling the under-supply of housing in England, (Wilson and Barton, 2018:6)).....16
Figure 2 Annual completions versus permissions. Source: Housing White Paper: Fixing our broken housing market, (DCLG, 2017, pg 13) 17
Figure 3 Housing capacities identified in the London plan have risen over time. Source: Housing in London report (GLA, 2018, pg 22).....19
Figure 4 Housing capacity by Local Planning Authority (LPA) (2019-20 to 2028-29). Source: SHLAA 2017 methodology, (GLA, 2017).....21
Figure 5 London Plan density matrix. Source: London Plan 2016 (GLA, 2016, pg 101) 24
Figure 6 transport investment (post 1987) overlaid on homes growth between 2005 and 2015. Source: Homes in London report, (GLA, 2018) and TfL transport investment spatial data. 25
Figure 7 SHLAA 2013 sites (phases 1 and 2) categorised by the number of residential units.....36
Figure 8 Completed planning applications categorised by the number of residential units.....36
Figure 9 capacity aggregation at ward level 38
Figure 10 capacity aggregation at LSOA level 38
Figure 11 A comparison of SHLAA sites before and after performing a union along LSOA boundaries 42
Figure 12 Before and after drawing a 50m buffer around pylons and performing a union along LSOA boundaries.....42
Figure 13 Before and after drawing a 400m buffer and performing a union along LSOA boundaries 42
Figure 14 LSOAs categorised by median house prices (2013).....43
Figure 15 SHLAA sites phases 1 and 2 categorised by the number of residential units 55
Figure 16 SHLAA capacity boxplot.....56
Figure 17 Absolute capacity density in London LSOAs 57
Figure 18 Comparison of capacity and delivery of residential units.....59
Figure 19 Comparison of capacity and delivery after filtering the LSOAs.....59
Figure 20 Completed planning applications since 2013 categorised by the number of residential units.....60
Figure 21 Absolute delivery density per LSOA.....61
Figure 22 Delivery rate of LSOAs with capacity > 30 residential units.....62
Figure 23 Delivery rate of all LSOAs.....62
Figure 24 Absolute difference in delivery and capacity in LSOAs.....64
Figure 25 Correlation matrix of all variables.....68

Acronyms:

AONB	Areas of Outstanding Natural Beauty
CAZ	Central Activity Zone
DLR	Docklands Light Railway
GIS	Geographic Information Systems
GLA	Greater London Authority
GWR	Geographically Weighted Regression
LDD	London Development Database
LEN	Lower Emission Neighbourhoods
LPA	Local Planning Authority
LU	London Underground
LSOA	Lower Super Output Area
MOL	Metropolitan Open Land
NIMBY	'Not in my backyard'
NPPF	National Planning Policy Framework
NR	National Rail
OLS Regression	One Least Squares Regression
PTAL	Public Transport Accessibility Level
SHLAA	Strategic Housing Land Availability Assessment
SINC	Sites of Importance for Nature Conservation
TfL	Transport for London
SIL	Strategic Industrial Locations
SINC	Sites of Importance for Nature Conservation
LSIS	Locally Significant Industrial Sites
NDIS	Non-Designated Industrial Sites

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Finally, I would like to thank my family for their unrestricted love, support and patience.

1.Introduction

London is projected to grow to almost 10 million people by 2031 and the consequent pressure on the housing market is greater than ever (City Hall, 2018). In order to address the housing crisis, it is important to consider where potential housing capacity has been identified and could be identified in the future by understanding where housing development has already occurred.

Traditionally, city planning and policy making within London relies on precedent or area-specific initiatives to develop thinking around residential development using local development capacity studies as an example. Beginning to understand and address the root of the housing crisis relies on implementing a coordinated London-wide approach to identifying, enabling and supporting residential development in the right places and at the right density. The purpose of this study is to explore the possibility of an overarching understanding of the variables which affect residential suitability on a city-wide scale so that city planners can approach their day-to-day decision-making with a macro-level understanding about housing capacity and the rate of delivery across London.

This study adopts a spatial approach by conducting a suitability analysis of factors which potentially influence housing capacity and delivery rates within London. The existing central government endorsed Strategic Housing Land Availability Assessment (SHLAA 2013) methodology is utilised, critiqued and adapted (in chapters 3-5) to add further insights towards understanding the suitability of potential sites for residential development. A weighted overlap analysis is performed using the SHLAA methodology factors to predict the notional residential capacity within London Lower Super Output Areas (LSOAs) and a second analysis focuses on expanding upon the factors covered in SHLAA with other policy, demographic

and transport related datasets to predict delivery rate and general residential suitability within London LSOAs.

1.1. Motivation

London is currently facing an acute housing crisis with the rate of house building consistently falling behind the demand for homes in the rapidly growing city. In order to maintain and bolster the vitality and attractiveness of living in London, it is important that London grows in a sustainable manner which caters to the needs of the population. Providing sufficient affordable and high-quality housing in well-connected and liveable areas following the Mayor of London's 'Good Growth' principles play a key role in shaping the future growth and planning of London. (GLA, 2019)

The motivation of this study emerged from the need to understand the relationship between housing capacity as identified by local government and the rate of housing delivery in London since 2013. Another key motivation is understanding which variables influence housing capacity and delivery rates within London and whether residential suitability can be modelled for London LSOAs.

Developing this understanding can allow city planners within London to understand the factors influencing housing capacity and delivery and where investment needs to be targeted and prioritised to enable future housing development to come forward.

2. Research objectives

The objective of this thesis is to explore the relationship between identified Strategic Housing Land capacity and housing delivery rates in London since 2013. This objective can be broken down into the following parts which will be addressed individually in the results, evaluation and conclusion in the order mentioned below:

1. What is the housing capacity in terms of residential units as identified in the last SHLAA from 2013 during the first two phases of the exercise? Spatially, where is this capacity situated and what are the underlying reasons behind this?
2. How much residential development in terms of residential units has been completed since 2013? Spatially, are there any patterns in delivery and what are the underlying reasons behind this?
3. What is the rate of housing delivery in London LSOAs and which areas of the city have met their capacity targets as opposed to under or over delivering against the identified capacity?
4. What is the impact of recreating SHLAA but assigning importance to the SHLAA variables using an One Least Squares regression (OLS) approach instead of the current probability-based approach. Can the regression-based approach be deemed reliable?

5. Investigate which other variables could be affecting the delivery density and the delivery rate of areas which under or over deliver in terms of housing delivery. Identify the variables which affect the delivery rate significantly and conduct a weighted overlap analysis to explore the cumulative impact of these variables on the suitability of residential development in LSOAs.
6. Outline the limitations of the methodology and suggest ideas for further research to improve the proposed approach.
7. Discuss how the outlined approach could enhance policy-making and enforcement for city planners.

2.1. Scope of the research

This study is conducted based on of the older 2013 SHLAA methodology rather than the latest 2017 SHLAA in order to provide more data to carry out the analysis (as explained within chapters 3 and 4). The study area initially includes all the Greater London boroughs and is conducted at Lower Super Output Area (LSOA) level - to capture nuances offered by the finer granular scale of the classification. The final analysis excludes any LSOAs which had an identified capacity of less than 30 residential units to align with the research objectives of SHLAA- focusing on large-site development and capacity. Effort was made to use older versions of the datasets which would be more reflective of the time period between 2013 - 2019. As a result, only SHLAA 2013 Phase 1 and 2 sites are included in the study - these are the sites which as outlined by the SHLAA should be delivered by 2020. The dataset was filtered again to include only the planning applications with ‘completed status between 2013-2019. This study first establishes the context and need for undertaking this research by forming a spatial

understanding of the pre-identified housing capacity, delivered residential developments and the rate of housing delivery within London. Following this, a 'residential suitability classification' is developed using the 2013 SHLAA as a basis. A model is developed using OLS and multi-linear regression to estimate the influence of various spatial factors on housing capacity and delivery rates in London. This influence is applied in a weighted overlap analysis to ultimately allocate residential suitability scores to London LSOAs and reclassify 2013 SHLAA sites based on their suitability and likelihood of potential development. Finally a comparison is made between the two suitability models for capacity and delivery rates and specific areas of interest are discussed further.

2.2. Study structure

The rest of the document is structured as follows:

Chapter 3: Literature review

An overview of the relevant existing literature around the research issue and relevant methodology is provided.

Chapter 4: Methodology, research design and utilised datasets

The utilised data and the steps taken to clean and prepare it are described. The steps taken to conduct the analysis for calculating the capacity densities, delivery densities, delivery rate and delivery differences, building the regression model, calculating and interpreting coefficients and conducting the weighted overlap analysis are presented.

Chapter 5: Results and analysis

The completed analysis and the results of calculations of capacity density, delivery density, delivery rate, delivery differences are presented. The results

and interpretation of the regression models are also discussed. Finally, the results of the weighted overlap analysis are presented in the form of final residential suitability maps.

Chapter 6: Evaluation and discussion of limitations

The findings from the analysis are contextualised and discussed in detail. The limitations of the research are discussed and proposals for further research are outlined.

Chapter 7: Conclusion

Final concluding remarks are presented to summarise answers to the outlined research questions.

Appendix 1.1 Other regression tests

3. Literature Review

The following section outlines the context around housing capacity and housing need in London using key arguments from academic and policy-based discourse. This section also discusses and critiques the SHLAA methodology in detail. The quantitative methods and software used to carry out the analysis are also introduced.

3.1. **Housing supply and housing need in England**

Academic literature and industry research estimate the number of new homes needed in England to be between 240,000 and 340,000 units per year. The supply of homes is lower than the estimated need and this backlog exacerbates issues of overcrowding, affordability and impaired mobility to name a few (Wilson and Barton, 2018, pg 3). This is visible in figure 1 which demonstrates that although supply of housing has increased, it is still below the levels of housing demand.

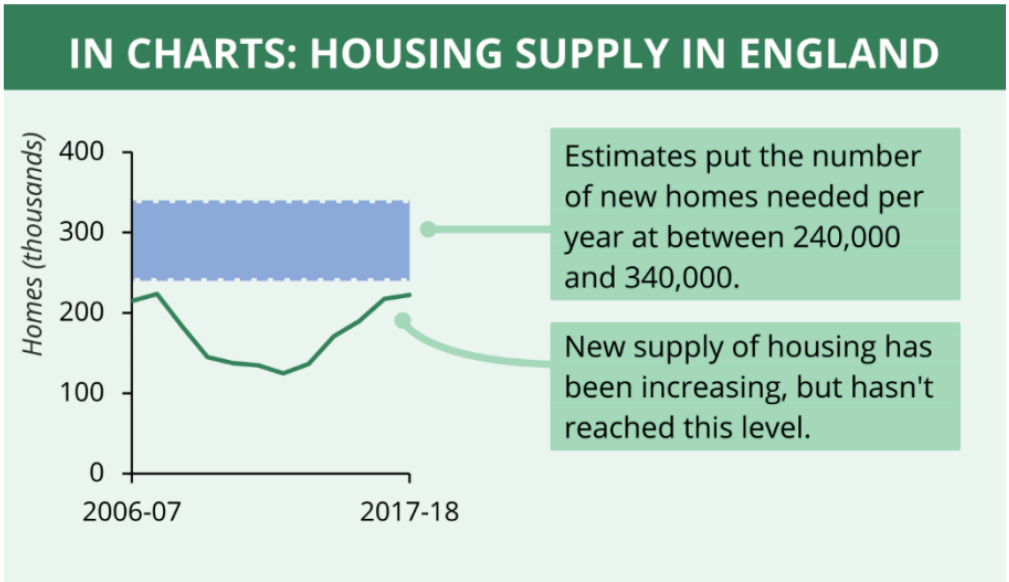


Figure 1 Housing supply in England compared with housing need (source: Tackling the under-supply of housing in England, (Wilson and Barton, 2018:6))

There is also a delivery issue as encapsulated within figure 2 – the rate of annual completions of residential units consistently lags behind the number of residential units granted planning permission.

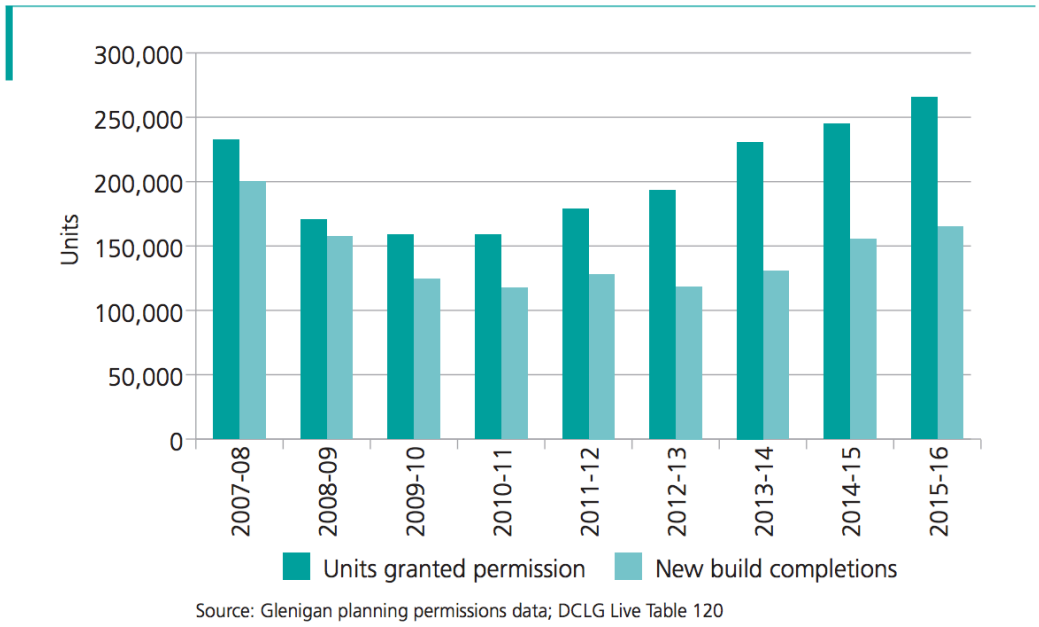


Figure 2 Annual completions versus permissions. Source: Housing White Paper: Fixing our broken housing market, (DCLG, 2017, pg 13)

The Housing White paper – 'Fixing our broken housing market' (2017, pg 18-19; also cited in Wilson and Barton, 2018, pg 4) discusses a four-tier approach to tackle these issues:

- 'Step 1: Planning for the right homes in the right places
- Step 2: Building homes faster
- Step 3: Diversifying the market
- Step 4: Helping people now' - this specifically includes investment in new affordable housing and tackling homelessness issues'

The aforementioned issues and the proposed framework are also highly applicable to the housing context of London. As a result, this study endeavours to put the first step in the Housing White Paper into practice by aiming to identify residential suitability by analysing existing housing capacity and delivery rates within London.

3.2. **London's housing crisis**

The housing narrative in London closely matches the national context and as a rapidly growing city it has consistently fallen behind on delivering the number of houses needed to meet the housing demand. This fact is well documented throughout academic and political discourses (Hill 2013; City Hall, 2017; Morphet and Clifford, 2019; Hilber, 2015). Empirical research points to a strong demand for housing in South East England resulting from rising economic and population growth as the reason behind the pressure on the housing market in London. The strength of the demand coupled with 'urban containment through 'green belts', strict controls on height, lack of fiscal incentives at the local level to develop and 'not in my backyard' (NIMBY) behaviour' are suggested to contribute to the highly pressurised housing market in London (Hilber, 2015, pg 4). There is a severe shortage of affordable housing in a landscape where there is a growing demand for social rent, market rent and housing for the older population (Morphet and Clifford, 2019).

However, the number of unimplemented planning permissions in London demonstrates that there are underlying issues beyond purely planning system related barriers (Centre for London, 2019). A crucial step towards tackling the housing crisis involves identifying and securing land for new

homes (GLA, 2018, Centre for London, 2019*)*. However, there is great debate regarding the direction, density and type of future housing growth in London. To name one topic of discourse - there are strong proponents for both the opposing perspectives on preservation and release of the currently restricted Green Belt and industrial land uses (DCLG, 2014; Rudlin and Falk et al 2014; Centre for London 2019). There are other debates about which areas of London are most suitable for residential development with a school of thought advocating "compact city" development by focusing on transit-oriented development (Bowie, 2017; TfL, 2018; Centre for Cities, 2019; Centre for London, 2019, City Hall, 2017). A compact city can be defined as a high-density and mixed-use way of development focused on revitalisation of existing centres, transport nodes and brownfield land (Chao et al., 2013).

3.3. **London Strategic Housing Land Availability Assessment (SHLAA)**

Since the establishment of Greater London Authority (GLA) in 2000, increasing capacity for potential housing supply has been identified in each iteration of the London Plan policy document as part of the SHLAA process (McPhillips and Gleeson, 2018).

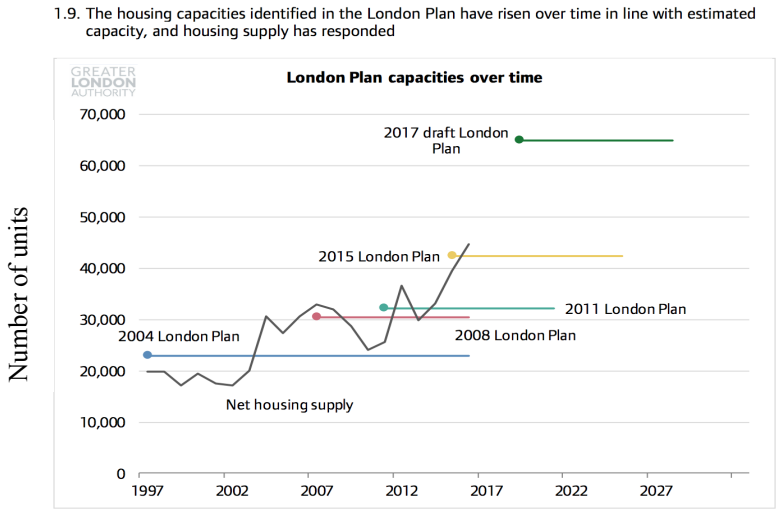
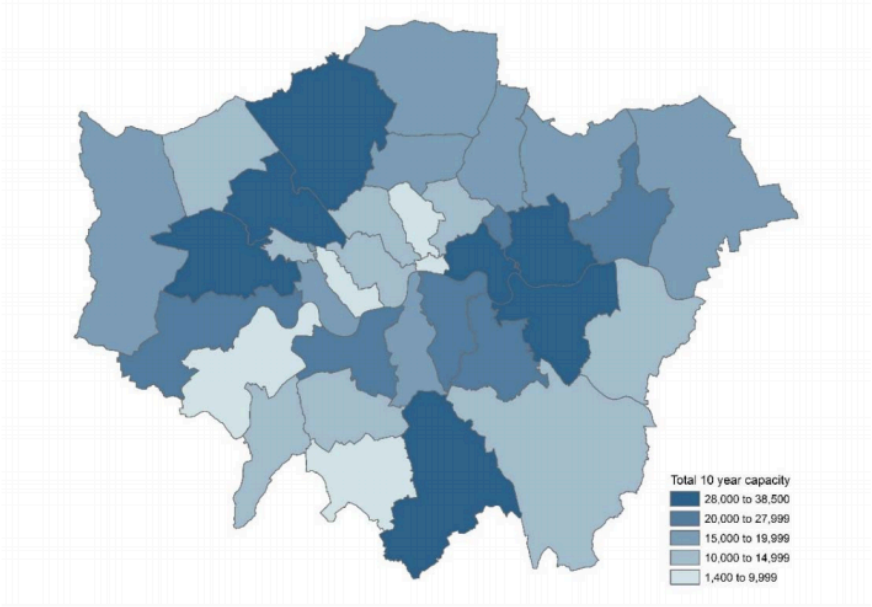


Figure 3 Housing capacities identified in the London plan have risen over time. Source: Housing in London report (GLA, 2018, pg 22)

The Strategic Housing Land Availability Assessment (SHLAA) mandated by the National Planning Policy Framework (NPPF) is a technical study to assess the availability, capacity, deliverability and suitability of potential housing land sites (DCLG, 2019). The London SHLAA focuses on assessing sites larger than 0.25 hectares (Ha) although separate modelling exercises are also undertaken to assess small site suitability (City Hall, 2017).

The most recent SHLAA study was completed in 2017 as part of the draft New London Plan (2019). It demonstrates that there is capacity for 649,350 homes to come forward during the next ten years (2019-20 to 2028-29) equating to approximately 65,000 homes per year. Of this number, Outer London is expected to contribute 55% to the capacity, with the boroughs- Barnet, Brent, Ealing, Greenwich, Newham, Tower Hamlets and Croydon having the highest ten year capacity. Large sites (>0.25 Ha) account for 62% of London's overall housing capacity over the ten year period (GLA, 2017; GLA, 2019).

Figure 1.1 – Housing capacity by local planning authority (2019/20 – 2028/29)



1

Figure 4 Housing capacity by Local Planning Authority (LPA) (2019-20 to 2028-29). Source: SHLAA 2017 methodology, (GLA, 2017)

Large sites are identified from a variety of sources including previous SHLAA assessments, planning permission records, development plans, GLA conducted development capacity studies as well as a London-wide 'call for sites' exercise where any interested parties can put forward sites for consideration. The assessment takes planning, environmental, economic and social policy, and a range of delivery constraints into account.

These constraints are visualised in the tables 1-3 overleaf. (GLA, 2013). The 2017 and 2013 SHLAA constraints are broadly similar, therefore the 2013 constraints are discussed in detail to align with the scope of this study.

Ref	Constraint	Source	Options	Default	Impact of yes	Impact of no	Borough editable
1	Designated open space	GLA, Borough designations, Local knowledge	Yes or no	Read from GIS	0% probability	none	Yes
2	SIL	GLA	Yes or no	Read from GIS	0% probability	none	Yes
3	Safeguarded Wharves	GLA	Yes or no	Read from GIS	0% probability	none	Yes
4	LSIS	Borough knowledge	Yes or no	No	Assumed probability: 40% 'Restricted' 50% 'Limited' 60% 'Managed'	none	Yes
5	Non LSIS or SIL industrial/warehousing site that borough's Local policies wish to retain.	Borough Knowledge	Yes No	No	Assumed probability 45% 'Restricted' 55% 'Limited' 60% 'Managed'	none	Yes

Table 1 SHLAA 2013 Planning Policy constraints and impacts on probability

Ref	Constraint	Source	Options	Default	Borough editable	Impact of "low" on probability	Impact of "medium" on probability	Impact of "unsuitable" on probability
6	Air Pollution (NO2 & PM10)	GLA GIS	Low Medium	Read from GIS	No	None	Cumulative reduction: 1"Medium" = 90% probability, 2"Mediums" = 75% 3"Mediums" = 66% 4"Mediums" =50%	0% probability
7	Flood Risk (3B unsuitable, 3A Low, 3A higher risk medium)	Environment Agency and GLA GIS	Low- Medium Medium High- medium Unsuitable	Read from GIS	Yes	None.		0% probability
8	Noise Pollution (Aircraft) and (Road)	GLA GIS	Low, Medium, Unsuitable	Read from GIS	No	None		0% probability
9	Pylons	GLA GIS	Low, Medium, Unsuitable	Read from GIS	Yes	None		0% probability.
10	Health and Safety executive consultation zones.	GLA GIS	Low (no HSE zone) Medium – middle zone and outer zone Unsuitable- inner zone	Read from GIS	Yes	None		0% probability
Sites that fall into flood risk categories medium and high have their probability reduced by a further 7% and 10% respectively.								

Table 2 SHLAA 2013 Strategic/ Environmental constraints and impacts on probability

Ref	Constraint	Source	Options	Default	Borough editable	Impact of Low	Impact of medium	Impact of unsuitable
11	Ownership	Borough Knowledge	Low, medium, unsuitable	Low	Yes	None	10% reduction	0 % probability
12	Local Infrastructure	Borough Knowledge	Low, medium, unsuitable	Low	Yes	None	10% reduction	0 % probability
13	Environmental Setting	Borough Knowledge	Low, medium, unsuitable	Low	Yes	None	10% reduction	0 % probability
14	Contamination	Borough Knowledge	Low, medium, unsuitable	Low	Yes	None	10% reduction	0 % probability
Cumulative impact; 4 Mediums = 60% probability, 3 Mediums =70% probability, 2 mediums 80% probability, 1 medium 90% probability.								

Table 3 SHLAA 2013 Local constraints and impacts on probability

The three categories of constraints are used to assign probabilities to each site in the SHLAA assessment. The lowest and most restrictive score out of the three categories is applied to determine the probability of a site coming forward for development. The probability score has implications regarding the phasing and density of a site with more constrained sites either being deemed unsuitable for development or being relegated to the later phases of the SHLAA due to deliverability challenges. This study develops a suitability classification using this probability-based approach as a foundational idea. However, the developed classification deviates from SHLAA as detailed in chapter 4.

3.4. **Limitations of SHLAA methodology**

As visible in the tables 1 to 3 above, the constraints approach to modelling housing potential on SHLAA sites does not take transport-related constraints into account. The Public Transport Accessibility Level (PTAL) methodology is applied in SHLAA when calculating density estimates using the London Plan density matrix (figure 5) which is out of date as of August 2019. Other than this, there is currently no formal way of incorporating the effects of transport on the residential suitability of a SHLAA site. Moreover, in practice, residential development is coming forward at higher densities than the

outdated London Plan matrix as evidenced by the Crossrail 2 density matrix which advocates and evidences support for higher density growth (Crossrail 2, 2016[1]). In summary, transport considerations are currently being incorporated on a case by case basis in the SHLAA (GLA, 2017). This can lead to inconsistencies in evaluation of capacity potential and understanding of delivery rates which can impact the ability of professionals to provide efficient mitigation to housing capacity and delivery related issues.

Setting	Public Transport Accessibility Level (PTAL)		
	0 to 1	2 to 3	4 to 6
Suburban	150–200 hr/ha	150–250 hr/ha	200–350 hr/ha
3.8–4.6 hr/unit	35–55 u/ha	35–65 u/ha	45–90 u/ha
3.1–3.7 hr/unit	40–65 u/ha	40–80 u/ha	55–115 u/ha
2.7–3.0 hr/unit	50–75 u/ha	50–95 u/ha	70–130 u/ha
Urban	150–250 hr/ha	200–450 hr/ha	200–700 hr/ha
3.8 –4.6 hr/unit	35–65 u/ha	45–120 u/ha	45–185 u/ha
3.1–3.7 hr/unit	40–80 u/ha	55–145 u/ha	55–225 u/ha
2.7–3.0 hr/unit	50–95 u/ha	70–170 u/ha	70–260 u/ha
Central	150-300 hr/ha	300–650 hr/ha	650–1100 hr/ha
3.8–4.6 hr/unit	35–80 u/ha	65–170 u/ha	140–290 u/ha
3.1–3.7 hr/unit	40–100 u/ha	80–210 u/ha	175–355 u/ha
2.7–3.0 hr/unit	50–110 u/hr	100–240 u/ha	215–405 u/ha

Figure 5 London Plan density matrix. Source: London Plan 2016 (GLA, 2016, pg 101)

This is a clear limitation because of the demonstrated link between housing delivery and transport investment in London. Evidence from TfL states 'Investing in new public transport capacity could unlock the delivery of hundreds of thousands of homes that may not otherwise come forward for development. In particular, it is estimated that Crossrail 2 alone could support 200,000 new homes and 200,000 jobs along its route' (TfL, 2017, pg12). This can also be demonstrated by figure 5 where a visual inspection shows that homes growth clusters around transport investment into the TfL

[1] The Crossrail 2 Density Matrix is included in the CR2 Strategic Outline Business Case submitted to Department for Transport in 2017. This matrix can be supplied upon request if necessary.

rail network. Current housing policies and the supporting evidence bases also encourage the need to 'focus development in and around town centres and public transport nodes, where there is scope to deliver housing at higher densities…' (GLA, 2016, p25-26).

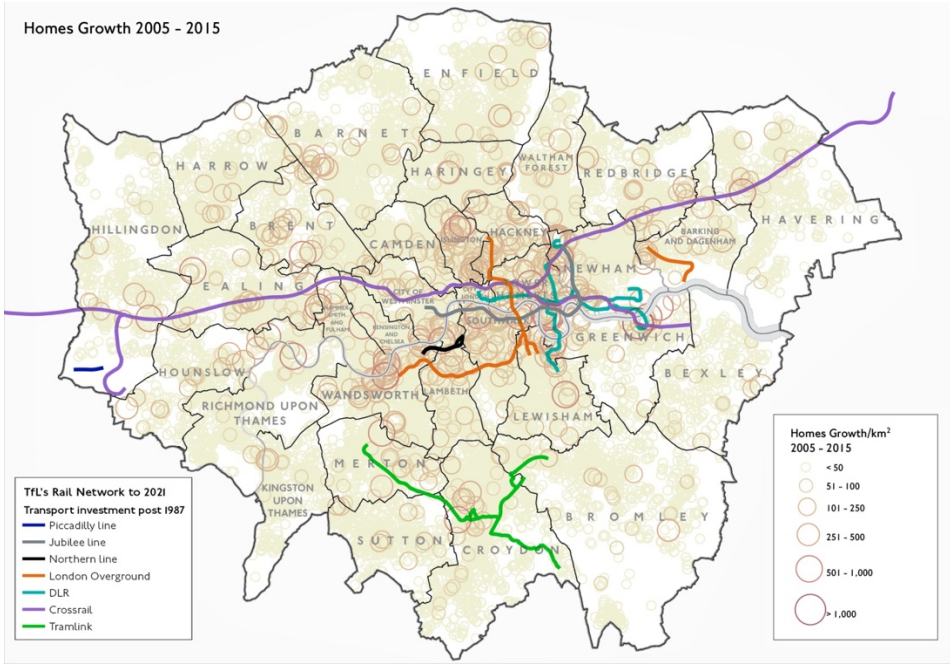


Figure 6 transport investment (post 1987) overlaid on homes growth between 2005 and 2015. Source: Homes in London report, (GLA, 2018) and TfL transport investment spatial data.

Another limitation to the methodology is the probability-based approach to the aforementioned constraints. The methodology does not justify why a certain probability figure is applied to a particular constraint. This causes difficulty in truly understanding the impact of one constraint in comparison to another.

In order to truly address issues around ‘land scarcity’ and identification of appropriate areas for potential housing, it is important to review the influence transport has on housing delivery. Building a fuller picture through the use of variables beyond the SHLAA-based constraints for example ‘Housing Zones’, ‘Opportunity Areas’ or transport accessibility would offer a clearer picture of suitable land for housing in London (Holman et al., 2015).

3.5. Spatial regression modelling and Geographically weighted regression (GWR) modelling

Spatial regression is a global spatial modelling technique. A key advantage of spatial regression modelling for this topic is that it allows us to study the dependence and significance amongst variables on a system-level. Specifically, this allows us to understand and interpret the influence of different types of variables on the phenomena being tested. Modelling complex phenomena such as housing delivery or residential suitability can be performed by aggregating spatial data at larger spatial units such as LSOAs. This enables the comparison of the variation in the data and interpretation of any emerging clustering or spatial patterns (Ward and Gleditsch, 2019).

Spatial dependence in data can be measured by evaluating the spatial autocorrelation (spatial pattern in values) of a dataset. This can be tested using measures such as Moran’s I or Geary’s C statistics. Not accounting for spatial variation can give misleading results due to correlations between the variables being tested (Srinivasan, 2016).

Ordinary Least Squares (OLS) is a widely known regression technique which creates a single global regression equation to represent the phenomena which is being modelled (Ward and Gleditsch, 2019). While OLS is performed for understanding relationships between a dependent variable and other attributes on a global level, other techniques such as geographically weighted regression (GWR) allow modelling of spatially dependent processes by understanding local variation in spatial behaviour (Duzgun et al., 2016).

In the context of this study, spatial regression modelling is used to understand the global level behaviour of capacity density and delivery rates in London in relation to specific tested variables. The main objective is to find the influence of the significant variables and investigate whether there are any similarities in areas with similar delivery rates. This approach allows us to estimate the coefficients of a linear regression equation which can then be used as weights for a weighted overlay analysis (Srinivasan, 2016; Ward and Gleditsch, 2019).

3.6. **Weighted overlay analysis for land suitability studies**

Weighted overlay analysis is a GIS technique suitable for approaching multicriteria problems where a lot of variables need to be assessed to determine cumulative impact from carrying out a land suitability analysis of a process or land-use (GrindGIS, 2015).

Land suitability analysis can be defined as the identification of patterns to specify a requirement or an activity (Hopkins, 1977, Colluns et al., 2001 cited in Malczewski, 2004). A site search analysis is a type of suitability analysis

which ranks areas based on characteristics in order to identify the most suitable site based on the specified criteria. Therefore, in this study, the residential suitability is related to capacity density and delivery rates of LSOAs.

This involves subdividing the study area into observable units and classification of these units based on a suitability classification. Land suitability classes are designed to reflect the degree of suitability of an area and it is recommended that the number of recognised classes be kept as small as possible with five being the maximum number of recommended classes in a suitability model (FAO, 1976).

In summary, the process of carrying out this analysis involves creating the suitability classification, subdividing the study area, selecting the factors to be tested and either choosing or calculating their importance. It is then necessary to convert any vector variable data into raster layers and multiply each by its normalised weight value of importance.

3.7. **Feature scaling of coefficients:**

The overlay analysis relies on the consideration of different factors by using a normalisation technique known as 'Min-Max feature scaling' to bring all the factors within the analysis to a consistent scale between 0 and 1. Subsequently the normalised assigned importance can be used to determine overall suitability. Min-Max scaling typically follows the following equation (Raschka, 2014):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad [1]$$

3.8. **GIS Tools**

Geographic Information Systems (GIS) have played an evolving role in city planning since their start as an aid for quantitative and computational geography. GIS tools have evolved into a science for processing and analysing spatial data and for providing an evidence-based approach for decision-making in city planning (ESRI, 2019; Malczewski, 2004). This study uses GIS tools to aggregate and visualise various spatial, socio-economic and demographic data followed by conducting the multi-criteria weighted overlay analysis.

QGIS is an open source Geographic Information System software. It enables the management, analysis and visualisation of vector and raster spatial data with guided support from extensive documentation and a library of plug-ins for various analyses. (QGIS3.14, 2019)

ArcGIS is a mapping platform for visualising and analysing spatial data. The ModelBuilder functionality in ArcGIS allows the creation of workflows for automating and executing outlined analytical processes (ESRI, 2019). The ModelBuilder is especially useful in multicriteria analyses such as this study where a lot of input raster variables need to be reclassified, assigned weight and overlaid (ESRI, 2019).

R is a statistical software which can be utilised for computing and visualising data within the same environment. A variety of statistical analyses such as OLS regression can be run and the outputs can be visualised with ease using packages and libraries (R Core Team, 2018).

3.9. **Summary**

The literature review establishes that on the whole there is consensus amongst academics, politicians and industry leaders that London is facing an acute housing crisis. Tackling this issue requires a careful consideration of existing patterns of housing capacity and housing delivery. While the SHLAA has proved successful in identifying increasing amounts of potential housing capacity in London, the demand still vastly outstrips identified capacity and on the ground delivery. Another key issue is the disparity between applied and implemented planning permissions. This justifies the need for adopting a multicriteria based approach based on spatial regression and a weighted overlay analysis. Since, this study relies on adding on to the existing SHLAA methodology with pre-determined site suitability scores and probabilities (referred to as 'developability' in SHLAA), it was considered appropriate to use a weighted overlay method to do a comparative analysis using the same SHLAA sites and reclassifying their suitability using an alternate and adapted method. These methods can allow us to explore potential city-wide patterns in housing capacity and delivery rates in London LSOAs whilst also shedding light on which variables contribute to suitability.

4. Methodology

This chapter outlines the utilised datasets and methods to perform this research question. Specifically, the study uses the SHLAA datasets as a basis alongside other transport, planning policy and demographic related datasets to investigate the relationship between the identified supply and delivered housing in London since 2013.

4.1. **Data collection**

The used data sources align with the time period of the study (2013 - 2018). All the datasets used within the study contain publicly available information and can be found online or be requested from the relevant public sector authority. Some specific transport related datasets and SHLAA datasets were supplied by Transport for London (TfL) and Greater London Authority (GLA). None of the data was deemed confidential and everything has been discussed in publicly available reports previously. Still, some information such as specific locations of Strategic Industrial Locations could be deemed sensitive from a planning perspective and therefore it is always analysed in the study at an aggregated LSOA level and is visualised in a way to obscure specific polygon geometry. Any datasets which were obtained directly from TfL and GLA and contain potentially sensitive information have been marked with an asterisk in table 4.

Data sources:

Dataset	Content / year	Format	Source
SHLAA sites 2013	• Geometry of sites from 2013 SHLAA • Classification of the SHLAA sites identified in 2013 into-'Approvals', 'Allocations', 'Potential development', 'Low probability' and 'Unsuitable' • Phasing information (phases 1-5) • Probability score of coming forward against each constraint category - 'Planning Policy constraints', 'Environment constraints' and 'Local constraints', • No of proposed residential units and area (in Ha)	.shp and .csv	TfL London Plan team
Planning Applications	• Easting, Northing of all planning applications that are currently ongoing ('not started' or 'under construction') or 'completed' since 01/04/2006. • No of proposed residential units and area (in Ha)	.csv	London Development Database (LDD) https://data.london.gov.uk/dataset/planning-permissions-on-the-london-development-database--ldd-
Spatial boundaries: GLA boundary, Borough boundaries LSOA boundaries	• Polygon geometry of datasets	.shp	https://data.london.gov.uk/dataset/lsoa-atlas
SHLAA Planning Policy constraint datasets			
Green Belt	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: yes or no	.shp	https://www.gigl.org.uk/mapping-londons-green-belt-and-mol/
Metropolitan Open Land (MOL)	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: yes or no	.shp	https://www.gigl.org.uk/mapping-londons-green-belt-and-mol/
Areas of Outstanding Natural Beauty (AONB)	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: yes or no	.shp and .TAB	https://www.gigl.org.uk/mapping-londons-green-belt-and-mol/
Sites of Importance for Nature Conservation (SINC)	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: yes or no	.TAB	https://www.gigl.org.uk/mapping-londons-green-belt-and-mol/
Strategic Industrial Locations (SIL) *	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: yes or no	.shp	TfL London Plan team
Locally Significant Industrial Sites	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis)	.shp	TfL London Plan team

(LSIS) *	• Categories: yes –(restricted, limited, managed) or no		
Non-Designated Industrial Sites (NDIS) *	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: yes –(restricted, limited, managed) or no	.TAB	TfL London Plan team
Safeguarded Wharves	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: yes or no	.TAB	TfL London Plan team
SHLAA Environment constraints			
Airport Noise Pollution	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: low, medium, high	.shp	GLA
Pylons	• Line and point geometry and SHLAA constraint probability scores (sum of 50m buffered area used in analysis) • Categories: yes - (medium) or no	.TAB	GLA
Health and Safety Executive Consultation Zones	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: low, medium, unsuitable	.shp	GLA
Flood Risk 3	• Polygon geometry and SHLAA constraint probability scores (sum of area used in analysis) • Categories: medium-low, medium, medium-high	.shp	GLA
Additional non-transport datasets – no probability related categorisation present as these were not part of SHLAA			
Listed Buildings	• Point dataset (count of listed buildings per LSOA used in analysis)	.shp	London Data Store
Conservation Areas	• Polygon geometry (sum of area used in analysis)	.shp	London Data Store
Protected Views	• Polygon geometry (sum of area used in analysis)	.TAB	London Data Store
Town Centres	• Point dataset (sum of 800m buffered area used in analysis)	.shp	TfL London Plan team
Opportunity Areas	• Polygon geometry (sum of area used in analysis)	.shp	TfL London Plan team
Housing Zones	• Polygon geometry (sum of area used in analysis)	.TAB	TfL London Plan team
Central Activity Zone (CAZ)	• Polygon geometry (sum of area used in analysis)	.shp	London Data Store
House Price Values	• Median house prices values per LSOA from 2013 (given median value used)	.csv	London Data Store
Dwelling Stock Age	• 2015 LSOA, MSOA data for number of properties (% of dwelling stock age from each time period per LSOA used) • Categories: Pre 1900, 1900 to 1918, 1919 to 1929, 1930 to 1939, 1945 to 1954, 1955 to 1964, 1965 to	.csv	London Data Store

	1972, 1973 to 1982, 1983 to 1992, 1993 to 1999, 2000 to 2009, 2010 to 2012, Unknown		
Regeneration areas	• Further Alterations to London Plan (FALP) 2006 regeneration areas polygon geometry	.shp	TfL London Plan team
Employment sites	• Polygon geometry and point data from 2013	.shp	TfL London Plan team
Population Density	• ONS Mid-year estimate from 2013 – number of people per hectare	.csv	London Data Store
Transport datasets			
Lower Emission Neighbourhoods (LEN)	• Polygon geometry of the 8 current LEN schemes (2019)	.shp	TfL London Plan team
London Underground and DLR stations	• Point geometry of station location	.TAB	TfL Strategic Analysis team
National Rail stations	• Point geometry of station location	.TAB	TfL Strategic Analysis team
PTAL	• Public Transport Accessibility Level % per LSOA (2015) • Categories- % 0-1 (poor access), % 2-3 (average access), % 4-6 (good access)	.csv	TfL Strategic Analysis team
London Underground 2011 AM Peak Crowding	• Line geometry with attribute data for number of people per square metre (2011)	.TAB	TfL Strategic Analysis team
National Rail 2011 AM Peak Crowding	• Line geometry with attribute data for number of people per square metre (2011)	.TAB	TfL Strategic Analysis team
Car Ownership	• % of households with 1, 2, 3 or 4 or more cars and vans per LSOA (2011)	.csv	London Data Store

Table 4 Summary of data sources

4.2. Data preparation

QGIS was used for data preparation including data cleaning, filtering and to carry out the spatial analysis. The British National Grid EPSG:27700 coordinate reference system was used throughout the model as most of the analysis required the variables to be calculated in meters and hectares. (EPSG, 2016)

- **Assumptions and data filtering**

After running an initial iteration of the analysis namely the steps for data aggregation, calculation of capacity and density metrics and the regression analysis, the following changes and assumptions were used to improve the methodology:

- The SHLAA sites dataset was filtered to only keep phase 1 and 2 sites in the dataset - these two phases cover 2013-2015 and 2015-2020 respectively (figure 7) and are expected to mostly have been built out by 2019 (GLA, 2015).
- The planning applications dataset was also filtered to only include the time period 2013 till 2019 (figure 8). This dataset was further filtered to only include entries with a 'completed' status to capture the true picture of how much residential development has been delivered since 2013. This avoids the effects of any 'land banking' - a practice where planning permission is sought with the purpose of increasing the value of the land rather than building it out (Elgot, 2018).

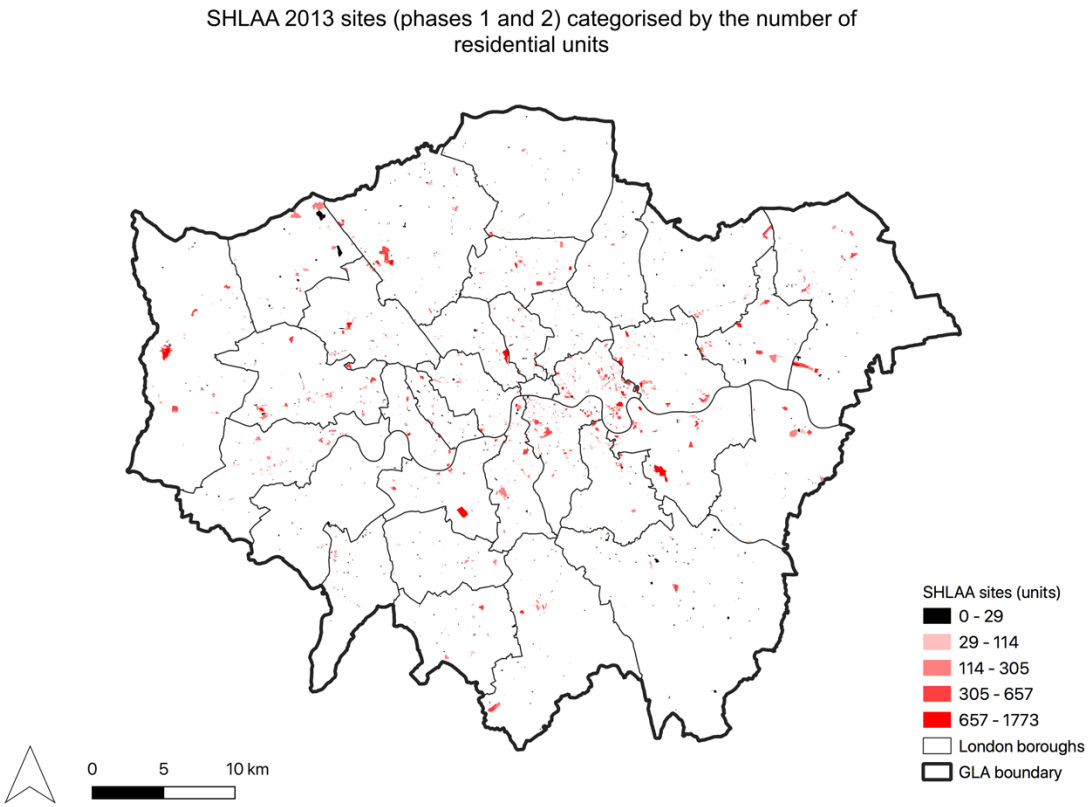


Figure 7 SHLAA 2013 sites (phases 1 and 2) categorised by the number of residential units

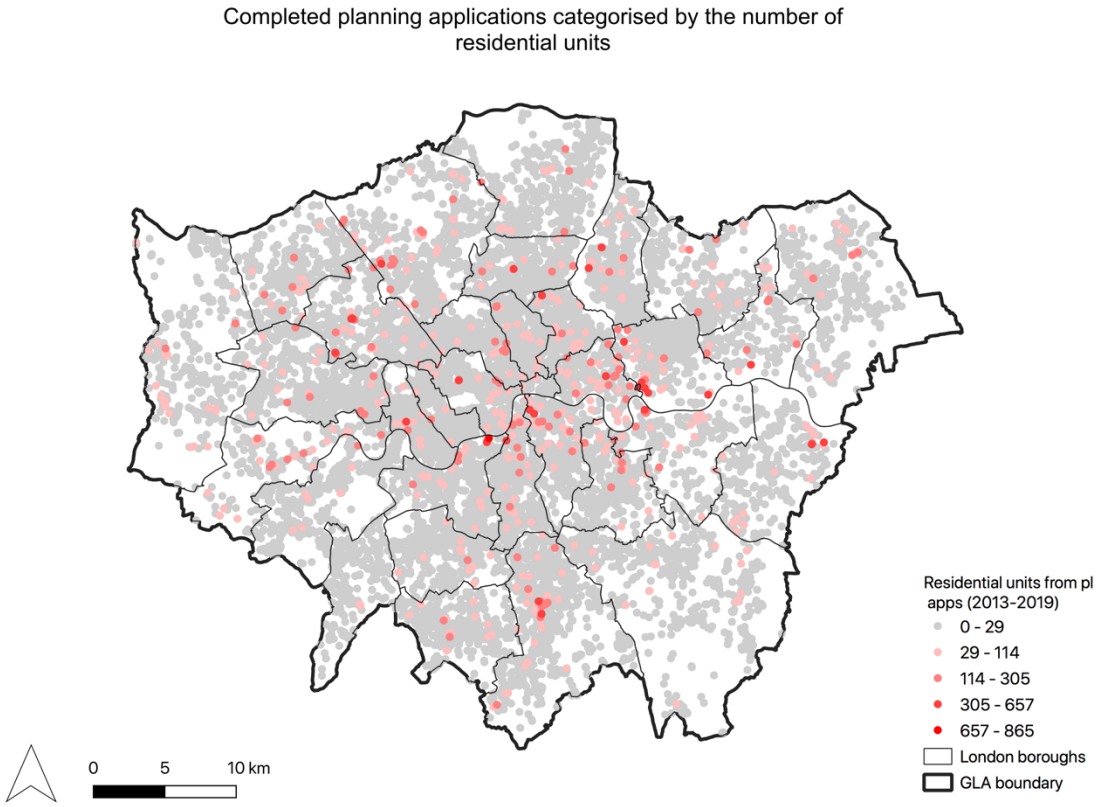


Figure 8 Completed planning applications categorised by the number of residential units

- LSOAs were used as the unit for spatial aggregation instead of Wards as this allowed the results of the analysis to be interpreted at a finer scale. The analysis was first done at a ward level as seen in figure 9 – however the larger ward sizes in outer London appeared to skew the results in an inaccurate manner. Wards in outer London with vast expanses of Green Belt were showing higher capacity and delivery densities than expected. This issue was resolved by replicating the data aggregation at LSOA.
- Residential units were used as the basis for aggregation rather than proposed residential area in hectares. Residential units offered insight into the vertical density of development whereas proposed residential area only covered information regarding the footprint of the ground floor. This was also skewing results inaccurately by showing that more delivery was coming forward in outer London than central London. This could be because, in outer London there is more scope for a larger ground floor footprint whereas there are much tighter space constraints in Central London. Again, after making the modification, the inaccuracy was resolved, and the maps appear to show the expected pattern of delivery and capacity densities. All the mentioned changes and their effects are highlighted in figures 9 and 10 with circles.

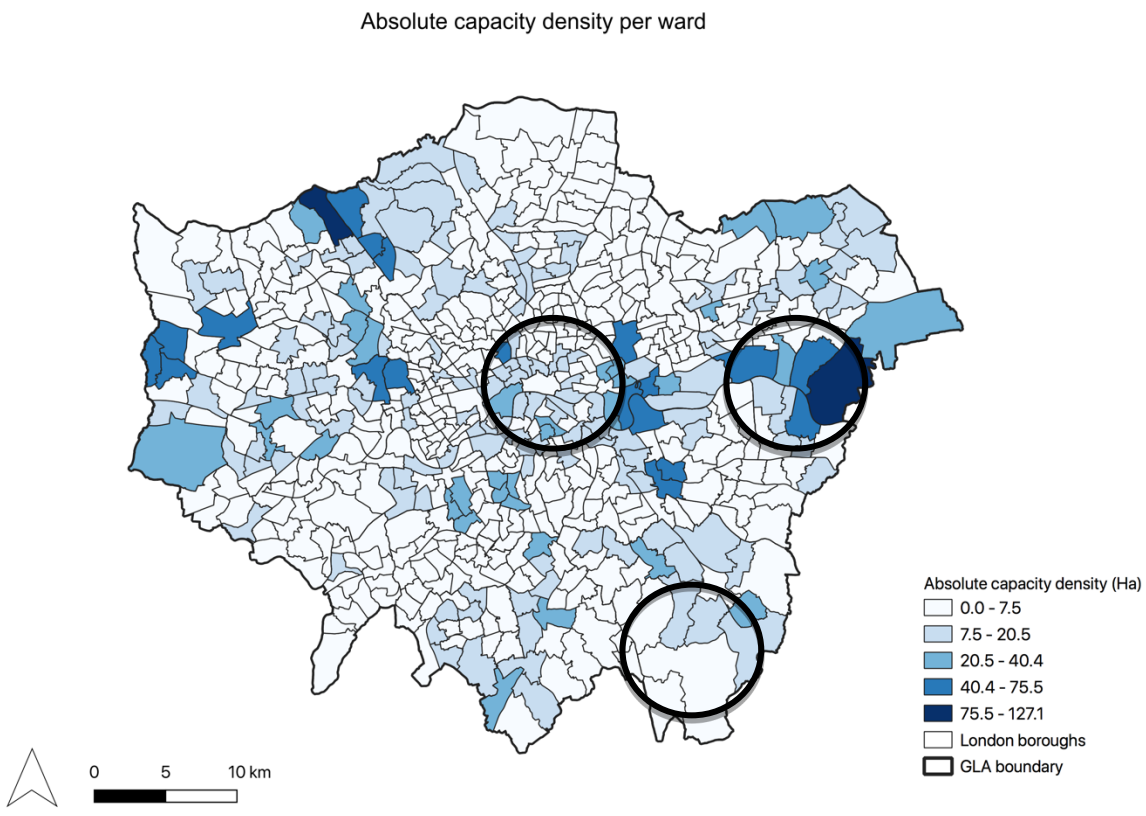


Figure 9 capacity aggregation at ward level

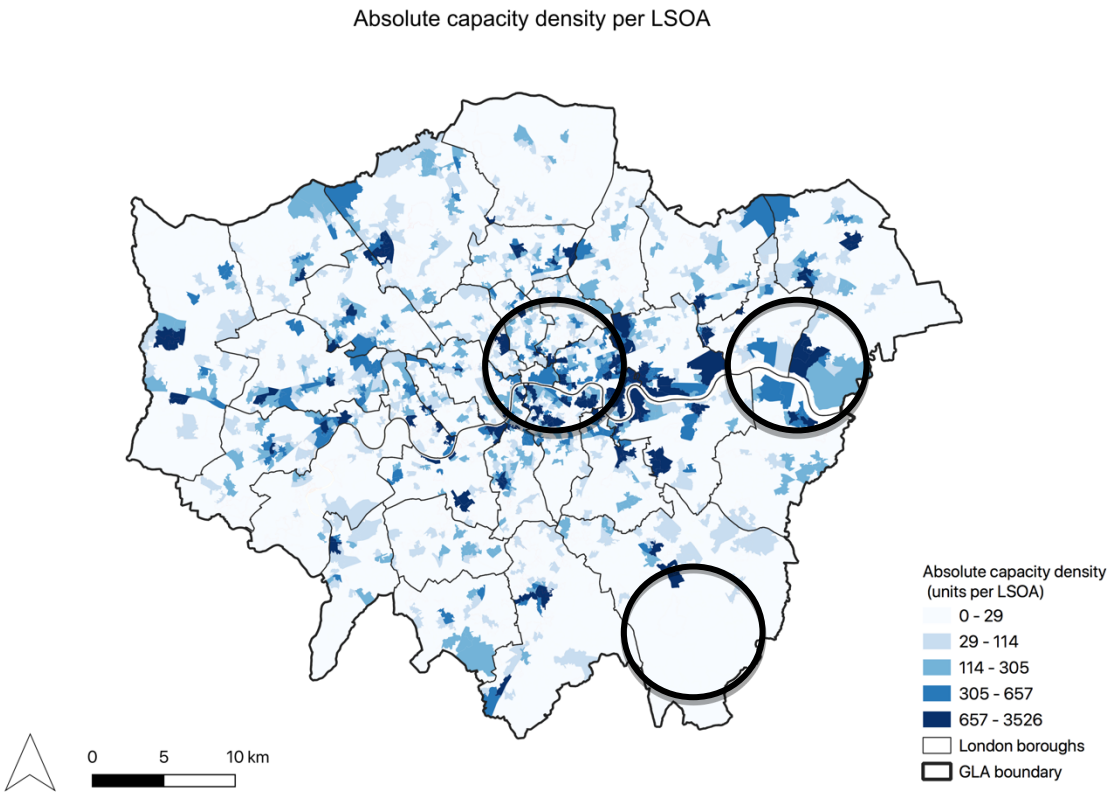


Figure 10 capacity aggregation at LSOA level

- The final stage was filtering the dataset based on the LSOA capacity. Most LSOAs had zero identified capacity as part of SHLAA phases 1 and 2. This resulted in most LSOAs showing a high delivery to capacity ratio. This study is focused on exploring residential suitability based on capacity of large potential sites (following SHLAA methodology) and the delivery rates of associated LSOAs. Therefore, all LSOAs containing less than 30 units of identified capacity were excluded from the analysis. This resulted in an improvement to the regression model (discussed in chapter 4).

- **Data cleaning**

Next, all the datasets were cleaned by replacing NULL values with zero values and invalid geometries were identified and fixed. This was done using the 'fix geometries' function in the QGIS Processing toolbox and the 'Topology Checker' plugin (QGIS2.18, 2019).

- **Data aggregation**

Preparing and joining the data

All datasets were spatially joined to the LSOAs using the 'spatial join by summary' function in QGIS so that the geometry and attribute information could be isolated and analysed on an LSOA scale.

All polygon shapefiles including SHLAA constraints and the additional constraints chosen except pylons were joined to the LSOA boundaries using a ‘union’ from Geoprocessing Tools. This was done to split the overlay layer along the LSOA boundary lines.

- Then, the area of the new geometry was calculated using the standard **‘$area / 10000’** calculation in the field calculator to obtain values in hectares. Any duplicate geometries or small geometries less than 0.05 Ha resulting from the union close to boundaries or those falling outside of London LSOAs were deleted. The spatial join to LSOA boundaries was then performed.

- The point datasets for planning applications and listed buildings were joined to the encapsulating LSOA using a ‘intersect’ spatial join. For other point datasets, buffers were drawn before performing a union and intersecting with the LSOA boundaries (figure 11). Any point transport datasets such as London Underground and DLR stations and National Rail stations used a 400 metre buffer following the advice outlined in literature deeming that as an acceptable walking distance to transit (Walker, 2011). For town centres, a larger 800 metre buffer was drawn. This reflects the latest policy outlined in the Draft New London Plan (Policy H1) emphasising the need for optimising

potential for housing delivery within 800m boundaries of town centres (GLA, 2019, p35).

- For line geometries such as pylons and the London Underground (LU) and National Rail (NR) crowding datasets different methods were employed. Following design guidelines for development near pylons, a 50m buffer was drawn around all line geometries. This area was then spatially joined to the appropriate LSOAs through union and intersection joins. For LU and NR crowding datasets, the line geometries were split along LSOA boundaries and then joined to the encapsulating LSOA. The spatial join was performed using the 'Join attributes by location (summary)' function in the QGIS processing toolbox - this enabled the calculation of the total sum of crowding along line segments in each LSOA.

- Datasets containing no geometry such as house price values, dwelling stock age, car ownership and population density were joined using the LSOA code columns (figure 14).

Figure 11 Before and after drawing a 400m buffer and performing a union along LSOA boundaries

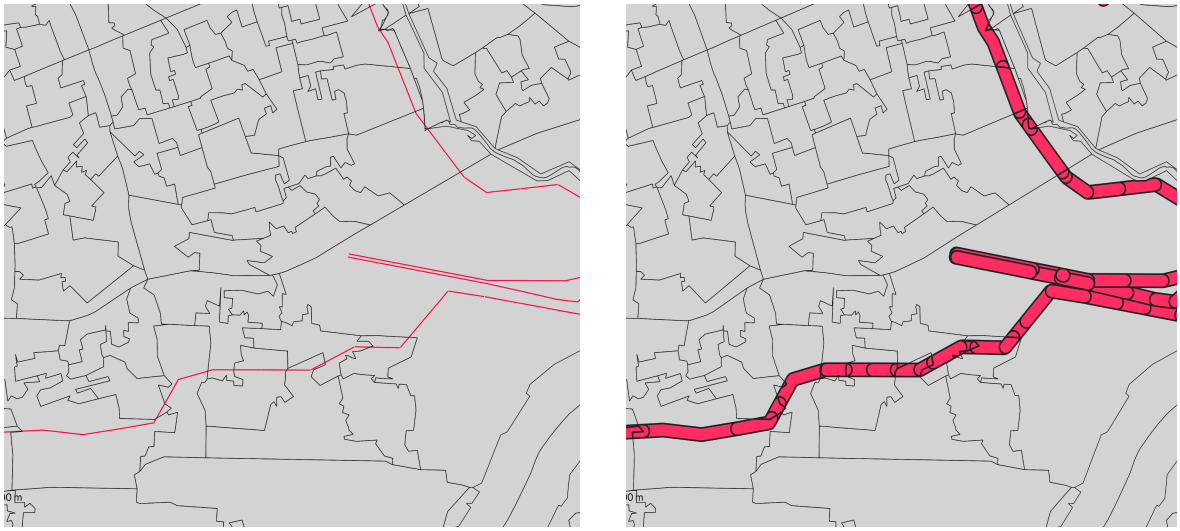


Figure 12 Before and after drawing a 50m buffer around pylons and performing a union along LSOA boundaries

Figure 13 A comparison of SHLAA sites before and after performing a union along LSOA boundaries

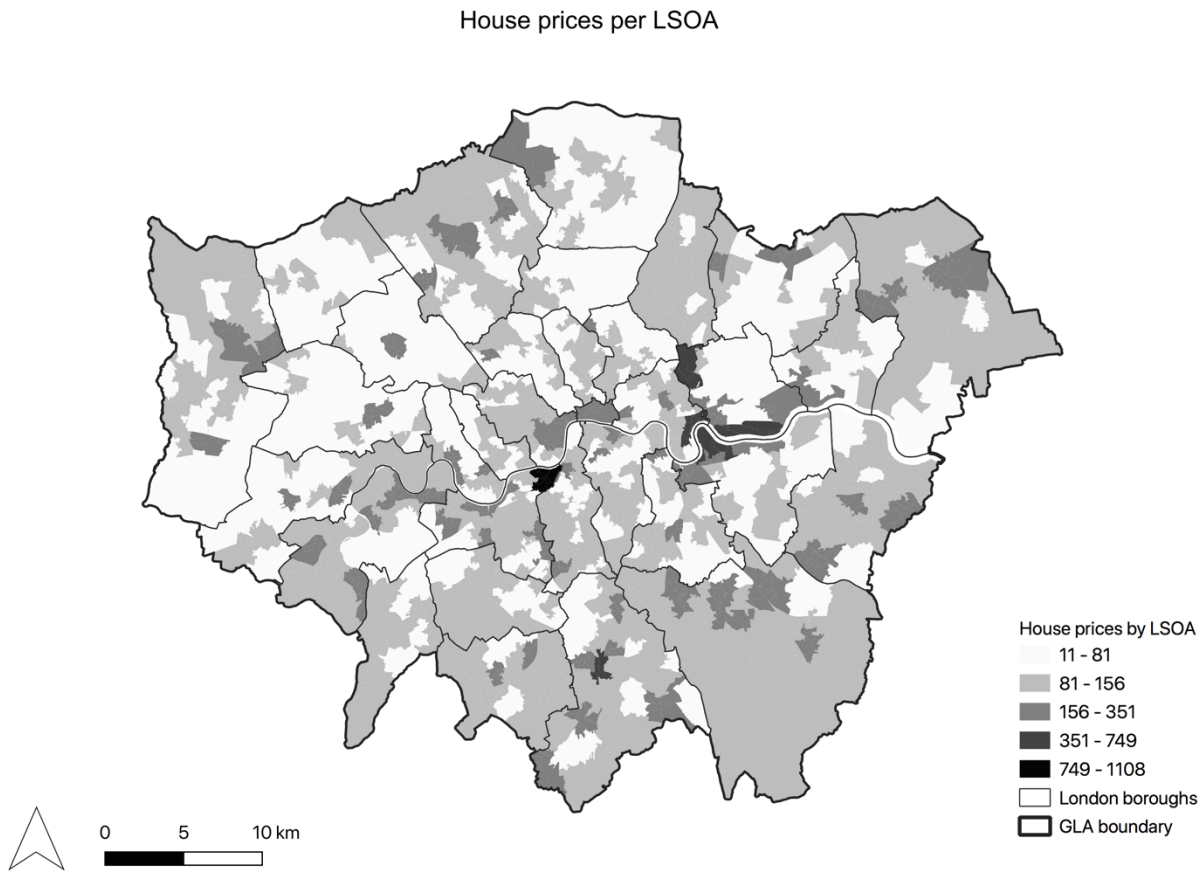


Figure 14 LSOAs categorised by median house prices (2013)

4.3. Deviations from the SHLAA 2013 methodology:

The basis of the datasets used to carry out this analysis relies on the SHLAA 2013 constraints led approach to determining the probability of residential sites coming forward. However, due to the unavailability of some data, some modifications were proposed as outlined below:

- Planning policy constraints were modelled exactly as included in the SHLAA 2013 table 2.4 (GLA, 2014)
- Due to unavailability of the constraint layers for air pollution data used in 2013 SHLAA - this dataset was excluded from the study. It was considered acceptable to exclude this dataset as it was excluded from the official SHLAA methodology in 2017 anyway.
- The environmental constraints for Flood Risk had conflicting instructions regarding the treatment of probabilities with inconsistent classification terminology - the options were presented as low-medium, medium, high-medium and unsuitable. However, the methodology does not specify which areas fall under each of the four categories, so it was not reproducible. Furthermore, extra instructions to reduce probabilities by 7% and 10% for ‘medium’ and ‘high’ classifications were provided although a ‘high’ category is not present in the classification. To mitigate this, the 2017 SHLAA methodology was used as reference to classify the sites and apply the further 7% and 10% restrictions. The probabilities are only relied upon in the first part of the analysis to recreate the SHLAA in order to provide a basis for comparison with the

proposed methodology therefore, the impact of this modification is not large.

- A key modification was the exclusion of the ‘local constraints’ from the model. Most of the variables in this category relied on borough-specific knowledge and local-level decision making which resulted in the final score for each site under this category. These datasets were not available on a London-wide level through TfL or GLA and as a result had to be excluded from the study. Although the scores for this category were available for each site, it was not possible to get estimates for all the LSOAs without any SHLAA sites present or to form a reliable understanding of the constraints beyond just the SHLAA site. This is a limitation as there are clear implications of ‘ownership’, ‘local infrastructure’, ‘environmental setting’ and ‘contamination’ as per table 3 on housing capacity and delivery rates within London and these will not be able to be modelled within this study. In the future, it is recommended that these datasets are collected at a London-wide level so that they can be input into research and models similar to this study’s proposal for a more comprehensive and accurate understanding of housing capacity and delivery rates in London.

4.4. Defining capacity, delivery and delivery rate aggregation

For the purpose of this study, information about the SHLAA sites (capacity) and the planning applications (delivery) was aggregated in order to conduct analysis and compare outputs at an LSOA level. The aggregated capacity and delivery variables are defined below and the rest of the report uses this terminology to maintain consistency and clarity.

Housing capacity in this study directly refers to the number of residential units in each SHLAA site. This is more reflective than using a measure for proposed residential area because the number of units accounts for building densities. This enables the accurate analysis of the effects of different variables on the land size as well as the height of the development.

As the sites had been split along LSOA boundaries wherever a site spanned more than one LSOA, it was necessary to make an approximation regarding the number of residential units in each separated part of the SHLAA site by recalculating the number for the new site area using the proportionality of units per hectare in the original site land parcel as demonstrated in equation 2 below. In order to aggregate housing capacity information, an ‘absolute capacity density’ was calculated per LSOA as outlined in equation 2.

$$Absolute\ capacity\ density\ per\ LSOA = \Sigma\left(\frac{SHLAA\ resi\ units\ in\ LSOA}{old\ total\ area\ of\ SHLAA\ sites\ in\ LSOA}\right) \times new\ site\ area \quad [2]$$

Another type of 'relative' aggregation was performed for comparison whereby the absolute capacity density was normalised by the LSOA area to offer a perspective of capacity per hectare across London. Although this is a normalised measure it has limitations because the size of the LSOA can heavily influence the density calculation. For example, a high delivery rate in a small LSOA could be purely because the identified capacity or delivery had a larger implication due to the smaller LSOA area. After comparison of regression results and consideration it was decided the absolute values would be used in the final model. The calculation for relative capacity density is summarised in equation 3.

$$Relative\ capacity\ density\ per\ LSOA = \frac{absolute\ capacity\ density}{area\ of\ LSOA} \quad [3]$$

The same steps for capacity aggregation were followed for delivery aggregation. Housing delivery is defined as the number of residential units in each planning application. Since the planning applications were in point data format, the extra step was recalculating the proportional number of residential units after the spatial join was not required.

The calculation methods for absolute delivery density and relative delivery density are summarised equations 4 and 5.

$$Absolute\ delivery\ density = \sum(residential\ units\ in\ a\ planning\ application\ in\ LSOA) \quad [4]$$

$$Relative\ delivery\ density = \frac{absolute\ delivery\ density}{area\ of\ LSOA} \quad [5]$$

Two aggregated measures combining the capacity and delivery were also created. The delivery difference is defined as the difference in the number of units between capacity density and delivery density of an LSOA (equation 6). When interpreting the difference – a greater difference signifies a larger gap between capacity and delivery. While most areas have a higher capacity than delivery and are in a state of 'under delivery', some areas of London have exceeded their capacity targets and have 'over delivered'. The delivery rate is defined as the rate at which delivery has come forward in an LSOA with respect to its outlined capacity (equation 7). These two aggregated measures are used to identify outliers and specific areas of interest which may be under or over delivering.

$$Delivery\ difference = absolute\ capacity\ density - absolute\ delivery\ density \quad [6]$$

$$Delivery\ rate\ (\%) = \left(1 - \frac{delivery\ difference}{absolute\ capacity}\right) \times 100 \quad [7]$$

4.5. Defining ‘residential capacity suitability’

For the purpose of this study, residential capacity suitability is defined as the propensity of LSOAs to have a high capacity density. This suitability analysis tries to investigate whether areas of high residential capacity suitability can be predicted by the investigated variables.

4.6. 'Residential capacity' suitability classification

As discussed in chapter 3, the 2013 SHLAA uses a rough classification to decide on density and phasing. Using the idea behind this, a suitability classification was developed. This classification immediately allows us to identify which areas in London are more suitable for capacity and a high delivery rate.

5 class categorisations for 'residential suitability' of a site:

Classification	Suitability score threshold
minimum suitability	1-2
low suitability	3-4
medium suitability	5-6
high suitability	7-8
maximum suitability	9-10

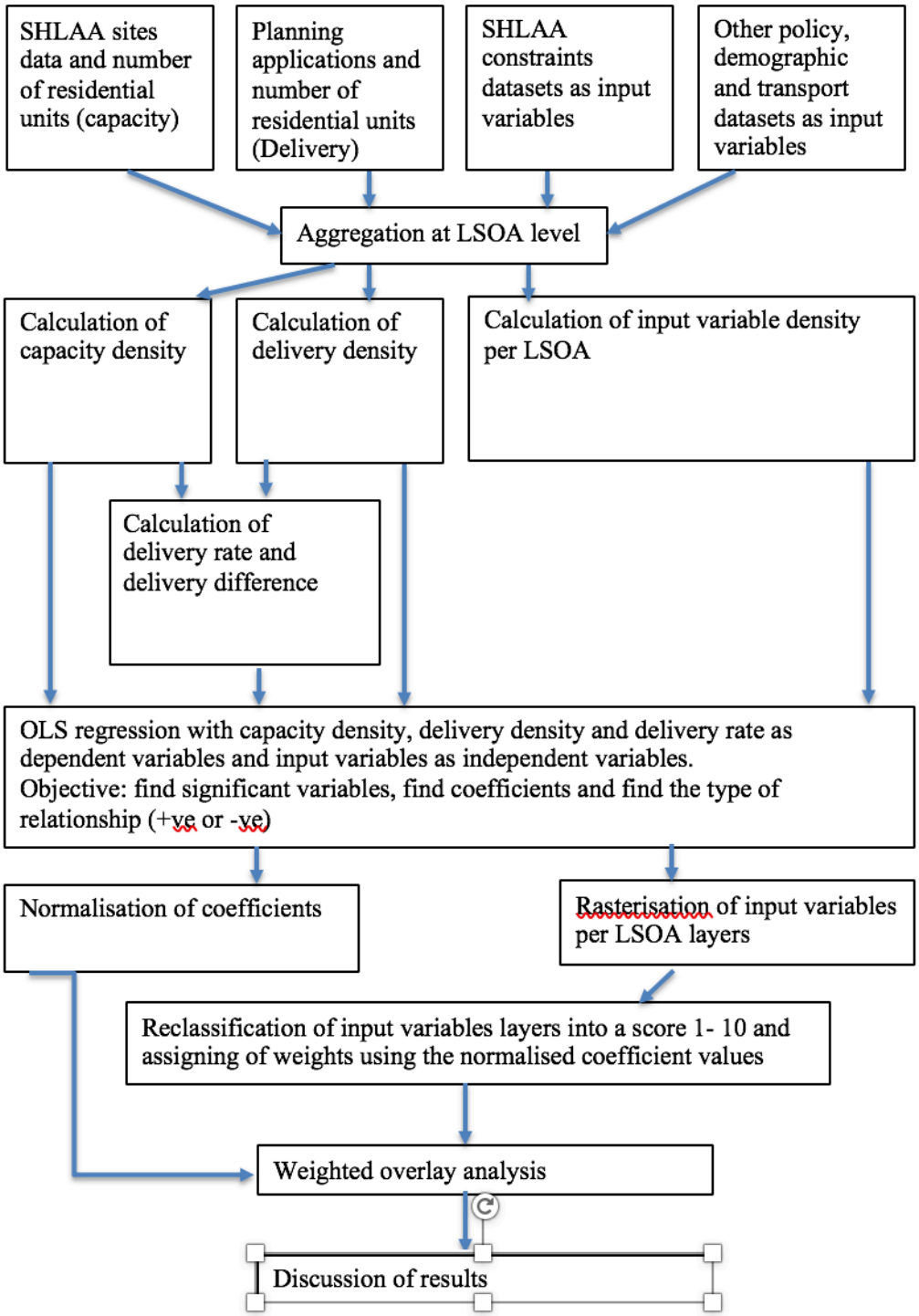
Table 5 Residential suitability classification

4.7. Quantitative methods, spatial analysis and the workflow

The following section describes how the quantitative methods for the spatial analysis were executed using the following themes:

- Workflow diagram
- Regression model build
- Weighted overlap analysis
- Rasterising layers
- Reclassifying the variables inputs
- Assigning weights to variable inputs using normalised coefficients

- **Workflow diagram**



- **Regression model build**

The regression model follows the following form in equation 8 (Hutcheson, 2011):

$$Y = \alpha + \beta 1X1 + \beta 2X2 + \beta 3X3 + \ldots + \beta nXn \qquad [8]$$

Where, **Y** is the dependent variable (absolute capacity density, absolute delivery density and delivery rates were tested in three separate regression tests)

α is the intercept,

β1, β2, βn are the coefficients which indicate the influence and the average change in **Y** influenced by a unit change in **X,**

And **X1, X2, Xn** are the dependent variables being tested (SHLAA, policy, demographic and transport input variables as detailed in the data sources table in the chapter three)

- **Regression tests table**

A series of regression tests were done to explore the relationship between absolute capacity, absolute delivery, the delivery rate and the tested variables. The following table explains how this analysis was structured and the respective objectives of each test. The highlighted tests in green are included in the results.

The other regression results can be found in appendix 1.1.

The following regression tests were conducted:

Iteration	Dependent variable	Independent variables / input variables	Objective of model
Model 1			
Model 1.1	Absolute capacity density	SHLAA planning policy and environment constraint datasets	• Test how well the existing SHLAA constraints explain the capacity density • Test which constraints are significant
Model 1.2	Absolute capacity density	SHLAA planning policy and environment constraint datasets, additional transport and non-transport datasets	• Test whether more of the variation can be explained by adding the non-SHLAA information • Test which variables are significant
Model 1.3	Absolute capacity density	Only significant variables from model 1.1	• Find coefficients which were normalised to be used as weights in the weighted overlay analysis 1.3
Model 1.4	Absolute capacity density	Only significant variables from model 1.2	• Find coefficients which were normalised and to be used as weights in the weighted overlay analysis 1.4
Model 2			
2.1	Absolute delivery density	SHLAA planning policy and environment constraint datasets, additional transport and non-transport datasets	• Test how well all tested variables explain the delivery density • Test which variables are significant
2.2	Absolute delivery density	Only significant variables from model 2.1	• Test how well all tested variables explain the delivery density
Model 3			
Model 3.1	Delivery rate	SHLAA planning policy and environment constraint datasets, additional transport and non-transport datasets	• Test how well all tested variables explain the delivery rate • Test which variables are significant
Model 3.2	Delivery rate	Only significant variables from model 3.1	• Test how well all tested variables explain the delivery rate • Test which variables are significant

4.8. Weighted overlay analysis

The following equation was used to carry out a weighted overlay analysis (Kumar et al., 2014):

$$Site\ suitability = \Sigma[input\ variables\ map\ (Cn) \times\ weight\ (Wn)] \quad [9]$$

Where Cn = raster layer

Wn = weight derived from OLS regression

4.9. Rasterising layers

The R packages- 'sp', 'raster' and 'rgdal' were used to rasterise all the significant input variable layers in preparation for the weighted overlay analysis. A master SpatialPloygonsDataFrame was created. This contained the attribute data for each input variable. The extent of the raster was set using the dimensions of the SpatialPloygonsDataFrame and a loop was created in order to rasterise each column of the data frame and save the raster as a GeoTIFF file. (Pebesma, 2018; Hijmans, 2019; Bivand, 2019)

4.10. Reclassifying the variables inputs

The 'reclassify' tool from Arc Toolbox was used to reclassify all the variable inputs into 10 classes to follow 'residential suitability' classifications approach mentioned in section 4.6 Each raster was classified into 10 classes from 1 to 10 with interval of 1. (ESRI, 2016)

4.11. Assigning weights to variable inputs using normalised coefficients

The weighted overlay analysis was performed using the 'weighted overlay' tool from Arc Toolbox. The weights were assigned to each reclassified raster layer using the normalised coefficients calculated after performing the min-max scaling procedure. (ArcGIS Help, 2014)

5. Results and analysis

The following section presents the results and analysis generated from the outlined methodology. This chapter is structured using the questions set out within the 'Research Objectives'.

5.1. What is the housing capacity in terms of residential units as identified in the last SHLAA from 2013 during the first two phases of the exercise? Spatially, where is this capacity situated and what are the underlying reasons behind this?

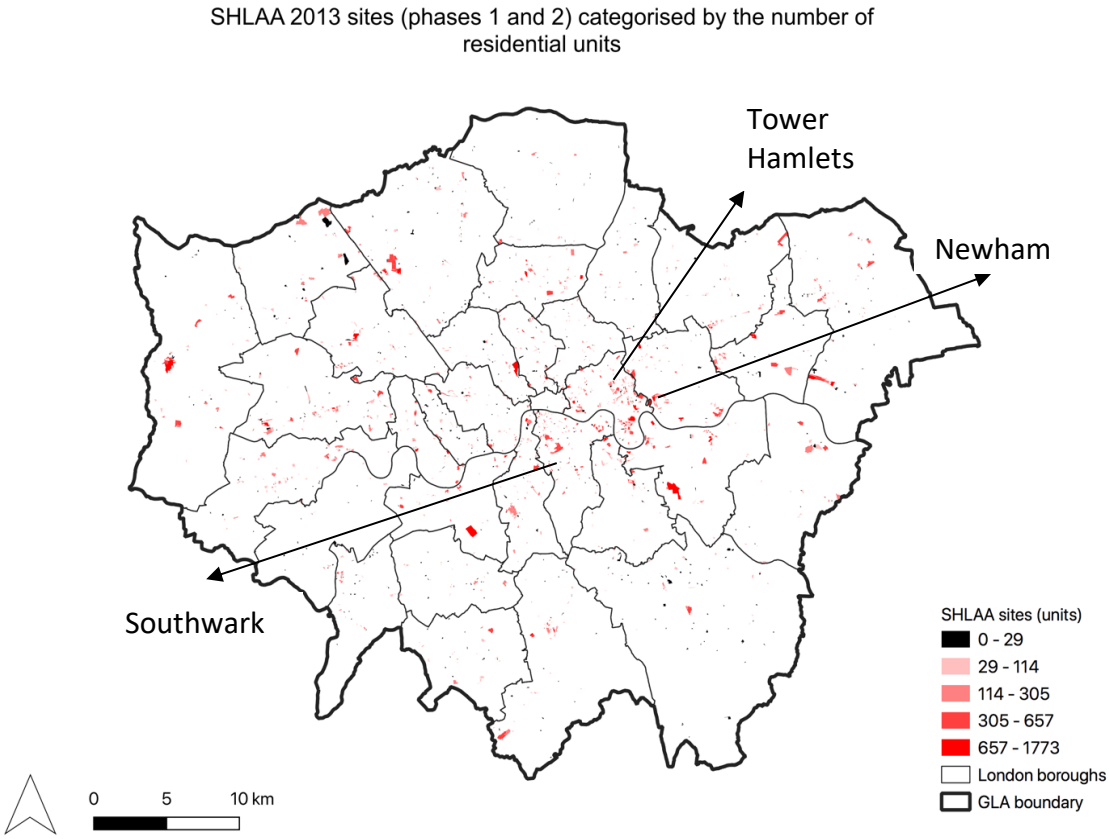


Figure 15 SHLAA sites phases 1 and 2 categorised by the number of residential units

There are more than 38,5000 residential capacity units identified in the first two phases of the SHLAA and as visible in figure 15 most LSOAs in London do not have any identified SHLAA capacity. This can also be seen in figures 16 and 18.

The boxplot in figure 16 shows a highly skewed distribution with majority of the LSOAs having zero identified capacity and small proportion showing extremely high capacities. These high capacities are the result of whole estate regeneration schemes being registered as a single SHLAA site. For example, the Aylesbury estate regeneration scheme in Southwark has an identified capacity of 2641 units on a single SHLAA sites.

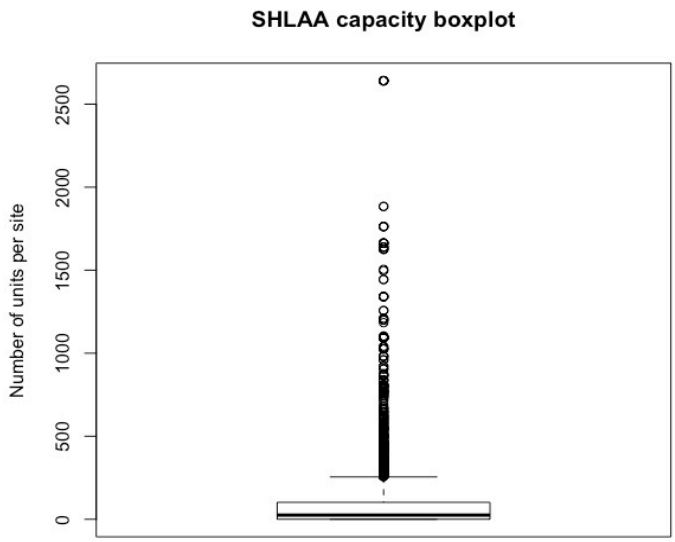


Figure 16 SHLAA capacity boxplot

Although the SHLAA sites are spread throughout London, there is a slight clustering of higher density sites in inner London boroughs, especially in Tower Hamlets, Newham and Southwark (as marked on figure 17). Since this study is mostly focused on understanding the relationship between residential capacity and delivery rates, the distribution of SHLAA capacity was used to identify and exclude outliers.

First, all LSOAs with zero capacity and LSOAs with less than 30 units were excluded as these values cannot enhance our understanding of large site SHLAA housing capacity in the scope of this research question. Following

this any values above 3 standard deviations were treated as outliers and removed. This results in the distribution visible in figure 19. The filtered distribution in figure 19 shows that boroughs such as Croydon have more delivery than capacity. Most LSOAs have more capacity than delivery which suggest that these areas have not fulfilled their outlined capacity targets in line with what the SHLAA phasing anticipated. This confirms that there is an issue of under delivery in some areas. Furthermore, this proves the case that we need to augment our understanding of the kind of conditions which make delivery suitable so that the outlined capacity allocation can take this information into account in potential future SHLAA exercises.

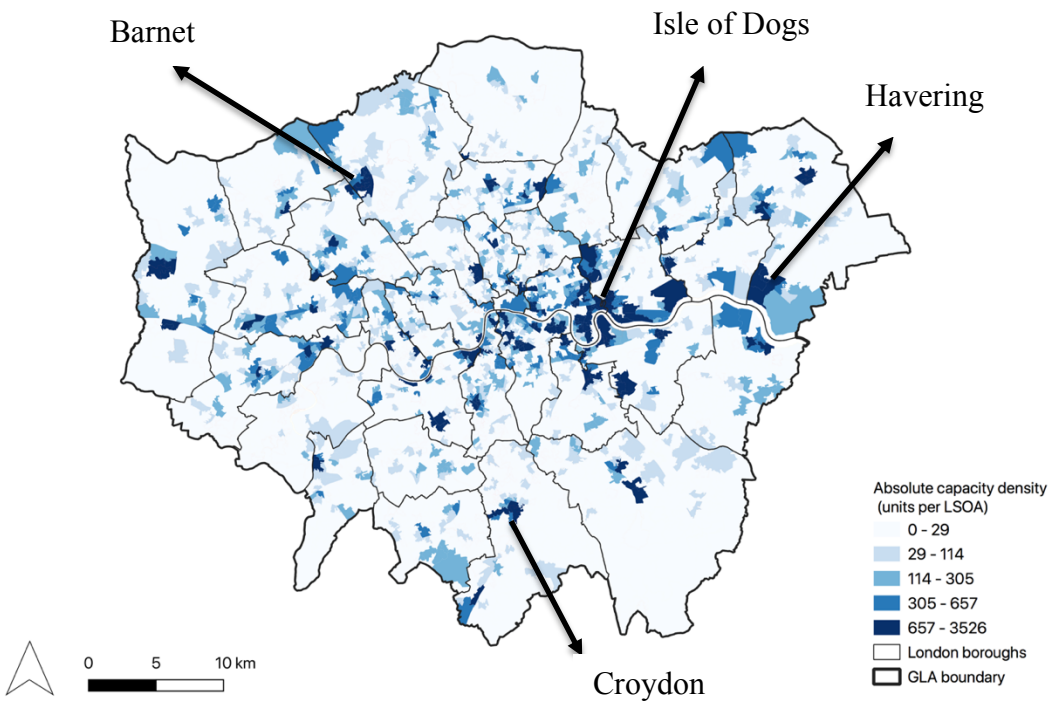


Figure 17 Absolute capacity density in London LSOAs

Spatially, most high density SHLAA capacity appears to be clustered in central London and around the industrial Docklands area in East London. Isle of Dogs is a clear hotspot for high density capacity identification. Other notable areas of interest on the map are sites in Barnet (Graham Park Estate), a cluster of sites close to East Croydon station and Beam Park in Havering.

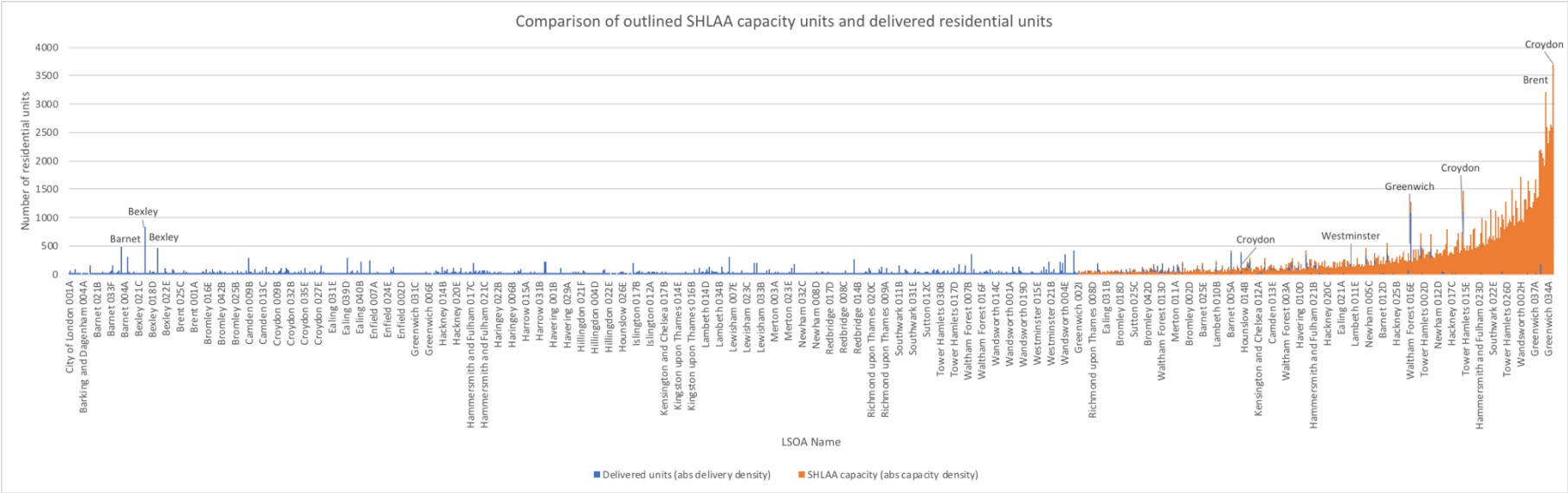


Figure 19 Comparison of capacity and delivery of residential units

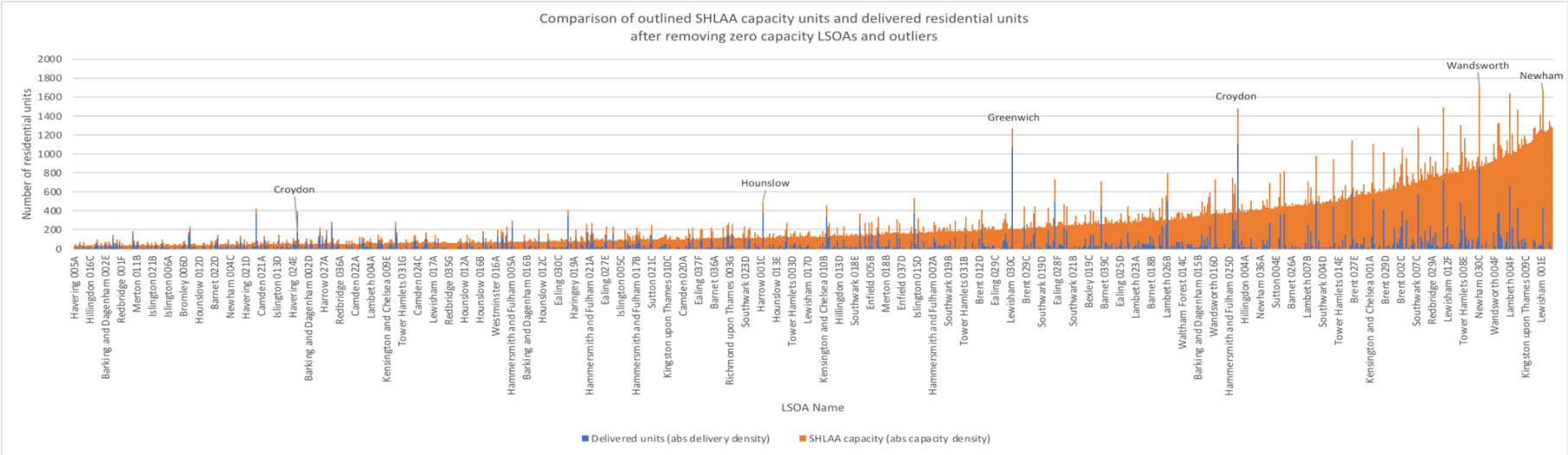


Figure 18 Comparison of capacity and delivery after filtering the LSOAs

5.2. *How much residential development in terms of residential units has been completed since 2013? Spatially, are there any patterns in delivery and what are the underlying reasons behind this?*

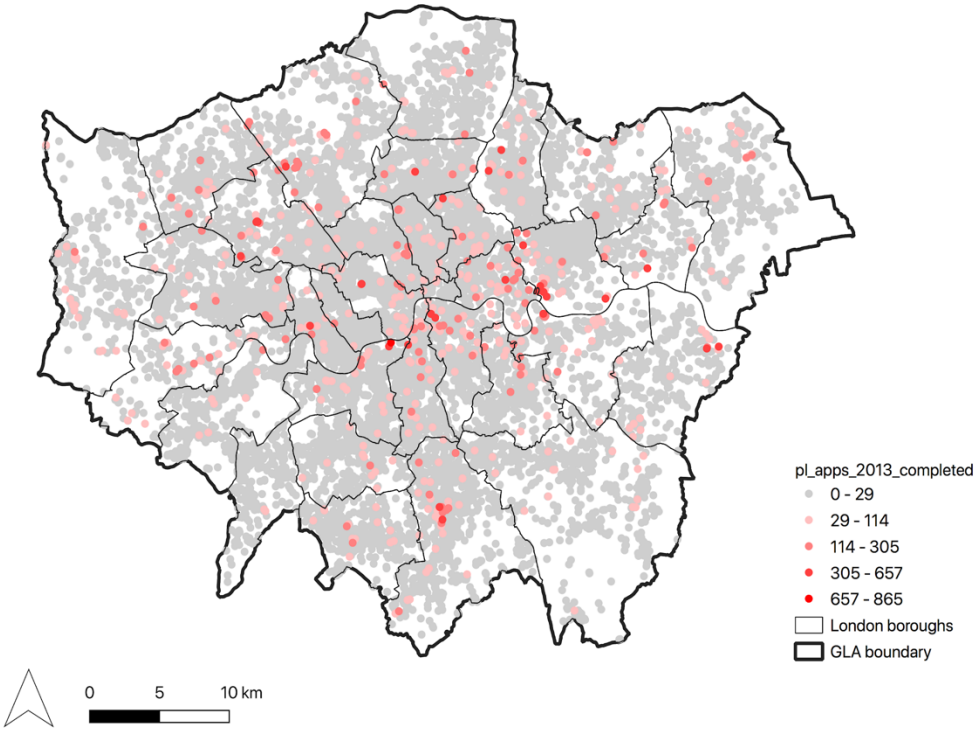


Figure 20 Completed planning applications since 2013 categorised by the number of residential units

Almost 113,000 residential units have been completed since 2013. Figure 20 shows the location and number of residential units per planning application. Similarly to residential capacity, most delivered high density developments are clustered towards the centre and in the eastern inner London boroughs. Interestingly, there is a rough emergent radial pattern and higher density planning applications appear to mirror the London Underground and National Rail network suggesting that residential delivery in London could be influenced by transport connectivity.

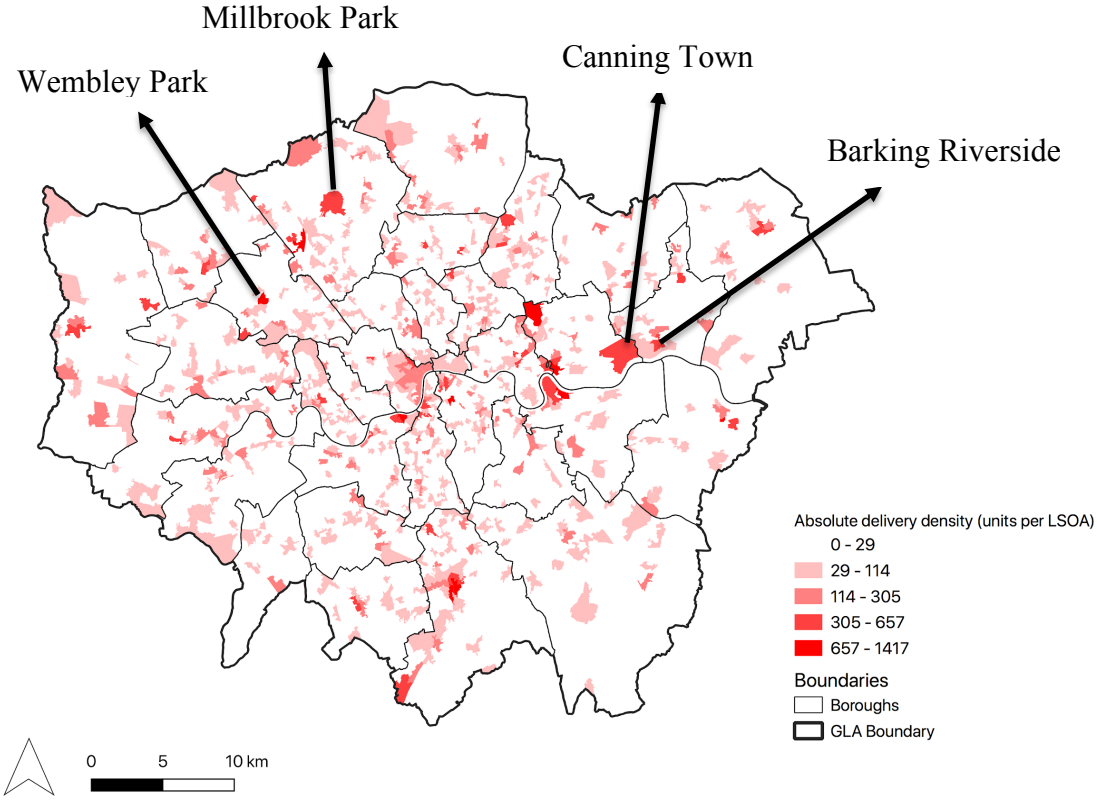


Figure 21 Absolute delivery density per LSOA

The absolute delivery density per LSOA is visualised in figure 21. Aggregating at LSOA level suggests that development is evenly spread out across London boroughs. Again, Tower Hamlets and Newham as well as City of London appear to have many high density developments present. Some particular areas of interest such as Barking Riverside and Canning Town are highlighted on the map.

5.3. What is the rate of housing delivery in London LSOAs and which areas of the city have met their capacity targets as opposed to under or over delivering against the identified capacity?

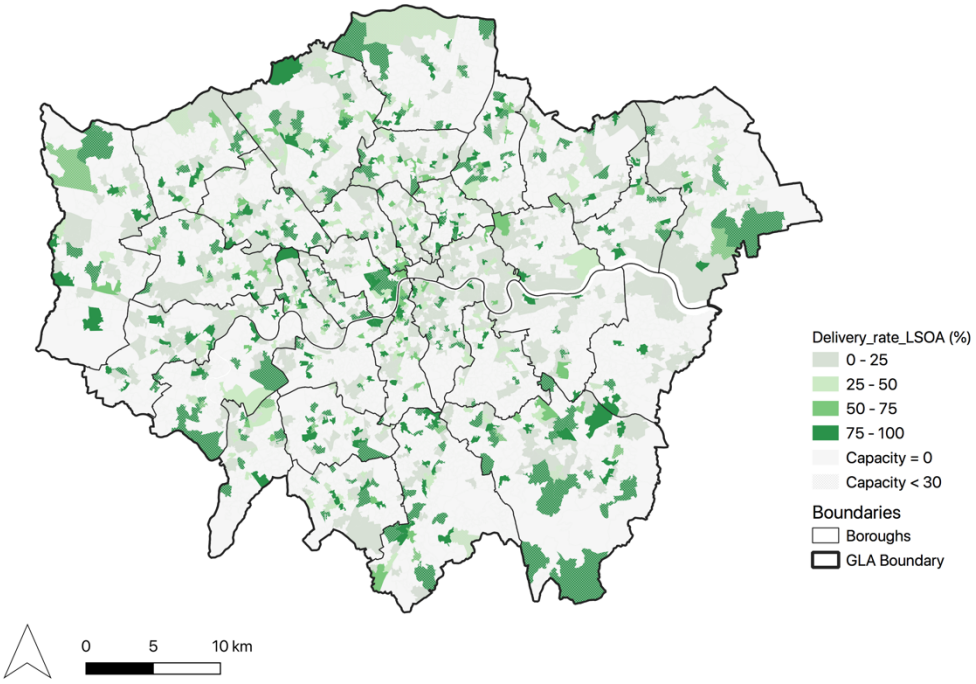


Figure 23 Delivery rate of all LSOAs

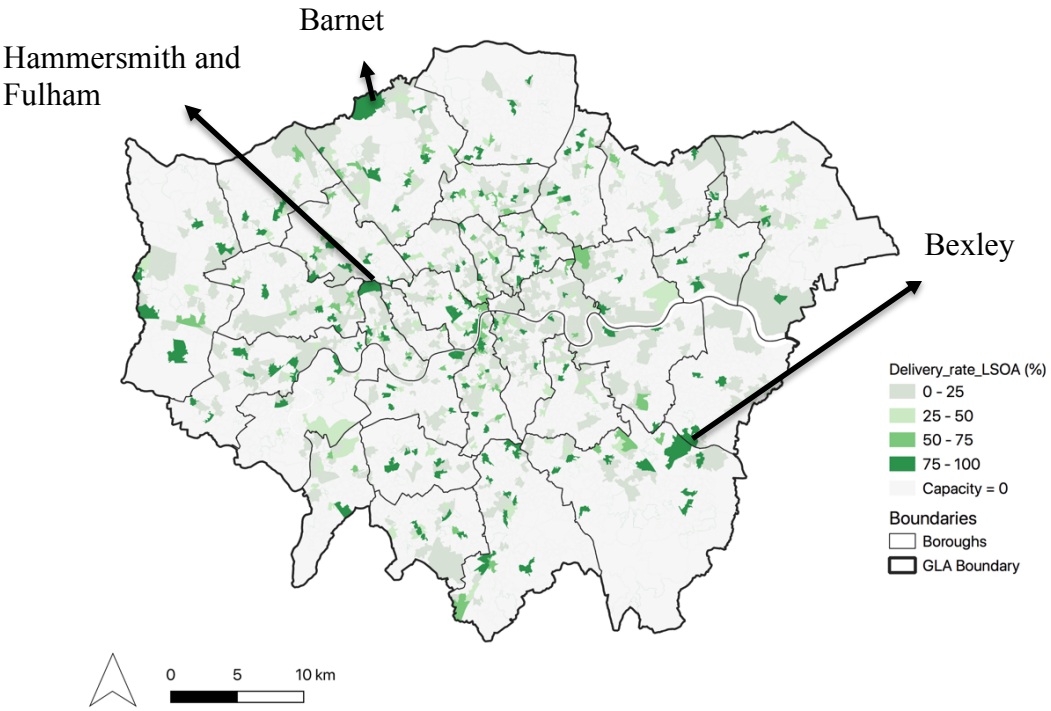


Figure 22 Delivery rate of LSOAs with capacity > 30 residential units

Figure 22 and 23 show the delivery rates at which delivered residential units have come forward in comparison to identified residential SHLAA capacity in each LSOA. As demonstrated, the rate of housing delivery fluctuates greatly throughout London. Most LSOAs have zero or low SHLAA capacity and can be misleading in showing a high delivery rate. Therefore all LSOAs with less than 30 capacity units were excluded from the visualisation in figure 23 and the regression analysis.

This allows us to focus purely on the delivery rates of LSOAs with some identified capacity. Most LSOAs with some capacity appear to have delivery rates lower than 50%. This reiterates the result demonstrating a mismatch in residential delivery and capacity in most LSOAs. The dark green areas signify that either capacity has been met or exceeded. Some notable areas of interest are marked on the figure.

Another useful way of analysing the delivery rates and the associated mismatch was by visualising the absolute difference (figure 24). This figure shows all the LSOAs which have ‘over delivered’ in comparison to the outlined capacity in yellow. Many of these LSOAs are in Outer London which suggests that not enough capacity is being identified here even though the conditions for delivery exist, More capacity could have been identified in these particular LSOAs. Conversely, the dark blue LSOAs have ‘under delivered’. These LSOAs have not yet been able to fulfil their outlined capacity because development here has not been fast or dense enough. A possible explanation for this is the anticipated effects of policy-making guiding the SHLAA process – which could be argued to be out of touch with the real dynamics of housing delivery. The light blue areas around the

docklands (as marked on the figure) are mostly protected Strategic Industrial Land (SIL). Despite their policy protection, these sites have come forward at a faster rate than anticipated by SHLAA. Based on this it can be suggested that there is a need for policy-making and enforcement of protection of certain land-uses to be reconsidered. Either the protection and its enforcement should be strengthened or the degree of protection should be amended.

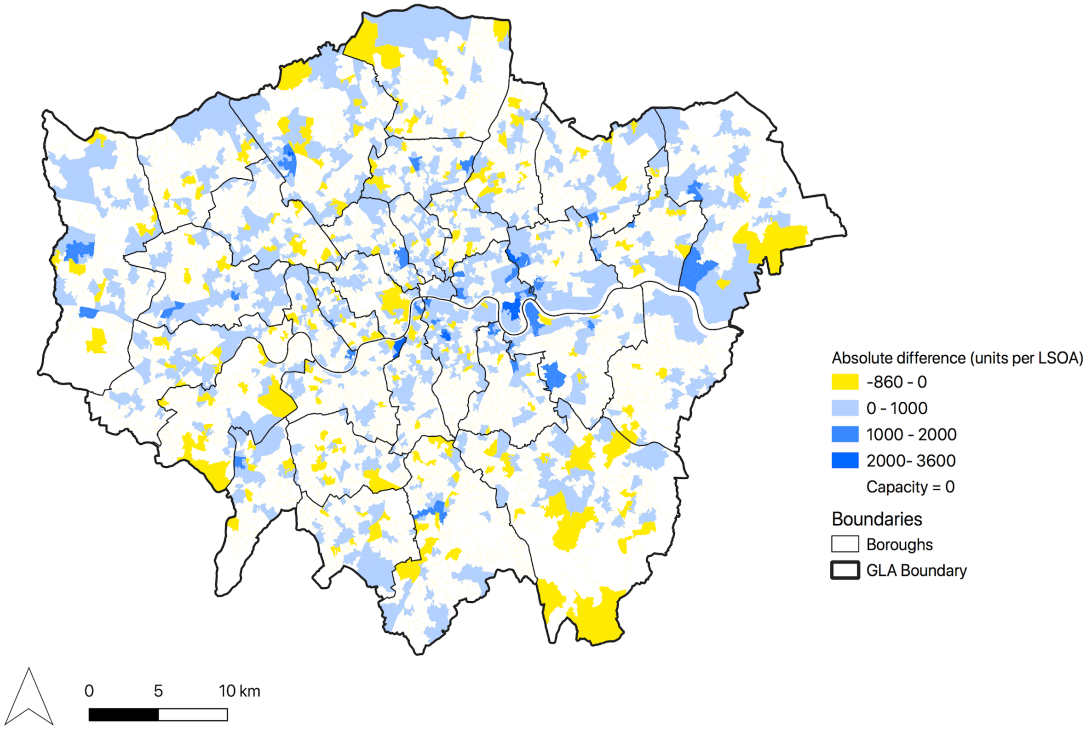


Figure 24 Absolute difference in delivery and capacity in LSOAs

5.4. Research questions 5.4.1 and 5.4.2 can be answered by analysing the regression results of models 1, 2 and 3.

- *What is the impact of recreating SHLAA by assigning importance to the SHLAA variables using an OLS regression approach instead of the current probability-based approach. Can the regression-based approach be deemed reliable?*

- *Investigate which other variables could be affecting the delivery density and the delivery rate of areas which under or over deliver in terms of housing delivery. Identify the variables which affect the delivery rate significantly and conduct a weighted overlay analysis to explore the cumulative impact of these variables on the suitability of residential development in LSOAs.*

OLS regression results:

- Model 1.3 absolute capacity density ~ significant SHLAA constraints

Model 1.3	ab_cap_den ~ shlaa only * only					
Adj R2	0.06455					
R2	0.06784					
F test	20.61 on 4 and 1133 DF					
p-value	< 2.2e-16					
Variable	coeff est	std error	t value	Pr(>|t|)	significance	Norm_coeff
(Intercept)	216.4811	8.5025	25.461	< 2e-16	***	
LSIS (managed)	22.3426	9.0007	2.482	0.0132	*	39.13052054
NDIL (lim)	21.7717	4.1667	5.225	2.07E-07	***	39.03907189
NDI (managed)	11.6547	4.5021	2.589	0.00976	**	20.89816923
Floodrisk (low-med)	0.5199	0.1206	4.31	1.78E-05	***	0.93223834

Table 6 Model 1.3 absolute capacity density predicted by significant SHLAA constraints

This regression test only used the significant independent variables found from running a OLS regression between absolute capacity density and all of the SHLAA constraints. As visible from the results, only 4 constraints were found to be significant in this model. Furthermore, the R square value of this regression test is extremely low at 0.06784. This signifies that the SHLAA constraints are only explaining 6% of the absolute capacity.

The coefficients themselves appear to follow expectation. Locally Significant Industrial Land is less strictly protected than SIL and the managed and limited release factors further support the argument for

capacity being found on these sites. Managed and limited release industrial land is generally more developable than restricted release industrial land, therefore the positive relationship between these variables and absolute capacity density makes sense. There is also a small positive relationship between absolute capacity and low-medium flood risk areas. While areas without any flood-risk would be considered most suitable, the low flood-risk category is the most developable and therefore the relationship makes sense.

- Model 1.4 absolute capacity density ~ significant SHLAA constraints, additional transport and non-transport datasets

Model 1.4	ab_cap_den ~ shlaa + + sig only				
Adj R2	0.2684				
R2	0.2832				
F test	19.13 on 23 and 1114 DF				
p-value	< 2.2e-16				
Variable	coeff est	std error	t value	Pr(>|t|)	significance
(Intercept)	279.50311	57.42132	4.868	1.29E-06	***
NDIL (lim)	14.01777	4.03193	3.477	0.000527	***
HSE zone (unsuit.)	28.51288	6.86351	4.154	3.51E-05	***
Floodrisk (low-med)	0.68217	0.1285	5.309	1.33E-07	***
Opp area	-0.70587	0.1057	-6.678	3.81E-11	***
Housing zone	1.23454	0.20195	6.113	1.35E-09	***
listed buildings	-1.24563	0.49302	-2.527	0.011658	*
CAZ	-0.96151	0.28991	-3.317	0.000941	***
Regen areas	-0.58591	0.13863	-4.226	2.57E-05	***
emplmnt sites	9.71972	2.23938	4.34	1.55E-05	***
HHOLDS	-2.73424	0.61223	-4.466	8.78E-06	***
AVHHOLDS	-0.24314	0.07662	-3.173	0.001549	**
dwell_age_1900_1918	-12.3354	4.44442	-2.775	0.005604	**
dwell_age_1919_1929	-13.62312	6.16421	-2.21	0.027305	*
dwell_Age_1930_1939	-8.99939	4.16008	-2.163	0.030732	*
dwell_Age_1955_1964	-19.22171	6.24517	-3.078	0.002136	**
dwell_age_2000_2009	17.57172	5.57122	3.154	0.001653	**
dwell_age_2010_2012	44.55388	6.70751	6.642	4.82E-11	***
no car ownership	0.46451	0.1101	4.219	2.65E-05	***
3 cars owned	-18.28039	7.03971	-2.597	0.009535	**
4 or more cars owned	48.56946	14.65389	3.314	0.000948	***
LU Crowding 0-2 sum	122.96038	33.81231	3.637	0.000289	***
NR Crowding 0-2 sum	-12.79666	4.29081	-2.982	0.002923	**
pop density	1.84682	0.54544	3.386	0.000734	***

Table 7 Model 1.4 ab_Cap_Den predicted by all SHLAA and additional datasets

This regression test builds upon model 1.3 by adding the additional transport and non-transport datasets in order to predict absolute capacity density. This causes the R square value to increase although at 0.2684, the overall prediction of the variation in the model is still low. This can be attributed to the fact that predicting capacity across London is a complex issue and this model is currently unable to factor in highly important effects around viability of development on the site.

When interpreting the coefficients, most of the signs follow expectation although some behave differently to what we might expect. For example, it could be expected that opportunity areas and regeneration areas would have a positive relation with absolute capacity density. However, this model shows the opposite – both coefficients hold small but negative influence on capacity density. This inconsistency could be attributed to collinearity between the input variables (Frost, 2019). This can be confirmed by looking at a correlation matrix of all input variables (figure 25). Both variables have correlation with other variables in the model and this could explain the reason behind the unexpected values.
On the other hand, some of the car ownership variables more or less follow expectation. Areas with low levels or no car ownership have a positive relationship with absolute capacity density – generally new-build high density developments are located close to good public transport accessibility and therefore have stricter car parking standards (GLA, 2017). However, no significant relationship was found between PTAL values and capacity density, therefore this observation cannot be treated as reliable.

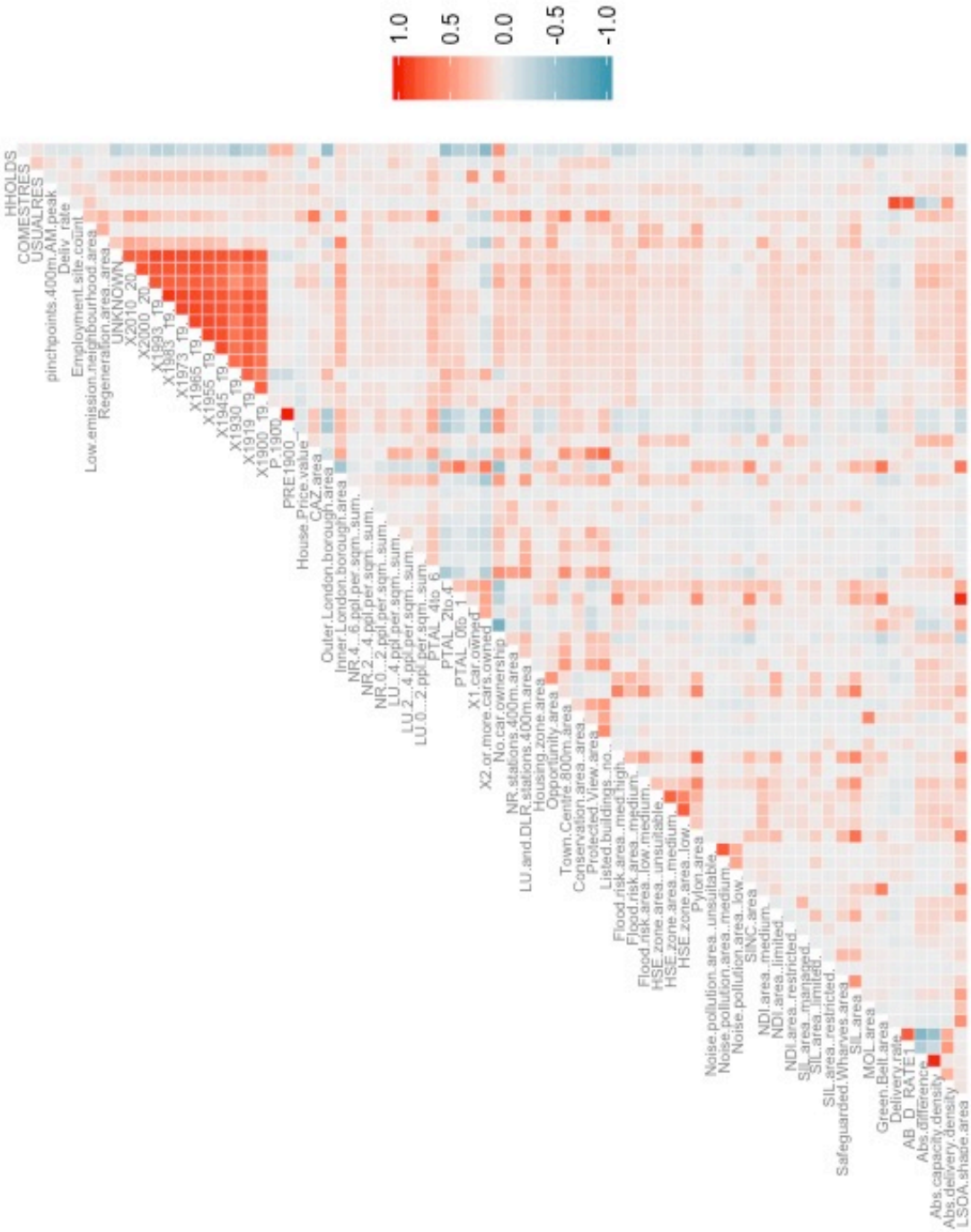


Figure 25 Correlation matrix of all variables

Models 2.2 and 3.2 use the significant SHLAA constraints, additional non-transport and transport datasets to predict the absolute delivery density and delivery rate respectively.

Model 2.2	ab_del_den ~ shlaa + + * only				
Adj R2	0.1911				
R2	0.2466				
F test	4.443 on 78 and 1059 DF				
p-value	p-value: < 2.2e-16				
Variable	coeff est	std error	t value	Pr(>|t|)	significance
(Intercept)	47.62	54.74	0.87	0.38452	
SIL	-0.5978	0.1957	-3.054	0.00232	**
PP_SILR_ar	-1.01E+01	4.36E+00	-2.311	0.02103	*
NDIL (lim)	7.357	1.648	4.464	0.00000889	***
Pylons	1.826	0.7482	2.44	0.01486	*
HSE zone (low)	17.31	2.034	8.509	<2e-16	***
HSE zone (unsuit.)	-9.815	4.423	-2.219	0.02668	*
Floodrisk (med-hi)	-0.6157	0.2526	-2.437	0.01497	*
LU, DLR stops	-0.2721	0.1332	-2.043	0.04134	*
CAZ	0.2681	0.1293	2.073	0.03838	*
PTAL 2-3	1.658	0.8214	2.019	0.04376	*
PTAL 4-6	1.723	0.7766	2.218	0.02674	*
Mdn_hous_pr	2.295	0.8145	2.818	0.00493	**
LU Crowding 0-2 sum	14.79	2.958	5	0.00000067	***

Table 8 Model 2.2 ab_Delivery_density predicted by all significant variables

Model 3.2	**deliv_rate~SHLAA only sig only**					
Adj R2	0.04537					
R2	0.05041					
F test	10.01 on 6 and 1131 DF					
p-value	8.64E-11					
Variable	**coeff est**	**std error**	**t value**	**Pr(>|t|)**	**significance**	**NORM_COEFF**
intercept	30.36618	2.03531	14.92	< 2e-16	***	
Noise pol (low)	0.23259	0.06767	3.437	0.00061	***	18.16840751
Noise pol (med)	-0.3376	0.13694	-2.465	0.013836	*	17.14922758
Noise pol (unsuit.)	0.43607	0.12547	3.475	0.000529	***	18.53211563
Pylons	1.28168	0.3058	4.191	2.99E-05	***	20.04359207
HSE zone (low)	4.67372	1.22192	3.825	0.000138	***	26.10665721
HSE zone (unsuit.)	-9.9319	2.38236	-4.169	3.29E-05	***	0

Table 9 model 3.2 delivery rate predicted by all significant variables

The same issue of a low R square value persists with these two models although model 2.2 is still able to account for around 25% of the variation. Considering the complexity behind predicting delivery, 25% is a good start to build upon (Grace-Martin, 2012). However, the current model for predicting delivery rate (model 3.2) has an extremely low R square value. Encouragingly, the p-value was low and significant in all the tested models (Minitab, 2014). This suggests that there is still a real relationship between the significant independent variables in and the dependent variables in the model. In the future, rather than

using the same list of input variables for all three processes of capacity, delivery and delivery rate; more bespoke models can be developed to best represent and predict the spatial variation of each process.

Weighted overlay analysis

The weighted overlay analysis aimed to provide proof of concept for moving beyond the SHLAA approach to predict capacity suitability in London using a more data-driven and spatial approach. Figures 25 and 26 are diagrammatic representations of the completed weighted overlay analysis. In figure 25, only the significant SHLAA constraints are mapped (following regression model 1.3), and most LSOAs have low capacity suitability and there is less overall variation in the suitability values.

In figure 26 (following regression model 1.4), there is greater variation in the suitability of LSOAs. This suggests that adding more datasets into the model allows us to better differentiate and determine capacity suitability. Since the outputs from the regression model have a degree of unreliability, it is difficult to determine how accurately the maps below can identify capacity suitability. However, when comparing figure 26 to figure 28 (which shows the absolute capacity density), there are similarities in the way LSOAs are classified. LSOAs belonging to suitability classes 4 and above have heavy alignment with identified residential capacity of 114 units and above. Using this as a basis, it can be argued that a spatial weighted overlay approach with more input variables than just SHLAA constraints is a reliable proof of concept and could be utilised for understanding and identifying residential capacity suitability in London.

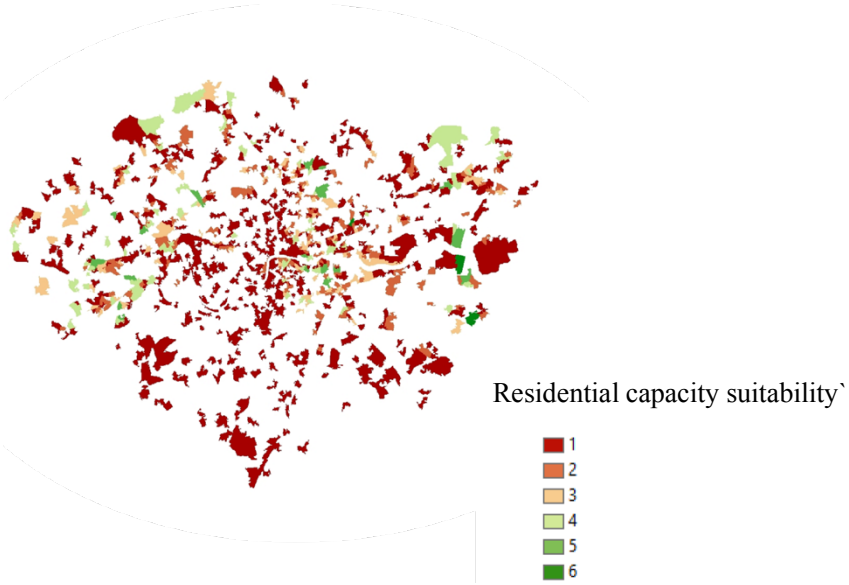


Table 10 Weighted overlay analysis for only SHLAA constraints``

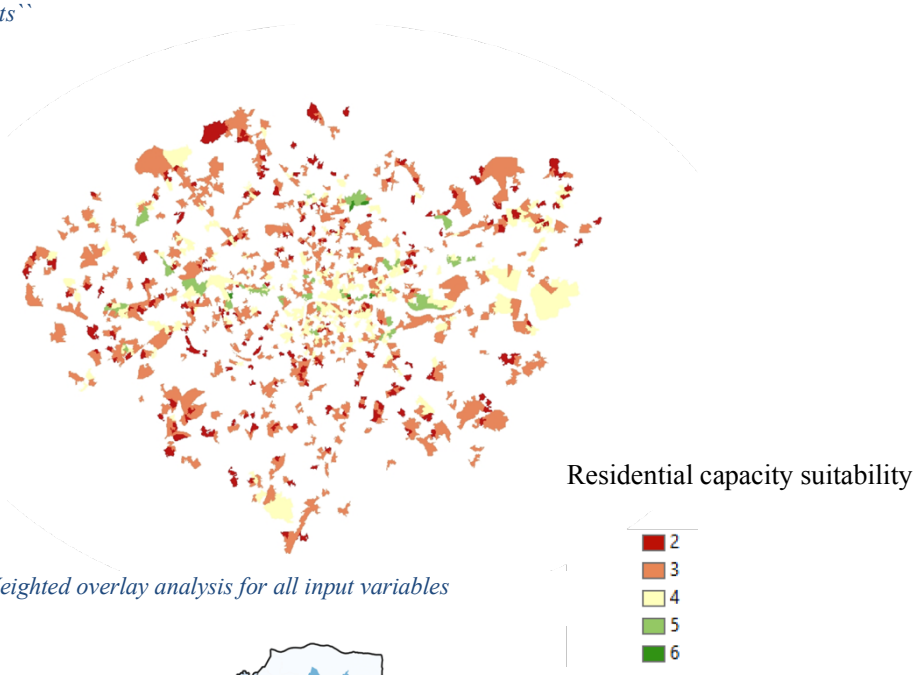


Table 11 Weighted overlay analysis for all input variables

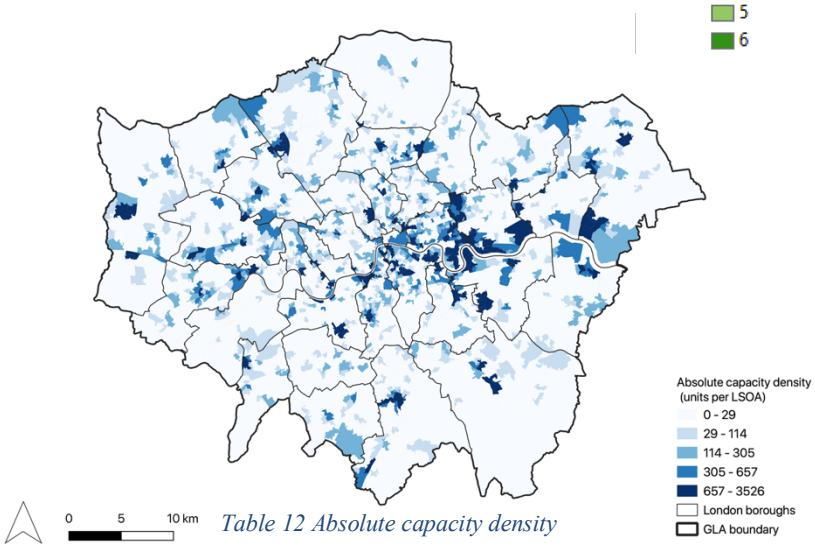


Table 12 Absolute capacity density

6. **Evaluation**

5.5. *Outline the limitations of the methodology and suggest ideas for further research to improve the proposed approach.*

5.6. *Discuss how the outlined approach could enhance policy-making and enforcement for city planners.*

Although, this study is able to build an understanding of the capacity, delivery and delivery rates successfully at LSOA level, it is less successful in using the regression model to understand which input variables affect these processes. The presented approach is an alternative towards exploring housing capacity in relation to SHLAA and it is ambitious in trying to consider capacity and delivery at the same time by trying to understand delivery rates within London. Consequently, there are currently severe limitations associated with the regression model.

A clear limitation and drawback is the lack of model fitting. This was not conducted as part of the methodology as the objective of the regression tests was purely to find the influence of each input variable. However in retrospect, after computing the results and finding inconsistencies in both the coefficients and a low prediction of the model variation, it is clear that the model would benefit from techniques to improve the fit before being able to draw conclusion reliably. Although an attempt was made at improving the fit by filtering the dataset and adding in additional variables, there are other approaches which could help to identify the reason behind any inconsistencies. There are multiple ways to attempt to increase the reliability of the results:

- Firstly, step-wise regression could be used to select the most optimum set of input variables for each model (Minitab, 2019).
- The residual fits plots could be checked – these would be able to reveal any unexpected patterns spatially which could then be targeted and improved (ESRI, 2019).
- Other datasets which could account for the viability of capacity and delivery of residential development could be added and tested within the model.
- The missing third category of SHLAA constraints is a severe limitation. Adding datasets around local ownership and contamination amongst other borough-specific issues could improve the reliability and prediction of the variation.
- Splitting the analysis further into LSOAs with high delivery rates and low delivery rates could also impact the regression results. It is possible that areas of London which over or under deliver share characteristics – it was difficult to discern this from the current regression model since all LSOAs with capacity above 30 residential units were considered within the same model. Stratifying further could reveal potential similarities.

7. Conclusion

The aim of this study was to develop a comprehensive understanding of the processes of housing capacity, delivery and the resultant delivery rates in London LSOAs. The study conducted exploratory mapping analysis to understand the existing context around these processes. A spatial data-led approach was proposed to identify how well the existing SHLAA methodology predicts housing capacity using regression testing and whether this can be improved by incorporating further datasets. Another key objective was to develop and explore a potential residential capacity suitability classification for London and investigate whether this model can be used as a basis for understanding the propensity of areas in London to have suitability for potential housing capacity identification. The SHLAA methodology was used to guide and structure thinking. This was expanded upon by incorporating the spatial regression and overlay analysis elements.

Some of the key findings showed that high capacity density tends to be clustered in central and east London and whereas delivery patterns are more spread out evenly. There is an imbalance between the outlined capacity and delivered densities in many LSOAs. Most LSOAs have no identified capacity which further fuels the imbalance because delivery is still coming forward in these locations.

The regression tests were used to see if significant variables could be used to predict the relationships between the input variables and housing capacity, delivery and delivery rates. Due to a lack of model fitting and low r-square scores the regression coefficients were deemed unreliable to draw firm conclusions.

However there were some interesting findings around car ownership and delivery and these findings should be validated in future more reliable regression models.

Finally, a weighted overlay analysis was conducted to compare how capacity suitability changes based on the amount of input variables considered. These provided encouraging results and should be explored further to develop a capacity suitability model using reliable regression coefficients as weights.

All of the research questions were addressed in the results, analysis and evaluation sections and will hopefully be helpful in guiding the thinking of city planners and policy-makers by disseminating key findings regarding housing capacity, delivery and delivery rates and raising important questions about the influence of various input variables on these processes.

8. References

1. “About Feature Scaling and Normalization.” *Dr. Sebastian Raschka*, 11 July 2014, https://sebastianraschka.com/Articles/2014_about_feature_scaling.html.
2. *Add and Connect Data and Tools, and Modify Elements—ArcGIS Pro | ArcGIS Desktop*. https://pro.arcgis.com/en/pro-app/help/analysis/geoprocessing/modelbuilder/add-connect-and-modify-data-and-tools-in-a-model.htm. Accessed 29 Aug. 2019.
3. Barton, Cassie, and Wendy Wilson. *Tackling the Under-Supply of Housing in England*. Dec. 2018. *researchbriefings.parliament.uk*, https://researchbriefings.parliament.uk/ResearchBriefing/Summary/CBP-7671.
4. “Benefits and Challenges of the Green Belt.” *Centre for Cities*, https://www.centreforcities.org/reader/benefits-challenges-green-belt/. Accessed 26 Aug. 2019.
5. Bivand, Roger. *Rgdal Package | R Documentation*. 2019, https://www.rdocumentation.org/packages/rgdal/versions/1.4-4.
6. Bosetti , Nicolas. *Planning and Design for Future Mobility in New Developments*. 2019, https://www.centreforlondon.org/project/planning-future-mobility/.
7. Bowie , Duncan. “Beyond the Compact City.” *Planning in London*, vol. 97, pp. 59-70.

8. Brown, Richard. *Is It Time to Review London's Green Belt?* 6 Aug. 2019, https://www.centreforlondon.org/blog/green-belt/.
9. Centre for London. *Capital Homes: Land and Planning Roundtable Report; Capital Homes – New Responses to London's Housing Crisis*. Aug. 2019, https://www.centreforlondon.org/publication/capital-homes/.
10. Chao, Sui, et al. "How Might Compact Cities Contribute to Sustainable Transport." *Applied Mechanics and Materials*, vol. 409–410, Sept. 2013, pp. 3–7. *DOI.org (Crossref)*, doi:10.4028/www.scientific.net/AMM.409-410.3.
11. Clifford, Ben, and Janice Morphet. "Local Authority Direct Provision of Housing." *RTPI*, https://www.rtpi.org.uk/knowledge/better-planning/better-planning-housing-affordability/local-authority-direct-provision-of-housing/. Accessed 23 Aug. 2019.
12. "Councils Must Protect Our Precious Green Belt Land." *GOV.UK*, https://www.gov.uk/government/news/councils-must-protect-our-precious-green-belt-land. Accessed 26 Aug. 2019.
13. DCLG. "Fixing Our Broken Housing Market." *GOV.UK*, 2017, https://www.gov.uk/government/publications/fixing-our-broken-housing-market.
14. ---. "National Planning Policy Framework." *GOV.UK*, https://www.gov.uk/government/publications/national-planning-policy-framework--2. Accessed 26 Aug. 2019.

15. “Delivering Growth in London and the South East Report by the Crossrail 2 Growth Commission.” *Crossrail 2*, 2016, https://crossrail2.co.uk/discover/new-homes/.
16. *Documentation QGIS 3.14*. https://www.qgis.org/en/docs/index.html. Accessed 27 Aug. 2019.
17. “Draft London Plan – Consolidated Suggested Changes Version July 2019.” *London City Hall*, 16 July 2019, https://www.london.gov.uk//what-we-do/planning/london-plan/new-london-plan/draft-london-plan-consolidated-suggested-changes-version-july-2019.
18. Düzgün, H. Sebnem, and Serkan Kemeç. “Spatial and Geographically Weighted Regression.” *Encyclopedia of GIS*, edited by Shashi Shekhar et al., Springer International Publishing, 2015, pp. 1–6. *Springer Link*, doi:10.1007/978-3-319-23519-6_1242-2.
19. Editor, Minitab Blog. *How to Interpret a Regression Model with Low R-Squared and Low P Values*. https://blog.minitab.com/blog/adventures-in-statistics-2/how-to-interpret-a-regression-model-with-low-r-squared-and-low-p-values. Accessed 30 Aug. 2019.
20. ESRI. *An Overview of the Reclass Tools—Help | ArcGIS for Desktop*. 2016, http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/an-overview-of-the-reclass-tools.htm.
21. ---. *ArcGIS Help (10.2, 10.2.1, and 10.2.2)*. 2014, http://resources.arcgis.com/en/help/main/10.2/index.html#//009z000000rq000000.

22. “FALP SHLAA 2013 Appendix 8; London Plan Technical and Research Reports.” *London City Hall*, 13 Nov. 2015, https://www.london.gov.uk//what-we-do/planning/london-plan/london-plan-technical-and-research-reports.
23. FAO AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS . *A Framework for Land Evaluation*. 1976, http://www.fao.org/3/X5310E/x5310e04.htm.
24. *Finding a Meaningful Model*. https://www.esri.com/news/arcuser/0111/findmodel.html. Accessed 30 Aug. 2019.
25. GLA. *FALP SHLAA 2013 Methodology*. Greater London Authority, Jan. 2014, https://www.london.gov.uk/file/15569/download?token=M9dckY12.
26. ---. *Housing in London 2018 Report – London Datastore*. 2018, https://data.london.gov.uk/blog/housing-in-london-2018-report/.
27. ---. “Housing SPG; EiP Library.” *London City Hall*, Mar. 2016, https://www.london.gov.uk//what-we-do/planning/london-plan/new-london-plan/examination-public-draft-new-london-plan/eip-library.
28. *GLA Population and Household Projections – London Datastore*. https://data.london.gov.uk/dataset/projections/. Accessed 20 Aug. 2019.
29. Grace-Martin, Karen. “Can a Regression Model with a Small R-Squared Be Useful?” *The Analysis Factor*, 14 May 2012, https://www.theanalysisfactor.com/small-r-squared/.

30. Greater London Authority (GLA). “Draft New London Plan.” *Draft New London Plan*, https://www.london.gov.uk/what-we-do/planning/london-plan/new-london-plan/draft-new-london-plan/ . Accessed 25 Aug. 2019.
31. Hijmans, Robert. *Raster Package | R Documentation*. 2019, https://www.rdocumentation.org/packages/raster/versions/2.9-23.
32. Hill, Dave. “London Housing Crisis: What Is It, Exactly?” *The Guardian*, 28 Oct. 2013. *www.theguardian.com*, https://www.theguardian.com/uk-news/davehillblog/2013/oct/28/london-housing-crisis.
33. Holman, Nancy, et al. *Housing in London: Addressing the Supply Crisis*. 2015, http://eprints.lse.ac.uk/64158/.
34. Hutcheson, G. D. “Ordinary Least-Squares Regression .” *Data Science Repo - Machine Learning, Stats, Etc*, https://datajobs.com/data-science-repo/. Accessed 29 Aug. 2019.
35. *Iterators—ArcGIS Pro | ArcGIS Desktop*. https://pro.arcgis.com/en/pro-app/help/analysis/geoprocessing/modelbuilder/iterators-for-looping.htm. Accessed 29 Aug. 2019.
36. Kumar, Santosh, and Ritesh Kumar. “Site Suitability Analysis for Urban Development of a Hill Town Using GIS Based Multicriteria Evaluation Technique: A Case Study of Nahan Town, Himachal Pradesh, India.” *International Journal of Advanced Remote Sensing and GIS*, vol. 3, no. 1, Apr. 2014, pp. 516-524–524.

37. Malczewski, Jacek. “GIS-Based Land-Use Suitability Analysis: A Critical Overview.” *Progress in Planning*, vol. 62, no. 1, July 2004, pp. 3–65. *DOI.org (Crossref)*, doi:10.1016/j.progress.2003.09.002.
38. Matters, Transport for London I. Every Journey. “The Mayor’s Transport Strategy.” *Transport for London*, https://www.tfl.gov.uk/corporate/about-tfl/the-mayors-transport-strategy. Accessed 26 Aug. 2019.
39. “Mayor Vows to Protect London’s Green Belt.” *London City Hall*, 27 Nov. 2017, https://www.london.gov.uk//city-hall-blog/mayor-vows-protect-londons-green-belt.
40. “Multicollinearity in Regression Analysis: Problems, Detection, and Solutions.” *Statistics By Jim*, 2 Apr. 2017, http://statisticsbyjim.com/regression/multicollinearity-in-regression-analysis/.
41. *OSGB 1936 / British National Grid - United Kingdom Ordnance Survey - EPSG:27700*. https://epsg.io/27700. Accessed 24 Aug. 2019.
42. Pebesma, Edzer. *Sp Package | R Documentation*. 2018, https://www.rdocumentation.org/packages/sp/versions/1.3-1.
43. *Perform Stepwise Regression for Fit Regression Model*. https://support.minitab.com/en-us/minitab/18/help-and-how-to/modeling-statistics/regression/how-to/fit-regression-model/perform-the-analysis/perform-stepwise-regression/. Accessed 30 Aug. 2019.
44. “Policy T6 Car Parking.” *Draft New London Plan*, 14 Nov. 2017, https://www.london.gov.uk/what-we-do/planning/london-plan/new-

london-plan/draft-new-london-plan/chapter-10-transport/policy-t6-car-parking.

45. Posted by Emmanuelle Rieuf on February 11, 2017 at 6:00pm, and View Blog. *How To Interpret R-Squared and Goodness-of-Fit in Regression Analysis*. https://www.datasciencecentral.com/profiles/blogs/regression-analysis-how-do-i-interpret-r-squared-and-assess-the. Accessed 30 Aug. 2019.
46. R Core Team. *CRAN: Manuals*. 2018, https://cran.r-project.org/manuals.html.
47. Rudlin, David, and Nicholas Falk. *Wolfson Economics Prize 2014 | URBED*. 2014, http://urbed.coop/wolfson-economic-prize.
48. *Run a Model—ArcGIS Pro | ArcGIS Desktop*. https://pro.arcgis.com/en/pro-app/help/analysis/geoprocessing/modelbuilder/run-a-model.htm. Accessed 29 Aug. 2019.
49. Srinivasan, Sumeeta. “Spatial Regression Models.” *Encyclopedia of GIS*, edited by Shashi Shekhar et al., Springer International Publishing, 2016, pp. 1–6. *Springer Link*, doi:10.1007/978-3-319-23519-6_1294-2.
50. “Strategic Housing Land Availability Assessment.” *London City Hall*, 11 Mar. 2016, https://www.london.gov.uk//what-we-do/planning/london-plan/new-london-plan/strategic-housing-land-availability-assessment.

51. “Tackling London’s Housing Crisis.” *London City Hall*, Greater London Authority (GLA), 30 Aug. 2017, https://www.london.gov.uk//what-we-do/housing-and-land/tackling-londons-housing-crisis.

52. *Topology Checker Plugin - Documentation for QGIS 2.18*. https://docs.qgis.org/2.18/en/docs/user_manual/plugins/plugins_topology_checker.html. Accessed 24 Aug. 2019.

53. Transport for London (TfL). “Mayor’s Transport Strategy: Supporting Evidence Challenges and Opportunities for London’s Transport Network to 2041;” *Transport for London - Travel in London Reports*, July 2017, https://www.tfl.gov.uk/corporate/publications-and-reports/travel-in-london-reports.

54. Walker, Jarrett. “Basics: Walking Distance to Transit.” *Human Transit*, 24 Apr. 2011, https://humantransit.org/2011/04/basics-walking-distance-to-transit.html.

55. “Weighted Sum Raster Overlay Analysis Using QGIS.” *Grind GIS-GIS and Remote Sensing Blogs, Articles, Tutorials*, 27 Aug. 2015, https://grindgis.com/software/qgis/raster-overlay-analysis-qgis.

56. *What Is ModelBuilder?—ArcGIS Pro | ArcGIS Desktop*. https://pro.arcgis.com/en/pro-app/help/analysis/geoprocessing/modelbuilder/what-is-modelbuilder-.htm. Accessed 29 Aug. 2019.

Appendix 1.1

Model 1.1	ab_cap_den ~ shlaa only					
Adj R2	0.08267					
R2	0.09961					
F test	5.879 on 21 and 1116 DF					
p-value	1.60E-15					
Variable	coeff est	std error	t value	Pr(>|t|)	significance	Norm_coeff
intercept	211.47681	9.22615	22.921	< 2e-16	***	
PP_GB_area	-0.06488	0.07883	-0.823	0.4107		2.37939465
PP_MOL_ar_	-0.13494	0.15223	-0.886	0.3756		2.337415941
PP_SIL_ar_	-0.79158	0.48723	-1.625	0.1045		1.94396891
PP_SW_ar_s	-0.69705	3.74932	-0.186	0.8525		2.000609608
PP_SILR_ar	-4.03595	12.78204	-0.316	0.7522		0
PP_SILL_ar	2.46607	4.60976	0.535	0.5928		3.89589496
PP_SILM_ar	23.03647	8.99631	2.561	0.0106	*	16.22131348
PP_NDIR_ar	4.66793	7.22487	0.646	0.5184		5.215210385
PP_NDIL_ar	25.5824	4.53123	5.646	2.08E-08	***	17.74678954
PP_NDIM_ar	8.93572	4.59104	1.946	0.0519	.	7.772394392
PP_SINC_ar	-0.09735	0.18958	-0.513	0.6077		2.359939202
EN_NPL_ar_	0.02239	0.27054	0.083	0.9341		2.431685285
EN_NPM_ar_	-0.47577	0.56254	-0.846	0.3979		2.133196656
EN_NPU_ar_	0.09769	0.50513	0.193	0.8467		2.476803708
EN_PY_ar_s	-2.14907	1.9608	-1.096	0.2733		1.130585
EN_HSEL_ar	3.42518	5.87906	0.583	0.5603		4.470576646
EN_HSEM_ar	9.83477	7.58267	1.297	0.1949		8.311089192
EN_HSEU_ar	10.87284	12.28499	0.885	0.3763		8.933082308
ENFRLM_ar_	0.76797	0.14443	5.317	1.27E-07	***	2.878423585
ENFRM_ar_s	1.4973	0.74868	2	0.0458	*	3.315425174
ENFRMH_ar_	-0.62096	0.68077	-0.912	0.3619		2.046201385

Model 1.2	ab_cap_den ~ shlaa + +					
Adj R2	0.2635					
R2	0.314					
F test	6.215 on 78 and 1059 DF					
p-value	< 2.2e-16					
Variable	**coeff est**	**std error**	**t value**	**Pr(>|t|)**	**significance**	**NORM_COEFF**
(Intercept)	211.00	147.40	1.43	0.15		
Green belt	0.03	0.12	0.24	0.81		1.28
MOL	-0.11	0.20	-0.52	0.60		1.28
SIL	-0.09	0.53	-0.18	0.86		1.28
Safeguarded Wharves	0.02	3.54	0.01	1.00		1.28
LSIS (restr)	-7.68	12.07	-0.64	0.52		1.28
LSIS (lim)	-3.13	4.41	-0.71	0.48		1.28
LSIS (managed)	10.19	8.46	1.20	0.23		1.29
NDI (restr)	3.34	6.66	0.50	0.62		1.28
NDIL (lim)	16.03	4.44	3.61	0.00	***	1.29
NDI (managed)	1.33	4.75	0.28	0.78		1.28
SINC	-0.10	0.18	-0.56	0.57		1.28
Noise pol (low)	-0.28	0.26	-1.07	0.28		1.28
Noise pol (med)	-0.39	0.53	-0.75	0.45		1.28
Noise pol (unsuit.)	0.12	0.50	0.24	0.81		1.28
Pylons	0.05	2.01	0.02	0.98		1.28
HSE zone (low)	4.66	5.48	0.85	0.39		1.28
HSE zone (med)	-4.60	7.31	-0.63	0.53		1.28
HSE zone (unsuit.)	27.16	11.91	2.28	0.02	*	1.29
Floodrisk (low-med)	0.66	0.16	4.16	0.00	***	1.28
Floodrisk (med)	0.16	0.77	0.20	0.84		1.28
Floodrisk (med-hi)	0.01	0.68	0.02	0.98		1.28
Shape_Area	0.00	0.00	-0.10	0.92		1.28
Town centre	-0.23	0.13	-1.74	0.08	.	1.28
Opp area	-0.71	0.14	-4.96	0.00	***	1.28
Housing zone	1.21	0.23	5.19	0.00	***	1.28
listed buildings	-1.30	0.65	-2.01	0.05	*	1.28
Protected view	-1.28	0.60	-2.12	0.03	*	1.28
Conserv area	0.07	0.21	0.33	0.74		1.28
LU, DLR stops	0.43	0.36	1.20	0.23		1.28
National rail stops	-0.14	0.43	-0.32	0.75		1.28
inner london boroughs	0.11	0.17	0.65	0.52		1.28
outer london boroughs	0.00	0.10	0.03	0.98		1.28
CAZ	-0.66	0.35	-1.91	0.06	.	1.28
Regen areas	-0.84	0.19	-4.42	0.00	***	1.28
low emission neighb	0.16	0.42	0.39	0.70		1.28
emplmnt sites	8.60	2.77	3.11	0.00	**	1.28
USUALRES	-0.06	0.09	-0.65	0.52		1.28
HHOLDRES	0.08	0.10	0.78	0.44		1.28
HHOLDS	-2.24	0.65	-3.43	0.00	***	1.28
AVHHOLDS	-0.48	0.20	-2.37	0.02	*	1.28
Rd casualties	1.22	0.98	1.24	0.21		1.28
dwell_agePRE1900	-3026.00	2985.00	-1.01	0.31		0.00
dwell_age_1900_1918	-10.32	5.12	-2.02	0.04	*	1.28
dwell_age_1919_1929	-15.03	6.96	-2.16	0.03	*	1.27
dwell_Age_1930_1939	-9.28	4.73	-1.96	0.05	*	1.28
dwell_age_1945_1954	3.54	7.15	0.50	0.62		1.28
dwell_Age_1955_1964	-15.22	8.05	-1.89	0.06	.	1.27
dwell_age_1965_1972	-11.37	8.91	-1.28	0.20		1.28
dwell_age_1973_1982	5.27	8.05	0.65	0.51		1.28
dwell_age_1983_1992	-15.10	9.87	-1.53	0.13		1.27
dwell_age_1993_1999	11.78	10.48	1.12	0.26		1.29
dwell_age_2000_2009	13.80	6.39	2.16	0.03	*	1.29
dwell_age_2010_2012	46.54	7.63	6.10	0.00	***	1.30
dwell_age_UNKNOWN	0.44	10.26	0.04	0.97		1.28
no car ownership	0.80	0.34	2.36	0.02	*	1.28
1 car owned	3.34	3.01	1.11	0.27		1.28
2 cars owned	0.00	3.49	0.00	1.00		1.28
3 cars owned	-16.58	9.19	-1.80	0.07	.	1.27
4 or more cars owned	61.50	15.94	3.86	0.00	***	1.31
PTAL 0-1	0.19	2.21	0.09	0.93		1.28
PTAL 2-3	1.53	2.09	0.73	0.47		1.28
PTAL 4-6	2.44	2.19	1.11	0.27		1.28
Mdn_hous_pr	0.00	0.00	-0.19	0.85		1.28
LU Crowding 0-2 count	0.30	7.96	0.04	0.97		1.28
LU Crowding 0-2 sum	99.04	55.57	1.78	0.08	.	1.32
LU Crowding 2-4 count	-1.25	4.91	-0.25	0.80		1.28
LU Crowding 2-4 sum	-12.15	33.19	-0.37	0.71		1.28
LU Crowding 4+ count	-3.27	3.43	-0.96	0.34		1.28
LU Crowding 4+ sum	28.64	19.16	1.50	0.14		1.29
NR Crowding 0-2 count	-15.58	7.76	-2.01	0.04	*	1.27
NR Crowding 0-2 sum	23.55	41.94	0.56	0.57		1.29
NR Crowding 2-4 count	0.44	5.08	0.09	0.93		1.28
NR Crowding 2-4 sum	-14.59	26.66	-0.55	0.58		1.27
NR Crowding 4+ count	-3.03	7.28	-0.42	0.68		1.28
NR Crowding 4+ sum	2.08	32.19	0.07	0.95		1.28
Rd network pinchpoints A	2.07	2.88	0.72	0.47		1.28
pop density	1.62	0.56	2.89	0.00	**	1.28

Model 2.1	ab_del_den ~ shlaa + +					
Adj R2	0.1911					
R2	0.2466					
F test	on 78 and 1059 DF					
p-value	value: < 2.2e-16					
Variable	coeff est	std error	t value	Pr(>|t|)	significance	NORM_COEF
(Intercept)	47.62	54.74	0.87	0.38		
Green belt	-0.02	0.05	-0.53	0.60		1.28
MOL	-0.02	0.08	-0.27	0.79		1.28
SIL	-0.60	0.20	-3.05	0.00	**	1.28
Safeguarded Wharves	1.97	1.32	1.50	0.13		1.29
LSIS (restr)	-10.34	4.48	-2.31	0.02	*	1.27
LSIS (lim)	0.50	1.64	0.31	0.76		1.28
LSIS (managed)	-4.26	3.14	-1.35	0.18		1.28
NDI (restr)	2.94	2.47	1.19	0.23		1.29
NDIL (lim)	7.36	1.65	4.46	0.00	***	1.29
NDI (managed)	1.21	1.76	0.69	0.49		1.28
SINC	-0.11	0.07	-1.68	0.09	.	1.28
Noise pol (low)	0.08	0.10	0.83	0.41		1.28
Noise pol (med)	-0.15	0.20	-0.78	0.43		1.28
Noise pol (unsuit.)	0.10	0.19	0.56	0.57		1.28
Pylons	1.83	0.75	2.44	0.01	*	1.29
HSE zone (low)	17.31	2.03	8.51	<2e-16	***	1.31
HSE zone (med)	-0.81	2.72	-0.30	0.77		1.28
HSE zone (unsuit.)	-9.82	4.42	-2.22	0.03	*	1.27
Floodrisk (low-med)	0.07	0.06	1.21	0.23		1.28
Floodrisk (med)	-0.33	0.28	-1.16	0.25		1.28
Floodrisk (med-hi)	-0.62	0.25	-2.44	0.01	*	1.28
Shape_Area	0.00	0.00	-2.04	0.04	*	1.28
Town centre	-0.04	0.05	-0.75	0.45		1.28
Opp area	0.05	0.05	0.98	0.33		1.28
Housing zone	-0.10	0.09	-1.16	0.25		1.28
listed buildings	-0.33	0.24	-1.39	0.17		1.28
Protected view	-0.36	0.22	-1.61	0.11		1.28
Conserv area	-0.05	0.08	-0.59	0.56		1.28
LU, DLR stops	-0.27	0.13	-2.04	0.04	*	1.28
National rail stops	-0.02	0.16	-0.13	0.89		1.28
inner london boroughs	-0.06	0.06	-1.00	0.32		1.28
outer london boroughs	0.03	0.04	0.91	0.36		1.28
CAZ	0.27	0.13	2.07	0.04	*	1.28
Regen areas	-0.11	0.07	-1.54	0.12		1.28
low emission neighb	0.11	0.16	0.68	0.50		1.28
emplmnt sites	0.23	1.03	0.22	0.83		1.28
USUALRES	-0.03	0.03	-0.87	0.39		1.28
HHOLDRES	0.01	0.04	0.17	0.86		1.28
HHOLDS	-0.25	0.24	-1.03	0.30		1.28
AVHHOLDS	0.09	0.08	1.16	0.25		1.28
Rd casualties	0.48	0.36	1.32	0.19		1.28
dwell_agePRE1900	-927.90	1109.00	-0.84	0.40		0.00
dwell_age_1900_1918	929.00	1109.00	0.84	0.40		2.57
dwell_age_1919_1929	2.56	1.90	1.35	0.18		1.29
dwell_Age_1930_1939	0.16	2.59	0.06	0.95		1.28
dwell_age_1945_1954	0.55	1.76	0.31	0.76		1.28
dwell_Age_1955_1964	0.41	2.66	0.15	0.88		1.28
dwell_age_1965_1972	-1.40	2.99	-0.47	0.64		1.28
dwell_age_1973_1982	-8.84	3.31	-2.67	0.01	**	1.27
dwell_age_1983_1992	2.82	2.99	0.94	0.35		1.29
dwell_age_1993_1999	-1.70	3.67	-0.46	0.64		1.28
dwell_age_2000_2009	-3.23	3.89	-0.83	0.41		1.28
dwell_age_2010_2012	3.07	2.37	1.30	0.20		1.29
dwell_age_UNKNOWN	3.55	2.84	1.25	0.21		1.29
no car ownership	1.22	3.81	0.32	0.75		1.28
1 car owned	0.02	0.13	0.14	0.89		1.28
2 cars owned	-0.58	1.12	-0.52	0.61		1.28
3 cars owned	-1.55	1.30	-1.19	0.23		1.28
4 or more cars owned	-0.40	3.41	-0.12	0.91		1.28
PTAL 0-1	2.38	5.92	0.40	0.69		1.29
PTAL 2-3	1.66	0.82	2.02	0.04	*	1.29
PTAL 4-6	1.72	0.78	2.22	0.03	*	1.29
Mdn_hous_pr	2.30	0.81	2.82	0.00	**	1.29
LU Crowding 0-2 count	0.00	0.00	-0.85	0.40		1.28
LU Crowding 0-2 sum	14.79	2.96	5.00	0.00	***	1.30
LU Crowding 2-4 count	-40.90	20.64	-1.98	0.05	*	1.23
LU Crowding 2-4 sum	0.64	1.82	0.35	0.73		1.28
LU Crowding 4+ count	-9.34	12.33	-0.76	0.45		1.27
LU Crowding 4+ sum	-2.97	1.27	-2.33	0.02	*	1.28
NR Crowding 0-2 count	11.87	7.12	1.67	0.10	.	1.30
NR Crowding 0-2 sum	-1.91	2.88	-0.66	0.51		1.28
NR Crowding 2-4 count	-10.66	15.58	-0.68	0.49		1.27
NR Crowding 2-4 sum	-1.33	1.89	-0.70	0.48		1.28
NR Crowding 4+ count	1.69	9.91	0.17	0.86		1.29
NR Crowding 4+ sum	3.91	2.70	1.45	0.15		1.29
Rd network pinchpoints AN	-18.89	11.96	-1.58	0.11		1.26
pop density	0.18	1.07	0.17	0.86		1.28

Model 3.1	deliv_Rate ~ shlaa + +					
Adj R2	0.1409					
R2	0.1999					
F test	on 78 and 1059 DF					
p-value	< 2.2e-16					
Variable	coeff est	std error	t value	Pr(>|t|)	significance	NORM_COEF
(Intercept)	7.76E+01	3.96E+01	1.958	0.050503	.	
PP_GB_are	-1.29E-02	3.27E-02	-0.396	0.692271		1.30
PP_MOL_a	-1.10E-02	5.46E-02	-0.201	0.840663		1.30
PP_SIL_ar_	-3.34E-01	1.42E-01	-2.357	0.018581	*	1.29
PP_SW_ar_	5.14E-01	9.52E-01	0.54	0.589487		1.30
PP_SILR_a	-2.43E+00	3.25E+00	-0.749	0.453792		1.26
PP_SILL_a	1.10E-01	1.19E+00	0.092	0.92634		1.30
PP_SILM_a	-1.45E+00	2.28E+00	-0.637	0.524277		1.27
PP_NDIR_a	-2.10E-01	1.79E+00	-0.117	0.906609		1.29
PP_NDIL_a	5.43E-01	1.19E+00	0.455	0.648926		1.30
PP_NDIM_	-9.35E-01	1.28E+00	-0.733	0.463786		1.28
PP_SINC_a	-8.12E-03	4.80E-02	-0.169	0.865586		1.30
EN_NPL_a	2.69E-01	7.02E-02	3.831	0.000135	***	1.30
EN_NPM_a	-1.99E-01	1.42E-01	-1.403	0.161051		1.29
EN_NPU_a	3.40E-01	1.35E-01	2.521	0.011858	*	1.30
EN_PY_ar_	2.05E+00	5.42E-01	3.779	0.000166	***	1.33
EN_HSEL_	5.61E+00	1.47E+00	3.81	0.000147	***	1.38
EN_HSEM_	3.15E+00	1.97E+00	1.602	0.109495		1.34
EN_HSEU_	-1.71E+01	3.20E+00	-5.342	1.12E-07	***	1.03
ENFRLM_a	5.66E-03	4.30E-02	0.132	0.895329		1.30
ENFRM_ar_	-1.77E-01	2.06E-01	-0.858	0.391013		1.29
ENFRMH_a	-4.00E-01	1.83E-01	-2.185	0.029082	*	1.29
Shape_Are	-1.61E-04	6.43E-05	-2.499	0.012597	*	1.30
J_TC_area	-3.23E-03	3.60E-02	-0.09	0.928524		1.30
J_OA_ar_s	6.97E-02	3.84E-02	1.818	0.069421	.	1.30
J_HZ_ar_su	-7.79E-02	6.25E-02	-1.247	0.212725		1.29
J_O_LB_A_	2.11E-02	1.75E-01	0.121	0.903957		1.30
J_O_VC_ar	-2.94E-01	1.63E-01	-1.809	0.070771	.	1.29
J_O_CA_ar	-2.78E-03	5.77E-02	-0.048	0.961636		1.30
J_TRLUDL	-9.36E-02	9.64E-02	-0.971	0.33174		1.29
J_TR_NR_	-1.73E-01	1.16E-01	-1.493	0.135617		1.29
J_ILB_Ar_s	-1.21E-01	4.55E-02	-2.661	0.007919	**	1.29
J_OLB_ar_	1.95E-03	2.70E-02	0.072	0.942487		1.30
J_CAZ_Ar_	2.21E-01	9.36E-02	2.364	0.018246	*	1.30
J_Regen_a	1.20E-01	5.08E-02	2.367	0.018118	*	1.30
J_LN_Ar_s	5.39E-01	1.13E-01	4.784	1.96E-06	***	1.30
J_Empl_s_	-1.41E+00	7.44E-01	-1.89	0.058972	.	1.27
J_USUALR	1.53E-03	2.39E-02	0.064	0.949052		1.30
J_HHOLDF	-3.01E-02	2.62E-02	-1.15	0.250209		1.29
J_HHOLDS	-4.61E-02	1.76E-01	-0.263	0.792836		1.29
J_AVHHOL	2.38E-01	5.48E-02	4.339	1.57E-05	***	1.30
J_Rd_casu	4.45E-01	2.63E-01	1.691	0.091043	.	1.30
J_PRE1900	-8.48E+01	8.03E+02	-0.106	0.915915		0.00
J_P.1900.	8.66E+01	8.03E+02	0.108	0.914074		2.62
J_1900_19	5.01E+00	1.38E+00	3.637	0.000289	***	1.37
J_1919_19	9.71E-01	1.87E+00	0.519	0.6041		1.31
J_1930_19	1.17E+00	1.27E+00	0.917	0.359489		1.31
J_1945_19	-1.04E+00	1.92E+00	-0.543	0.587191		1.28
J_1955_19	1.86E+00	2.17E+00	0.86	0.38974		1.32
J_1965_19	-3.91E+00	2.40E+00	-1.629	0.103517		1.24
J_1973_19	-1.04E+00	2.17E+00	-0.478	0.632785		1.28
J_1983_19	1.02E+00	2.65E+00	0.386	0.699829		1.31
J_1993_19	-3.66E+00	2.82E+00	-1.3	0.194048		1.24
J_2000_20	-3.60E-01	1.72E+00	-0.21	0.834091		1.29
J_2010_20	8.27E-01	2.05E+00	0.403	0.686919		1.31
J_UNKNOW	-9.95E-01	2.76E+00	-0.361	0.718285		1.28
J_TR_CO_	-2.68E-01	9.14E-02	-2.928	0.003489	**	1.29
J_car1....	-1.90E+00	8.09E-01	-2.351	0.018891	*	1.27
J_cars2...	-2.25E+00	9.38E-01	-2.397	0.016721	*	1.26
J_cars3...	1.29E+00	2.47E+00	0.52	0.602994		1.31
J_cars4...	-4.15E+00	4.29E+00	-0.967	0.333812		1.23
J_PTAL_0t	1.40E+00	5.95E-01	2.347	0.019101	*	1.32
J_PTAL_2t	1.36E+00	5.62E-01	2.418	0.015782	*	1.32
J_PTAL_4t	1.51E+00	5.90E-01	2.554	0.010775	*	1.32
J_Mdn_hou	-7.96E-06	9.82E-06	-0.81	0.417944		1.30
J_TR_LU02	1.81E+00	2.14E+00	0.845	0.398453		1.32
J_TR_LU0_	-2.27E+01	1.49E+01	-1.516	0.129881		0.95
J_TR_LU24	1.10E+00	1.32E+00	0.83	0.406771		1.31
J_TR_LU2_	-1.08E+01	8.93E+00	-1.207	0.227592		1.13
J_TR_LU4.	-4.25E-01	9.22E-01	-0.461	0.644579		1.29
J_TR_LU4_	-3.14E-01	5.15E+00	-0.061	0.951406		1.29
J_TR_NR0	4.25E+00	2.09E+00	2.039	0.041665	*	1.36
J_TR_NR0_	-1.95E+01	1.13E+01	-1.731	0.08372	.	1.00
J_TR_NR2	-3.09E-01	1.37E+00	-0.226	0.821439		1.29
J_TR_NR2_	-3.14E-02	7.17E+00	-0.004	0.996502		1.29
J_TR_NR4	1.93E+00	1.96E+00	0.986	0.324446		1.32
J_TR_NR4_	-9.42E+00	8.66E+00	-1.088	0.276866		1.15
J_Pinchpts	-9.65E-01	7.75E-01	-1.245	0.21357		1.28
J_pop_den	1.16E-02	1.51E-01	0.077	0.938629		1.30