University of Zurich[UZH]

Facility location modeling scenarios to optimize obstructive sleep apnoea health facilities in the East of England

GEO 620 Master's Thesis

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ABSTRACT

Obstructive sleep apnoea (OSA) is a major cost-intensive public health concern, with up to 85% of the OSA population going undiagnosed (Rejón-Parrilla et al., 2014). Poor accessibility of OSA facilities due to long travel distance is a barrier in diagnosing and treating patients in the UK. It is crucial to understand the current state of OSA testing for patients in the operating area of the Royal Papworth Hospital (RPH) to identify reasons for the high rate of undiagnosed cases. In this research procedure, patients' oximeter surveys are analysed to get clarity about the patient home and clinic distribution, the choice of clinic, and the current accessibility problem. Two allocation models (*P*-median and conditional *P*-median), using the three different demands (patients, population, and risk-weighted population), are applied to determine optimal location of oximeter facilities to reduce traveling distance. Results of the current situation show that patients have a tendency to visit the main RPH hospital, even if other oximeter facilities are located nearer to the patient's home. Furthermore, clinics have an uneven number of appointments, and there are regions in the study area where the RPH provides insufficient clinic accessibility. The location allocation analysis reveals that the accessibility of OSA facilities in the study area can be improved by relocating, adding, or reducing facilities in subareas of the RPH's operating region. The location allocation analysis illustrates the advantages and disadvantages of the different demand scenarios. The OSA risk model proposed in this study improves the location allocation model by shifting the optimal facilities to the higher-risk regions. Optimal OSA oximeter facility location reduces the accessibility barrier and potentially decreases the undiagnosed and untreated OSA population.

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LIST OF ABBREVIATIONS AND ACRONYMS

AHI	Apnoea/ hypopnoea index
BMI	Body Mass Index
CCG	Clinical commissioning group
CPAP	Continuous Positive Airway Pressure
ESS	Epworth Sleepiness Scale
GP	General practitioner
LAD	Local Authority District
LAP	Location Allocation Problem
NHS	National Health System
OA	Output Areas of Census 2011
ODI	Oxygen desaturation index
OS	Ordnances Survey - UK
OSA	Obstructive Sleep Apnoea
RPH	Royal Papworth Hospital
RQ	Research Question
RSSCCSS	Papworth Respiratory Support and Sleep Centre

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1 INTRODUCTION

1.1 Context and Motivation

This Master's research study took place within the framework of the Track and Know project of the European Union's Horizon 2020 Research and Innovation Programme. Task 6.3 of this project is thematically orientated towards healthcare and is called Pilot 2. Pilot 2 focuses on a specific disease called OSA.

OSA is characterised by paused breathing during sleep occurring in repetitive episodes (British Lung Foundation, 2015). OSA is usually associated with a reduction in blood oxygen saturation, which can be measured with an oximeter – an instrument used for diagnosing OSA (Romem et al., 2014). The most common treatment method for OSA involves patients wearing a Continuous Positive Airway Pressure (CPAP) machine during sleep, which counteracts the obstruction of the upper airway (Martinez & Faber, 2011). Without any treatment, patients have an increased risk of suffering from permanent brain damage due to insufficient oxygen (Martinez & Faber, 2011) and are predestined to suffer from daytime sleepiness, which negatively effects their quality of life (Batool-Anwar et al., 2016). Furthermore, untreated OSA vehicle drivers are more likely to be involved in traffic accidents because of the negative impact of OSA on their level of daily sleepiness (Garbarino et al., 2016) Treating OSA patients with CPAP therapy could reduce the volume of traffic accidents (George et al., 1997) and the associated health costs due to such accidents (Rejón-Parrilla et al., 2014).

In the UK, an estimated 1.5 million people are affected by OSA, of whom an estimated 85% are undiagnosed (Rejón-Parrilla et al., 2014). Reducing the number of undiagnosed OSA cases is an important public health issue, as this would, in turn, reduce daytime sleepiness and vehicular accidents. By treating all moderate and severe OSA patients, an estimated 1,047 car accidents could be prevented annually in the Cambridgeshire and Peterborough Clinical Commissioning Group (CCG) (British Lung Foundation, 2015). The estimated prevalence of OSA is not evenly distributed across the UK (Steier et al., 2014). A study using the five most common OSA risk factors – namely, obesity, gender, age, hypertension, and diabetes (Steier et al., 2014) – calculated, for the first time, the relative predicted prevalence of OSA per health area in the UK. This study ranked the vulnerability factors and described obesity as the most important indicator and sex as the least important. The risk factors were ranked based on the knowledge of sleeping experts from the British Lung Foundation's expert group. To calculate risk groups, the researchers multiplied the most important risk factor by a factor of five and the least important risk factor by a factor of one (British Lung Foundation, 2015).

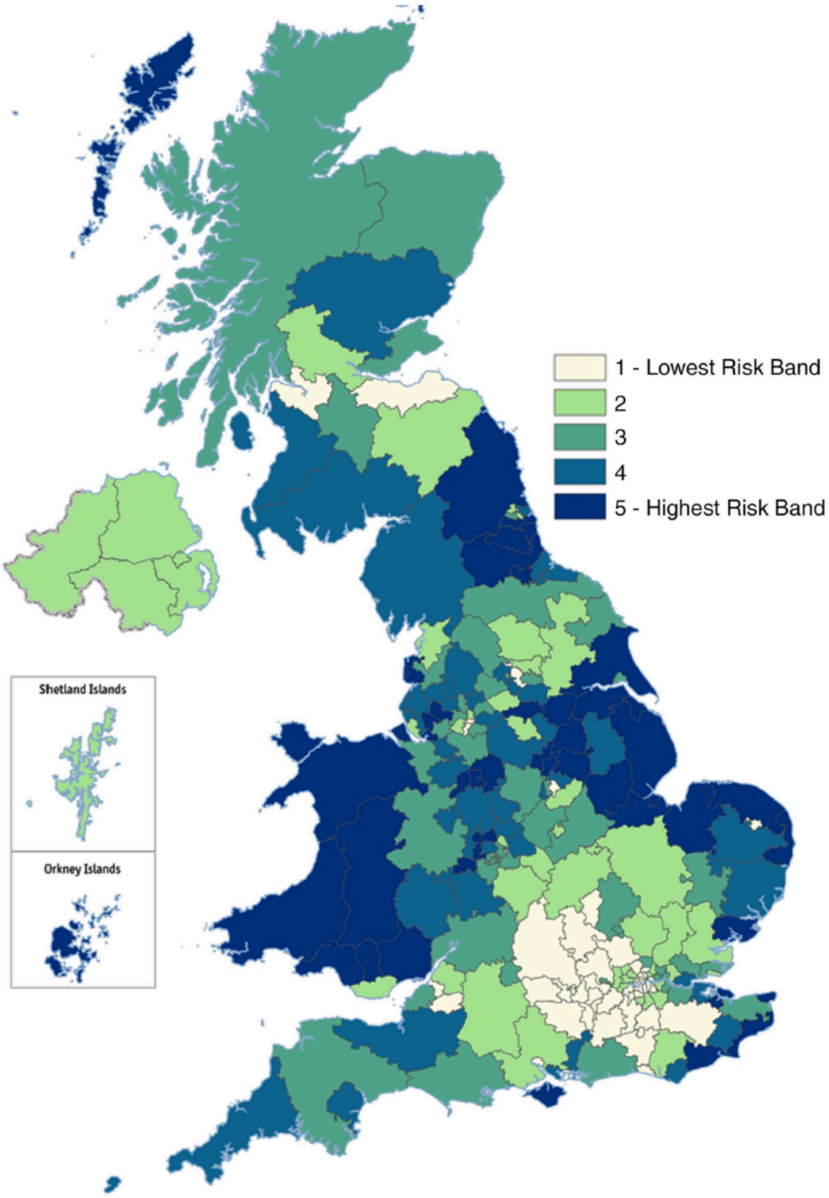

Figure 1.1: Relative predicted OSA risk in UK (Steier et al., 2014, p. 2)

Figure 1.1 shows healthcare administrative areas in the UK across the four nations – CCGs in England, Health and Social Care Trusts in Northern Ireland, National Health System (NHS) Health Boards in Scotland, and Local Health Boards in Wales. The map illustrates the risk of OSA using five quintiles, where the lowest risk band is shown in yellow and the highest risk band in blue. The absolute number and percentage of the OSA population cannot be extracted from the map, because the risk bands are in risk quintiles and the population density varies. The high-risk regions are rural areas, where the population tends to be older and is more likely to be affected by OSA. Patients in those rural areas are likely to have insufficient accessibility to sleep services due to the traveling distance to sleep clinics (Steier et al., 2014). The hotspots for a mismatch between the highest risk group and a lack of OSA healthcare facilities are regions in the East of England and parts of the East Midlands, Wales, and several islands. Limited access to sleep clinics negatively affects the number of diagnoses. Previous studies have shown that the consultation and attendance rates of patients decrease with additional distance to a general practitioner (GP) (Parkin, 1979) or outpatient clinics (Cawley & Stevens, 1987). There are no accessibility studies for OSA, but based on previous disease-related literature from the UK, it is likely that OSA shows similar accessibility patterns. Consequently, in these identified rural areas, the number of undiagnosed OSA patients is likely to remain high. Steier et al. (2014) found that there is a considerable mismatch between OSA risk and sleep clinics but could not provide information about insufficient accessibility in specific areas. In their study, they estimated the OSA risk band per health area in the UK and visually compared these regions to sleep clinic locations. The study is sufficient for an overview and shows the problematic areas, but it does not allow categorisation of the different regions in terms of the accessibility problem.

1.2 Approach

The East of England region should be analysed in detail to find out more about the problem of accessibility in terms of distance to health services. First of all, the current situation in terms of OSA accessibility should be analysed. There is a high proportion of undiagnosed cases in the study area, and healthcare accessibility is a factor leading to a low rate of diagnosis. An analysis of the current degree of patient access to care was undertaken in this study, using historical oximeter data from the Royal Papworth Hospital (RPH) in the East of England. The analysis established the importance of access to treatment for the disease OSA in the defined study area.

An analysis of the current situation highlights the areas lacking in accessibility, but does not present a solution to solve the problem. Therefore, solutions to the problem of accessibility were determined and are discussed in the second part. Furthermore, the optimal location for OSA healthcare facilities should be identified according to the demand in order to improve the accessibility in the study area. Subsequently, the OSA facilities should be located according to different demand scenarios to figure out suitable locations for these facilities. The facilities were first located using historical home location information of patients from the oximeter data survey of the RPH. The facilities were also located according to the population in the study area and the associated weighted risk for that population. Thus, risk grouping was applied on a more fine-grained geographical level than in the study by Steier et al. (2014).

1.3 Research Aims

The accessibility of the East of England population to OSA health facilities was analysed based on the location of the RPH, its partner GPs, and its outreach clinics. The East of England region is one of the hotspots for OSA, and includes several CCGs with the highest OSA risk band (Steier et al. 2014). Accessibility in terms of travel distance was analysed using data for RPH OSA patients treated between 2013 and 2018. Furthermore, the study analysed the risk hotspots in East of England and the accessibility of OSA health facilities in these hotspots. This is the first study that analyses health facility accessibility for the disease of OSA. Therefore, it constitutes a milestone in improving accessibility to OSA health facilities with the objective of reducing the undiagnosed population. Based on the results of the accessibility analysis, new optimally located OSA health facilities are proposed.

The research started by documenting and exploring the current situation with regards to the provision and use of OSA facilities and services. These initial analyses (RQ.1) then formed the basis for the subsequent research (RQ.2, RQ.3), which focused on determining the optimal number and locations of facilities for given scenarios as well as the allocation of population to the proposed facilities.

RQ.1: What is the current situation of OSA health service accessibility in the East of England?

- Hypothesis 1.1: A large number of people do not visit the nearest pick-up facility.
- Hypothesis 1.2: People living far from a pick-up facility are more likely to be no-shows.
- Hypothesis 1.3: The share of oximeter-tested people is higher for areas close to a facility than those far from a facility.

RQ.2: What is the optimal number of and which are the optimal locations for pick-up facilities based on different demands (Patient Demand Scenario, Census Demand Scenario, and Risk Demand Scenario)?

- Hypothesis 2.1: The number of facilities is currently not optimal.
- Hypothesis 2.2: There is a mismatch between the current pick-up locations and the optimal pick-up locations, suggesting the need for a redistribution of pick-up locations.

RQ.3: What proportion of the population should be referred to each of the optimal pick-up facilities?

1.4 Thesis Structure

Chapter 2 gives an overview of the disease OSA and its epidemiology. Following this overview, the location allocation is introduced, and the *P*-median problem is defined. In Chapter 3, the data and study area are introduced and explained. In Chapter 4, the research methods are discussed with a focus on the current situation analysis, risk estimation, and location allocation analysis in order to give detailed information about the study's analysis. The Results section (Chapter 5) presents the current situation and gives an overview of patients' tendencies regarding choosing a facility and the spatial distribution of current OSA facilities and patients. Additionally, this chapter presents the estimated risk and the optimal facility location calculated by the location allocation analysis based on three different demand scenarios: Patient Demand Scenario, Census Demand Scenario, and Risk Demand Scenario. Chapter 6 places the results into the context of existing literature and discusses the suggested improvement in OSA health facility planning. In Chapter 7, the main findings are synthesised to conclude the discussion.

2 THEORETICAL FRAMEWORK AND BACKGROUND

2.1 Obstructive Sleep Apnoea (OSA)

OSA is a temporary breathlessness illness appearing during sleep. During sleep temporary cessations of breathing appear, caused by narrowing or closure of the upper airway (British Lung Foundation, 2015). The temporary cessation of breathing is a short event and appears several times per night. During the period of breathlessness, the oxygen level falls and the effort made to breathe increases. The brain causes the body to wake up and the breathing starts again, often with a gasp or body movement, and the person is often not sure about the reason for awakening (British Lung Foundation, 2015). This OSA cycle is presented in Figure 2.1.

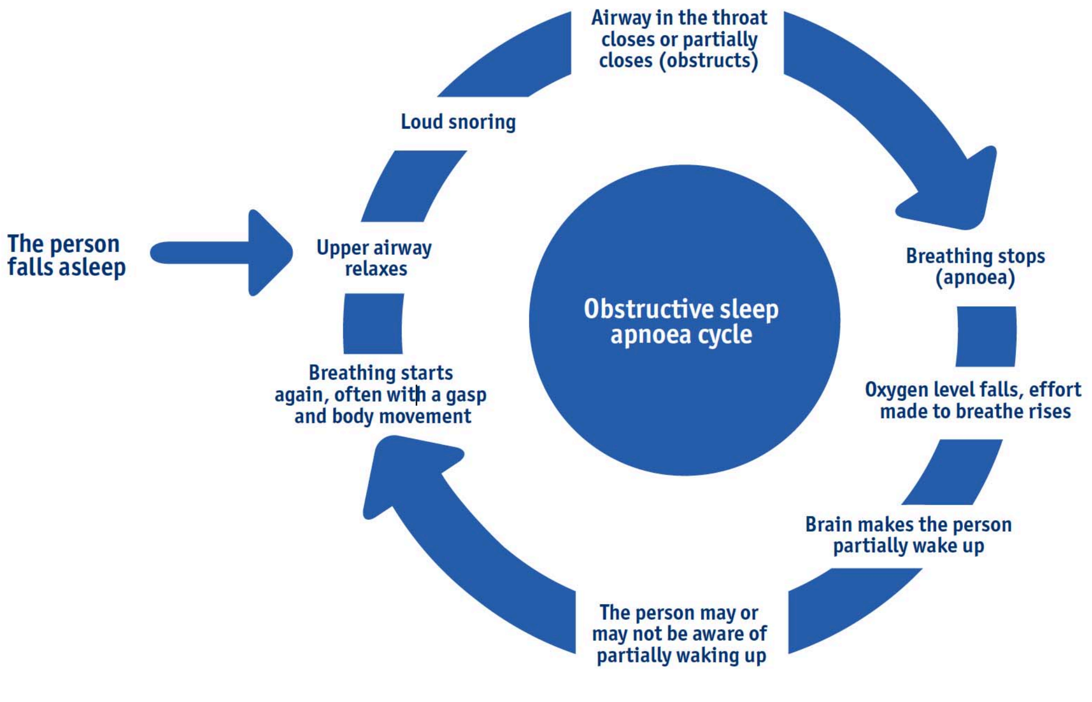

Figure 2.1: Cycle of OSA (British Lung Foundation, 2015, p. 6)

OSA symptoms can be separated into symptoms that occur during the night and those that occur during the day. During the night, typical symptoms are loud snoring, breathing pauses (witnessed by partner/friend), sudden body movements, restless sleep, frequent awakening and feelings of choking or gasping for breath (British Lung Foundation, 2015). During the day typical symptoms are sleepiness, having no energy and sleepiness-related symptoms (Smith & Quinnell, 2011). A common indicator for the severity of OSA is the apnoea/hypopnoea index (AHI). The AHI is calculated by counting all the apnoea and hypopnoea periods lasting 10 seconds or longer per hour of sleep (Martinez & Faber, 2011). The severity of OSA is classified into AHI of 5, 15 and 30 describing mild, moderate and severe OSA, respectively (Martinez & Faber, 2011).

2.1.1 Diagnosis

OSA often be detected based on examination and health history alone (Martinez & Faber, 2011). There are questionnaires such as the OSA 50 and the STOP Bang to scale and diagnose OSA (British Lung Foundation, 2015). OSA is also detectable using an objective measurement instrument (British Lung Foundation, 2015). These objective measurements monitor the patient with an oximeter in an over-night study. An oximeter measures the bloods oxygen saturation, called oximetry, which is a simple, cheap and reasonable measurement method (British Lung Foundation, 2015). Amongst oximeters we distinguish between single-channel and multi-channel devices. While single channel oximeters measure pulse oximetry, multi-channel oximeters provide additional measurements such as chest movement and nasal airflow (Romem et al., 2014). Both types of oximeters can be used for sleep studies at home, rather than requiring an overnight stay at a sleep centre (British Lung Foundation, 2015). The results of such an objective measurement establish the extent and severity of OSA (Martinez & Faber, 2011). Use of an oxygen desaturation index (ODI) allows for oximetry measurement comparisons. The ODI calculates the average number of episodes of desaturation per hour. Desaturation is defined as the haemoglobin saturation level (SaO_2) to be less than 4% of the baseline level (Chiner et al., 1999). Sleep-disordered breathing is diagnosed when ODI > 5 (Mooe et al., 2001).

2.1.2 Risk Group of OSA and Treatment

OSA can affect anyone, but there are health-related characteristics which predispose people to be affected by OSA. It is possible to screen people based on these risk factors. The most common risk factors for OSA are obesity, age, male sex, excess alcohol intake, smoking, pregnancy, low physical activity, unemployment, neck circumference

> 40 cm, being a surgical patient, tonsillar and adenoidal hypertrophy, craniofacial abnormalities (e.g. pierre robin, down’s syndrome), neuromuscular disease (Martinez & Faber, 2011), snoring, female sex past menopause and type 2 diabetes (British Lung Foundation, 2015). People having one or more of these characteristics are part of the potential OSA risk group (British Lung Foundation, 2015). In further literature there are different outcomes based on the significance of these risk factors. The most important health risk factors are therefore explained in detail:

Obesity: Obesity is the major risk characteristic (Martinez & Faber, 2011). The prevalence of OSA is increases with increasing body mass index (Young et al., 2004). Additionally, for obese patients weight loss is likely to have a positive effect on AHI (Martinez & Faber, 2011). Controversially, Young et al. (2004) are not conclusive about the importance of weight loss as a means of reducing OSA.

Age: Bixler, et al. (1998) showed that the prevalence of OSA tends to increase with age, while the clinical significance (i.e., treatment effectiveness) decreases. In contrast, a study for middle aged adults suggest no continuous increasing prevalence with increasing age for AHI > 5, therefore it is not a strong indicator for middle aged persons (Young et al., 1993). Even the prevalence of OSA is not increasing in every age group, there is evidence of the increased prevalence with increasing age (Young et al., 2004).

Male sex: Males are twice as often affected as females (Martinez & Faber, 2011). Males are therefore predisposed to suffer from OSA.

Excess alcohol intake: Young et al. (2004) showed that the alcohol consumption has an acute effect on the frequency of OSA. The study does not allow any indication on the long-term effect of alcohol consumption on OSA and literature is therefore just certain about the short-term effect.

Smoking: Wetter et al. (1994) showed that current smokers have a significantly higher risk for moderate sleep-disordered breathing than people who have never smoked (odds ratio, 4.44). The study has widely spread confidence intervals (0.95) between 1.44 and 13.01, so the impact of smoking on OSA is vague.

Pregnancy: During pregnancy, 50% of women suffer from intermittent sleep-disordered breathing (Martinez & Faber, 2011).

Tonsillar and adenoidal hypertrophy, craniofacial abnormalities: It is associated with pharyngeal obstruction and therefore with OSA (Martinez & Faber, 2011).

Neuromuscular disease: People suffering from neuromuscular diseases are more likely to suffer from sleep-disordered breathing due to an exaggerated reduction in lung volumes during supine sleep (Aboussouan, 2015).

Woman past menopause: Studies show that the appearance of OSA for postmenopausal women is higher than premenopausal women (Young et al., 2002). The studies are often associated with hormone replacement therapies (Young et al., 2002).

Type 2 diabetes: Type 2 diabetes is strongly correlated with OSA (British Lung Foundation, 2015). Type 2 diabetes is associated with obesity that causes higher insulin resistance and should therefore not be named as a stand-alone risk factor (Al-Goblan et al., 2014).

Unfortunately, research is still not able to show any consistent causality between a potential risk factors and OSA. Weight is the only risk factor having strong evidence for causality to OSA (Young et al., 2004). Additionally, the interaction between these characteristics is still not well-understood.

The different risk factors suggest different treatments methods for diagnosed patients. Affected patients can change their cigarette and alcohol consumption to treat the disease OSA. Obese patients might treat OSA with a weight loss therapy (Martinez & Faber, 2011). Other risk factors cannot be treated because they are innate characteristics of human beings. For these patients, an overall and widely beneficial treatment method is the CPAP therapy. In CPAP therapy the patient wears a breathing mask during sleep, which maintains a pressure in the mask higher than the surrounding air pressure. This high pressure reduces the effort of breathing, because the higher air pressure releases the obstruction. This treatment has a positive effect on AHI and ODI measurements and therefore on the quality of life (Batool-Anwar et al., 2016). It can improve life expectancy for some patients subgroups (Martínez-García et al., 2012).

2.1.3 OSA as Community Risk

OSA brings several medical and social consequences with it and should therefore not be underestimated. OSA is a risk factor for several diseases: “OSA is an independent risk factor for serious neuro-cognitive, endocrine, and cardiovascular morbidity and mortality in all age groups. OSA is furthermore associated with the risk of low socioeconomic status and unemployment” (Martinez & Faber, 2011). Cardiovascular morbidity and mortality is incontrovertibly linked to hypertension (Young et al., 2002). There is consequently strong evidence that OSA is a risk factor for hypertension.

Drivers' sleepiness is associated with vehicular accidents caused by human-error. A systematic review shows that between 1% to 41% of accidental injuries are attributable to sleepiness of the driver (Dinges, 1995). Vehicle drivers with OSA are more likely to be involved in traffic accidents because they are usually suffering from daytime sleepiness (Young et al., 1997a). A review of 10 representative studies shows that OSA has a strong adverse effect on accidents especially for undiagnosed drivers (Garbarino et al., 2016). Particularly, commercial motor vehicle drivers suffering from OSA have a fivefold higher risk of being involved in serious crashes than healthy drivers (Burks et al., 2016). The risk of OSA for vehicle drivers can be reduced with CPAP therapy as a driving simulation testing study shows (George et al., 1997). In the UK, people having moderate to severe Epworth Sleepiness Scale (ESS) (ESS of > 17/24), which is related to OSA, are classified as high-risk drivers (British Thoracic Society, 2018). The Driver and Vehicle Licensing Agency promotes OSA diagnosis and treatment to have safer roads and can hold a patient's driving license based on the results of the GP and/or sleep specialist (British Thoracic Society, 2018). Garbarino et al. (2015) show that around 7% of road traffic injuries for population of male drivers are related to OSA. The British Lung Foundation's (2015) OSA calculator shows a potential prevention of 1,047 road accidents annually by treating all moderate and severe OSA patients in the Cambridgeshire and Peterborough CCG.

For the patients themselves an undiagnosed OSA is a financial risk. Kapur et al., (1999) shows that patients have reduced annual health care costs after the OSA diagnose compared to the prior annual health costs. However, the study does not conclude about the effect of treatment on the patient's health costs.

In summary, OSA is a risk for serious public and community health concerns, so it is important to diagnose and treat OSA. With reducing the undiagnosed rate and therefore untreated ratio of OSA-population, the health costs, due to traffic accidents (Rejón-Parrilla et al., 2014), and dangerous morbidities and mortality can be reduced (Young et al., 2002). Furthermore, the diagnosed OSA population likely saves health costs (Kapur et al., 1999).

2.1.4 Prevalence of OSA

In 24 representative studies, the overall population's prevalence for AHI > 5 ranges between 9% to 38% while the prevalence for AHI > 15 ranges from 6% to 17% (Senaratna et al., 2017). A comprehensive study in Wisconsin USA calculated the prevalence of sleep-disordered breathing defined by a AHI > 5 as 24% for men and 9% for women among middle aged adults (Young et al., 1993). For an AHI > 10 the results showed a prevalence of 15 percent for men and 5 percent for women. The male-female ratio is therefore about 3:1 and sex is consequently a risk factor for AHI > 5. Young et al. (1993) results additionally show that obesity is a significant indicator for AHI > 5. Furthermore, the study suggests no continuous increasing prevalence with increasing age. Therefore, age is not a strong indicator for middle aged adults with AHI > 5 (Young et al., 1993). The OSA prevalence differs from subgroup to subgroup, and increases between 14% to 55% depending on the subgroup (Peppard et al., 2013).

In the UK, Rejón-Parrilla et al. (2014) have estimated the amount of the UK population suffering from OSA at around 1.5 million (82.4% of total population), which is 2.5% of the adult population and 2.3% of the total UK population. The NHS North of England Specialised Commissioning Group (2012) suggests that in the UK 85% of people with OSA are undiagnosed and consequently remain untreated. Only 330,000 of the 1.5 million total population of adults with OSA are treated (Rejón-Parrilla et al., 2014). This suggestion is similar to a representative OSA prevalence study in the USA where "93% of women and 82% of men with moderate to severe OSA have not been clinically diagnosed" (Young et al., 1997b).

The prevalence of OSA is not evenly distributed all over the entire UK, some sub-regions (mainly rural regions) are likely to have a higher prevalence. OSA risk factors are unevenly distributed so that the OSA risk and the prevalence shows a spatial variety (Steier et al., 2014).

2.2 Accessibility

Access is a complex concept which includes the various different dimensions of availability, accessibility, accommodation, affordability, and acceptability (Penchansky & Thomas, 1981). These different dimensions all need to be considered in health care planning. Focusing on the spatial distance, accessibility relates to the ability to get from one place to another (Daskin & Dean, 2005). With regards to health, accessibility is the ability of a patient to reach the health care facility (Daskin & Dean, 2005). Haynes and

Bentham (1979) found that spatial accessibility, defined as distance, negatively affects the usage and attendance of a hospital in East Anglia. Parkin (1979) found that a longer distance to the clinic has a negative impact on the attendance rate of patients for certain subgroups (women, the elderly, and Social Classes III, IV, and V). Thus, spatial accessibility is not universally difficult, but some population groups, such as elderly people, may be affected more than others (Watt et al., 1993). Lovett et al. (2002) investigated the accessibility of GPs for patients in East Anglia. They determined the accessibility for patients in terms of car travel times and public transport as defined by the number of daytime services every weekday. They found that 90% of the population can reach the closest primary medical care within 10 minutes. On the other hand, 13% of the patients have no daytime bus service to a surgery on a weekday, leading to the conclusion that the accessibility of GPs for the majority of the population is good. However, the road and public transport networks may have changed since Lovett et al.'s (2002) study was conducted; thus, the results may not be up to date anymore. Spatial accessibility seems to be an important factor for patients in terms of clinic choice, and around 61% of patients are going to the closest clinic (Smith et al., 2017).

This study focuses on the spatial accessibility of OSA health care facilities. There is clear evidence that spatial accessibility is an important barrier to health care access (Syed et al., 2013). Spatial accessibility is a significant factor in patient satisfaction (Cabrera-Barona et al., 2017) and can always be improved. It is important to consider the context of accessibility. Patients are willing to travel greater distances to receive specialised or higher-quality health care than to receive general health services (McLafferty, 2003). In the USA, a study determined that patients are willing to travel 33 km driving distance and 28.4 minutes of driving time to a routine health care facility (Yen, 2013). That distance threshold value might vary when looking at different areas and patients. Distance as a barrier to health care cannot be uniformly defined; it depends on the health status and resources of patients, complexity of services provided, and urgency of service (Buzza et al., 2011). It is, thus, expected that personal opinions regarding a satisfactory travel distance would involve a wide distance range because of heterogeneous population characteristics. For this study, using spatial accessibility allows one to compare the current accessibility with an optimal accessibility solution to a location allocation problem. Hence, the solutions to the location allocation problem can be put in the context of the current distance accessibility situation.

2.3 Location Allocation Problems (LAPs)

The Location Allocation Problems (LAP) tries to locate facilities in an optimal location based on the demand's location. Generally, each location of demand should be allocated to a facility location, such that the demand is covered, or the cost (e.g., average travel distance) is minimized. The problem was firstly introduced by Cooper in 1963 and expanded by several models. The original LAP formulation minimizes the transport distance between the demand and the facilities and minimizes the number of facilities (Cooper, 1963). The model uses three inputs (Cooper, 1963): First, the location of the potential facilities and the demand. Secondly, the demand at each potential facility location. Thirdly, the transport cost at the region of interest.

Cooper's (1963) location allocation approach simultaneously determines the following three results: Number of facilities, location of each facility, and capacity of each facility. Such a model is based on the following assumptions: It has no restrictions on the permissible source capacities and the transportation costs are independent to the total source output (Cooper, 1963).

In a health context, location allocation models are applied to locate health services facilities. The covering model, maximal covering model, and the *P*-median model form the heart of location planning in health care (Daskin & Dean, 2005).

The covering model locates as many facilities as needed, so that every demand location has access to one facility. A single facility has a defined coverage area, within which all demand belongs to this single facility. It is an optimization problem, which tries to find a minimal number of facilities to cover the location of demand. The covering model has two major problems. Firstly, the number of required facilities for covering all the demands is likely to be too large and consequently realistic. Second, the covering model does not distinguish between high and low demand areas (Daskin & Dean, 2005).

The maximal covering model was introduced by Church & ReVelle (1974). The aim of the maximal covering model is to locate the facilities at a location where the facility's covered demand is maximal. All the facilities have a defined coverage area, within which all the demand in that coverage area are referred to the facility. Based on the optimization the percentage of covered demand can be determined. For instance, five facilities need to be positioned to reach a coverage of 80% of the demand, but nine facilities are required for a 100% coverage (Church & ReVelle, 1974; Daskin & Dean, 2005). To cover the whole demand, the problem of having too many facilities arises (Daskin & Dean, 2005).

The *P*-median problem addresses the problem of locating too many facilities for covering the whole demand (Daskin & Dean, 2005). Consequently, it is a proper model for health facilities location analysis. Compared to the covering model, the *P*-median's facilities have no restrictions on a covering distance. The aim of the *P*-median is to minimize the demand weighted total distance from the demand's location to the facility's location (Daskin & Dean, 2005).

Location allocation models are frequently used in health care planning. Several studies have used LAPs to allocate health facilities in development countries as Rahman & Smith (2000) reviews in their article. Jia et al. (2014) used a *P*-median problem to allocate health care centres additionally using visual analytics. Meskarian et al. (2017) used the maximal covering location problem to determine the optimal locations for sexual health services in Hampshire, UK. They applied the problem to different demand scenarios including demand forecast and compared the result of different optimization algorithms. LAPs are further successfully applied in ambulance deployment planning (Eaton et a., 1986; Knight et al., 2012). A capacitated *P*-median is used to locate blood facilities and blood services in Norfolk, Virginia in (Jacobs et al., 1996). Mohan (1983) applied the *P*-median problem for health service planning in North East of England and discusses the problems and limitations of such LAPs in the context of health planning. Fo & da Silva Mota (2012) compared the results of different LAPs, such as the maximal covering problem and the *P*-median problem in a real case scenario in Brazil and found out that the *P*-median problem is the model providing the best solutions.

Concluding, the *P*-median solution is an appropriate location allocation model providing good solutions (Fo & da Silva Mota, 2012) and having compared to other location allocation model strength in determine an proper number of facilities (Daskin & Dean, 2005). Furthermore, the *P*-median does not need any arbitrary input variable. Compared to covering model where the covering area has to be arbitrary defined, the *P*-median does not need any arbitrary input variable.

2.3.1 Ordinary *P*-median

Hakimi (1964) proposed the *P*-median problem to solve this LAP using a weighted graph. In a weighted graph he tries to find the one absolute median, called 1-median problem, describing the node of the minimal distance to the other nodes. The optimal facility is therefore always at a node of the network (Hakimi, 1964). The weighted graph can be represented by a street network where the street length or the travelling time can represent the graph's weight. The graph problem has one definite minimal solution where the summed weight of each node to the centre is minimal. This minimal solution might occur at several nodes. Hence, the centre has no definite node (Hakimi, 1964). In the *P*-median problem a defined number of medians (Hakimi, 1965) and not as in Hakimi (1964) a single median. Consequently, the optimal location of a defined number of *P* has to be found. The optimal location is at the position where the sum of the demand weighted distances to the nearest facility are minimal. This demand weighted distance is the distance of the demand node to the facility multiplied by the demand of the demand node and is defined in the equation 2.1. The result of the *P*-median returns the *P* nodes where the sum of demand weighted distance is optimal.

Daskin & Maass (2015) have formulated the problem according to Hakimi (1964) for *P* number of facilities to locate:

h_i = demand at node i

d_{ij} = distance from demand node i to candidate location j

P = number of facilities to locate.

$$y_j = \begin{cases} 1 \ if\ a\ facility\ is\ located\ a\ candidate\ site\ j \\ 0\ otherwise \end{cases}$$

$$x_{ij} = \begin{cases} 1\ if\ demand\ at\ node\ i\ is\ assigned\ to\ the\ candiate\ at\ site\ j \\ 0\ otherwise \end{cases}$$

The demand weighted distance is the equation to be minimized, which is formulated as:

$$\text{minimize } \sum_{i \in I} \sum_{j \in J} h_i d_{ij} x_{ij} \quad (2.1)$$

with formula 2.1 subject to the following constraints:

$$\sum_{j \in J} x_{ij} = 1 \ \forall\ i \in I \quad (2.2)$$

$$\sum_{j \in J} y_j = P \quad (2.3)$$

$$x_{ij} - y_j \ \leq 0\ j \ \forall\ J\ ; i\ \forall\ I \quad (2.4)$$

$$y_j \in \{0,1\}\ j\ \forall\ J \quad (2.5)$$

$$x_{ij} \in \{0,1\}\ j\ \forall\ J\ ; i\ \forall\ I \quad (2.6)$$

Formula 2.1 is the objective function which minimizes the demand weighted total cost. Constraints 2.2 state that the demand i must be assigned to one facility j. Constraints 2.3 defines the exactly P facilities have to be located. Constraint 2.4 mean that the demand node x_i have to be assigned to an open facility. Constraint 2.5 defines that the candidate facility must be binary, where 1 describes locating a candidate facility and 0 not to choose a candidate facility. Constraint 2.6 stipulates that the assigned demand has to be positive, where 1 states that the demand is assigned to the facility and 0 indicates that it is not assigned (Daskin & Dean, 2005) .

Hamiki (1965) solved the problem using a distance matrix in which the rows are the demand points, the columns are the candidate facilities and each cell is the distance between the demand and the facility. The distance matrix is row-wise weighted by the demand so that every cell of the matrix represents the demand weighted distance. He used direct enumeration to locate three facilities in a network of 10 nodes, where each node is a candidate and a demand location. Finding the optimal location by direct enumeration is computationally intensive. The binomial coefficient in this example is $\binom{10}{3}$ which equals 120 possibilities to locate the 3 medians in a network of 10 nodes. For every possibility each demand point is connected to the closest of the 3 demand points, which is the cell with the minimal distance between the demand node and the facility node. The weighted cells that have the minimal distance between the demand node to and the facility node are summed up to obtain the total weighted distance. The optimal solution consists of three nodes where the total weighted distance is minimal.

In large networks, the binomial coefficient is immense and therefore solving the optimization problem with direct enumeration is time intensive and often unfeasible. Heuristic algorithms are utilized in order to reduce the calculation time. In a heuristic optimization, the solution is solved approximately and is therefore not identical to the direct enumeration. One of the best known algorithms for the P-median model is the exchange algorithm of Teitz and Bart (1968) which optimizes the demand weighted distance in a matrix (Daskin & Dean, 2005). The optimization consists of the following steps (Teitz & Bart, 1968):

i. Choose initial P candidate facilities from the list S (List of candidate facilities) and store in the array V_1.
ii. Find for every demand node the closest facility in V_1 and calculate the demand weighted distance.

iii. Choose one facility f_1 that is not on the list V_1.

iv. Substitute/swap the f_1 with every candidate of the array S and calculate the demand weighted distance.

v. Find the facility of V_1, where the demand weighted distance is minimal when substituted. Replace the facility of V_1 that has the minimal distance with the facility f_1 and rename the node list V_2.

vi. Choose one facility f_2 which is not in the list V_1, V_2 or not previously tried. Repeat the steps (iv.) to (vi.) until there is no facility to choose, which is not in a previous list (V_1 ... V_2)

vii. When there is no facility to choose, which is not in a previous list (V_1 … V_i), define V_i as the new V_1 and repeat the steps (ii) through (vii). Such complete repetition is called a cycle.

viii. When one complete cycle of (ii) through (vii) does not reduce the demand weighted distance, the procedure terminates. The final *Vi* is the estimated *P*-median of the network.

2.3.2 Conditional *P*-median

The *P*-median problem always assumes that in order to satisfy the demand the candidate facilities are the first facilities to be located in a defined area. The optimal solution is where the demand weighted distance is minimal. Usually the study area has some existing open facilities. In this case the conditional *P*-median problem is introduced. It tries to locate *P* optimal new facilities in the network when *Q* existing facilities are already operating (Drezner, 1995). It assumes that the customers go to the closest facility whether new or existing. This model is therefore useful for expansion problems, where an institution tries to become accessible to more customers from other areas. The conditional *P*-median problem can be formulated as following: “We need to locate *P* new facilities Z_i for $I = 1...P$ (denoted by the vector *Z*) so as to minimize the total weighted distance between the demand points and their closest facility (whether new or existing)” (Drezner, 1995). The conditional (*P,Q*)-median problem cannot be solved using a standard linear optimization algorithm like the exchange algorithm of Teitz and Bart. Therefore, Drezner (1995) adjusts the objective function of the *P*-median problem as follows: “We adjust the weights by multiplying each weight by its distance savings (the difference between distance matrix of existing, and the actual distance), and maximize the total adjusted weight of the covered demand points.” Furthermore, he suggests a heuristic algorithm to solve the problem. For every iteration the algorithm only considers the points that are closer to any of the *P* candidate facility than to any of the *Q* existing facilities. The weighted distance savings are optimized to find the optimal solution for the *P* candidate facilities (Drezner, 1995).

Regarding OSA health care, the accessibility to health care is problem as Steier et al. (2014) showed in his study. In the rural areas of the East of England where the risk is highest, the current accessibility situation needs to be improved. Applying the *P*-median problem allows to compare the currently operating facilities with and optimal facility locations. The conditional *P*-median determine cost efficient solutions, where some additional facility suggestions improve the accessibility. The RPH wants to analyse and improve the oximeter pick-up facilities in their study area. All the hospital, GPs, clinics and pharmacies are able to operate as an oximeter pick-up facility and without any investing risk. The *P*-median and the conditional *P*-median can determine an optimal solution for any additional partner health facility where oximeters can be picked-up.

3 STUDY AREA AND DATA

3.1 Study Area

The study area represents the catchment area of the RPH and its partner facilities. It therefore does not have the same extent as the region of East of England, it is rather defined according to the patients' homes postcodes. The study area includes 98% of the patients undergoing oximeter testing in the RSSCSS or its partner facilities between 2013 and 2018. Every patient is weighted equally, no matter how often a patient did an oximeter test. The patients' homes are defined with the home location where they lived at during the first oximeter test. Patients might have moved to another postcode during the oximeter data survey, but the first pick up is the relevant one for choosing the clinic to visit. The extent of the study area is defined using a bounding box with two restrictions. First, the study area has to cover the entire East of Anglia peninsula. Second, the study area has to exclude London, therefore the maximal southern extent is defined at the A406 circular road which is the northern ring road and lies on the latitude 51.6°N. In the determination algorithm, the origin point, which is in the upper right position of the bounding box is defined with the coordinates 53°N latitude and 1.77°W longitude. This origin point underlies the first restriction and is consequently placed in the ocean of the northeast of the East of Anglia peninsula where the latitude coordinate is at the northernmost point of the peninsulas coast and the longitude coordinates is at the easternmost point of the peninsula. In an iterative process, the lower left point of the bounding box is determined by adding an 0.01° additional extent in southern and western direction until the bounding box includes 98% of the patient's home. The resulting bounding box has the northern extent of latitude 53°N, the eastern extent of longitude 1.77°W, the southern extent of latitude 51.6°N and the western extent of longitude 0.76°E. The study area has an area of 26,881 km^2 and is illustrated in Figure 3.1. It consists of 34 CCGs whereof 15 entirely lie within the study area. The Cambridgeshire and Peterborough CCG is the RPH's core operating area with its main sleep clinic RSSCCSS in the west of Cambridge. There are six cities in the study area, St. Albans, Chelmsford, Cambridge, Norwich, and the historical city of Ely, which currently just has 20,000 inhabitants. In the UK, towns and cities cannot be distinguished by inhabitants, so that Luton represents the settlement with the most inhabitants.

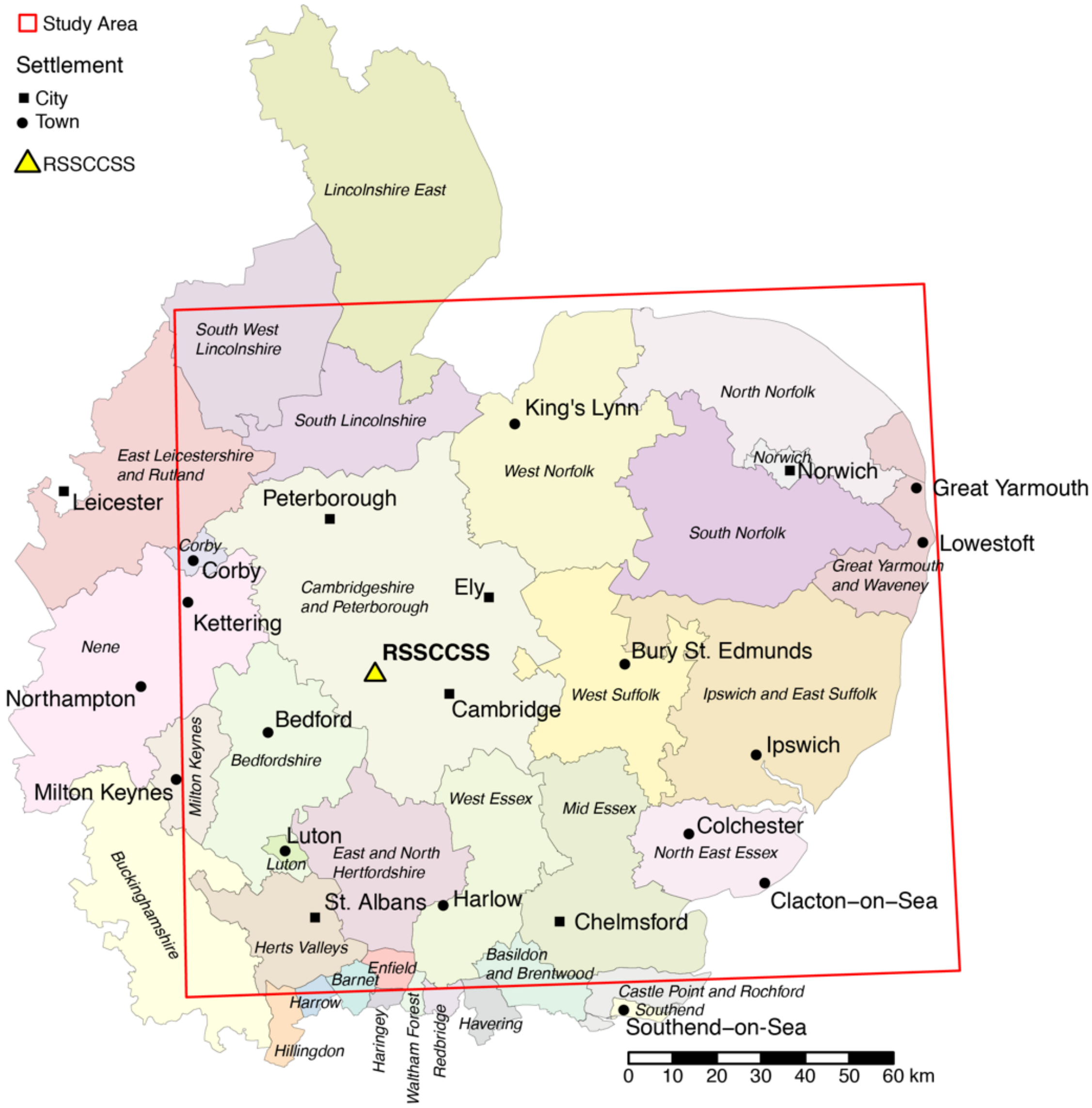

Figure 3.1: Study Area

3.2 Spatial Units of the UK

This section gives an overview about the relevant spatial units in the UK. The UK distinguishes between administrative, census, electoral geography, health and postal geography (Office for National Statistics, 2018a).

The administrative geography of the UK includes the four countries England, Scotland, Wales and Northern Ireland. The countries England, Scotland and Wales collectively make up Great Britain. Each country itself is responsible for defining the administrative units. England is separated into nine regions, while the other three countries are not further divided. This study focuses on the region East of England, which is the peninsula in the northeast of London. The region had 5,847,000 inhabitants in the 2011 census survey (Office for National Statistics, 2011a). The largest cities in East of England, are Cambridge in the west of the region, Colchester and Ipswich in the south east, Norwich in the north west and Peterborough in the north west. England has 326 Local Authority Districts (LAD) where of 69 lie within the study area. The LADs are the spatial units that are forming the local government.

The census geography is directly associated with the UK census, which is surveyed every 10 years. The census units are called Output Areas (OAs), which are the base units of the Census data releases. The OAs change with every census data release as a result of population changes so that the OA have a similar populations size and are as socially homogenous as possible. England has 171,372 OAs which have an average population of 309 (Office for National Statistics, 2018a). The minimal OA size is 50 inhabitants and the maximal size is 625 inhabitants (Office for National Statistics, 2018b). OAs preferably entirely consist of postcodes and tends to be separated at obvious boundaries such as major roads (Office for National Statistics, 2018a). OAs are additional provided as a population weighted centroid. The centroid is calculated with a median centroid algorithm using coordinates and the populations of each household (Office for National Statistics, 2019).

In health geography, four NHS England (Regions) represent England. They are divided into 14 NHS England (Region, Local Offices). A NHS England (Region, Local Offices) consists of several CCG which are responsible for the delivery of primary health care. Each of the 207 CCGs manages all GPs in their geographical area.

In a postal geography, the royal mail organizes a UK-wide system of postcodes to identify postal delivery areas. There are several postcode levels, which allow an optimal postal delivery. The postcode units are the base units of the postal geography which typically consists of 15 addresses. Based on the postcode units code the relation to any postcode level can be reconstructed. The postcodes areas do not align to other geographical units. Nevertheless, the postcodes can be referenced to any other geographical unit (Office for National Statistics, 2018a).

3.3 Royal Papworth Hospital (RPH)

The RPH is a leading heart and lung hospital and annually treats about 100,000 patients. The hospital includes UK's largest Respiratory Support and Sleep Centre called RSSCCSS which is a major centre for the provision of ventilatory support and sleep medicine with a national referral base (Papworth Respiratory Support and Sleep Centre (RSSC), 2019). The RPH is located in the village of Papworth Everard in the Cambridgeshire and moves to Cambridge in summer 2019. Papworth Everard lies about 16 km west of Cambridge, 10 km south of Huntingdon and 15 km east of St. Neots. In the health service perspective, the RPH is situated inside the Cambridgeshire and Peterborough CCG in which it is the major facility for diagnosing and treating OSA. This study focuses on the diagnostic process of OSA, which is organized the following way: In the UK, the National Health System (NHS) distinguishes between primary, secondary and tertiary care. The primary care is represented by GPs and pharmacies. On the other hand, secondary and tertiary care take place at a hospital. The secondary and tertiary care are classified by the seriousness of the disease, where tertiary is more serious than secondary care. In non-emergency cases, the patient must first go to a primary service, which decides on referring the patient to the secondary or tertiary care or not depending on the seriousness of the disease. In the context of the RPH and the OSA diagnostic this is similar. OSA patients are referred from a primary health facility to a RPH facility for a detailed examination with an oximeter. The RPH facilities consist of the main hospital RPH with its sleep centre RSSCCSS, which works with partner GPs and operates with its own outreach clinics to improve accessibility and the diagnostic process. Outreach clinics operate once or twice a month at different places, where the RPH takes lodgings with an existing health facility. All the current RPH pick-up facilities are listed in the Table 3.1 and illustrated in Figure 3.2. The diagnosis is always proceeded with single channel oximeters which are stored in the RPH. GPs have 1 or 2 oximeters on permanent loan, while the oximeters at the outreach clinics are not permanently stored. Outreach clinics get oximeters from the RPH oximeter stack during their operating period. Most of the oximeters are stored in the RPH itself, in which most of the patients are tested.

The oximeter pick-up process consists of two pathways, which can both be used for patients referred to the RPH. The referring GP decides on the pathway of the patient. In the first and most common pathway, a GP refers the patient to the RSSCCSS where all the consultant at RPH decides on the procedure. These patients pick up and drop-off the oximeter at the RSSCCSS or at an outreach clinic. In the second pathway, the patients complete the oximetry test at a partner GP of the RPH, where the patient picks-up and drops-off the oximeter. The results are sent to the RPH where the results are reviewed. For patients having a positive oximeter test, which are the ones where the oximeter test screens a ODI > 5, the patient will have an appointment at the RPH independently to the pathway. This appointment has two kinds of scenarios, either it is coupled or it is uncoupled. In the coupled scenario, the oximeter is picked up at day one and dropped off at day two at the RPH. On the drop-off day, the patient has an appointment at the RPH, where the patient is informed about the results. The coupled scenario only can take place for the first pathway. In the uncoupled scenario, the patient picks up the oximeter on day one and drops it off on day two at any of the pick-up facilities. The patient has an appointment at the RPH on another day if the oximeter results are positive. In the case of a negative oximeter result identifying no OSA-symptoms, no appointment takes place. Thus, the uncoupled process reduces unnecessary travel and frees up appointment slots at RPH. The coupled scenario is in 2018 the most frequent scenario, because it makes sense to combine this scenario with the first pathway which is the most common one. A disadvantage of the coupled scenario is the appointment times slot planning at the RSSCCSS, because the appointment might be cancelled in cases where the oximeter test is negative. In the distance aspect, the coupled and the uncoupled scenario have their advantages. In an uncoupled scenario in combination with the GP pathway, the patients can save a lot of travel distance, because they can go to the nearest facility. On the other hand, when the oximeter test is positive, the patient has an additional journey to the RPH. In case of a positive oximeter test result, the coupled scenario has an advantage in distance compared to the uncoupled scenario, due to saving an extra journey.

Table 3.1: Current RPH oximeter pick-up facilities

RPH Code	Organisation Name	Organisation Type
RSSCCSS	RPH	Hospital (till summer 2019)
RSSCCSS	New Papworth	Hospital (from summer 2019)
Manea	Manea	Soon opening Outreach Clinic
CSSTHET	Thetford	Outreach Clinic
SWHSS	Swaffham	Outreach Clinic
RSSCHAR	Harlow	Outreach Clinic
CSSNOR	Norwich	Outreach Clinic
RSSCSTEA	Stevenage	Outreach Clinic
CSSSTO	Stowmarket	Outreach Clinic
CSSBRO	Bromham	Outreach Clinic
CSSCLS	Clarkson	GP
CSSTHIS	Thistlemoor	GP
CSSPMC	Park	GP
CSSNQS	Queen St	GP
CSSBRAMP	Alconbury and Brampton	GP
CSSSPINN	Spinney	GP
CSSCEDAR	Cedar House	GP
CSSRAIN	Rainbow	GP
CSSELY	Cathedral	GP
CSSDODD	Doddington	GP
CSSNUFF	Nuffield	GP
CSSQUE	Queen Edith	GP
CSSBAR	Barley	GP

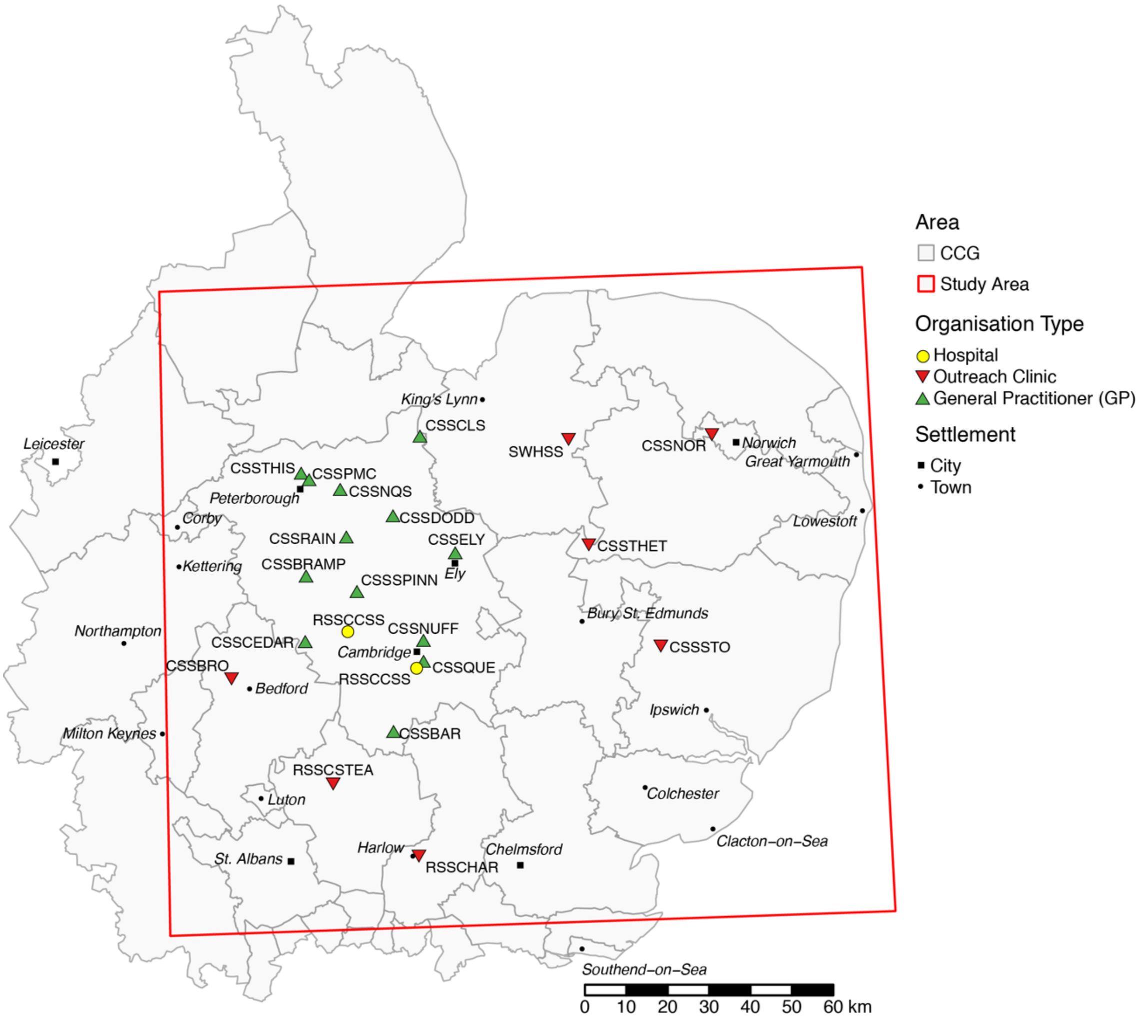

Figure 3.2: Currently operating RPH pick-up facilities

3.4 Data

3.4.1 Spatial Units

3.4.1.1 Postcodes

The National Statistics Postcode Lookup includes all the postcodes of the UK and is provided a *csv* document. The data includes around 2,608,956 postcodes and has the following relevant attributes. Firstly, every postcode has a unique *code* all over the UK. Secondly, the *latitude/longitude* of the postcodes which are calculated by the Office for National Statistics using a 1m grid (Office for National Statistics, 2018d).

3.4.1.2 Local Authority Districts

A LAD represents subnational government districts in which the local government is located. The boundaries of the LADs are provided as a feature polygons in *shapefile* format. It includes the *LAD code* which is unique for the entire UK. The feature extents the full realm (usually this is the Mean Low Water mark but in some cases boundaries extent beyond this to include off shore islands). Additionally, the LAD boundaries features clipped to the coastline (Mean high water mark) are used (Office for National Statistics, 2018c).

3.4.2 Health Related Data

This project uses oximeter flow data provided by the RPH and open general health data. The oximeter flow data is a OSA oximeter testing survey by the RPH and its partner facilities. The general health data are general health surveys provided by different government organisations.

3.4.2.1 Oximeter Data

The RPH provides data about every oximeter test of their RSSCCSS and its partner facilities. The dataset includes information about every patient’s oximeter test appointment between the 11. November 2013 and the 11. September 2018. A single row in the data represents a single oximeter test in which a patient takes the oximeter at home to measure the blood oxygen saturation overnight. For every oximeter event the following attributes are provided: *Patient’s ID, pick-up date, clinic code, home postcode, home latitude, home longitude, clinic postcode, clinic latitude, clinic longitude, attended*. Details about the attributes gives the Table 3.2. The RPH has changed its patient recording system in June 2017. Therefore, the patient’s postcodes are newly recorded after 2017 and consequently can differ between before and after June 2017 in cases where the patient has moved to another postcode. In cases where a patient moved between 2013 and June 2017 or between June 2017 and 2018, the data shows the first collected postcode of the time period. The data includes 46,258 oximeter tests from 23,970 different patients.

Table 3.2: RPH's oximeter data

Attribute	**Description**
Patients ID	RPH internal unique identification number of the patient.
Pick-up date	Date of oximeter pick-up.
Clinic code	RPH internal unique clinic abbreviation where the patient picks up the oximeter.
Home postcode	Postcode of the clinic. For any appointment pre-June 2017 the postcode reflects what was recoded on the RPH records system for that patient in June 2017. For any appointment after this date, the postcode reflects what was on record on the new system during September 2018.
Home latitude	Latitude of the postcode.
Home longitude	Longitude of the postcode.
Clinic postcode	Postcode of the clinic.
Clinic latitude	Latitude of the clinic's postcode.
Clinic longitude	Longitude of the clinic's postcode.
Attended	All no-show pick-up appointments are coded with a 0 while the appeared patients are coded with a 1.

3.4.2.2 General Health Data

Excess weight in adults (aged 18+)

The excess weight data gives information about the proportion of the adults' population classified as overweight or obese. The adults' overweight level (including obese) is defined as an Body Mass Index (BMI) greater than 25 kg/m^2. The overweight data is surveyed by patients' self-reported measurements. The bias of self-reporting is adjusted afterwards with likelihood corrections. The data is published on the geographical level of a LAD for the period 2016/2017 (Public Health Profiles, 2018).

Health facilities in UK

The current operating health facilities including hospitals, GPs, clinics and pharmacies are obtained from the NHS datasets website in a *csv* format (NHS, 2018b). Every facility type is a single dataset including the following information for each facility: *ODS-code, the organisation type, organization name, address, city, county, postcode,* *latitude/longitude*. Table 3.3 gives information about the number of facilities in the study area.

Table 3.3: Health facilities in the UK and the study area

Facility Type	**Number of Facilities in the UK**	**Number of Facilities in the Study Area**
Hospitals	1,234	155
GPs	9,063	1,072
Clinics	18,801	2,137
Pharmacies	11,378	1,336

3.4.2.3 CCG boundaries

The CCG boundaries of England, provided as *shapefile* format, define the boundaries of the CCGs as polygon features. The CCG boundaries include a unique CCG identifier code. The boundaries are provided according to the LAD as full realm and clipped to the coastline (Office for National Statistics, 2018e).

3.4.3 Census Survey 2011

The 2011 census data is the most recent census release in the UK. Every household answered a questionnaire including 56 questions pertaining to work, health, national identity, passports held, ethnic background, education, second homes, language, religion and marital status (Office for National Statistics, 2011c). Furthermore, general information about the household residents' sex and age were collected. The census data are aggregated to an OA, which is the finest geographical level at which the census is published. The census data were obtained from the NOMIS interface with the attributes *OA code*, *sex* and *age structure* (Office for National Statistics, 2011c). The *OA code* is a unique ID for each OA of census 2011. The attribute *sex* provides information about the men to women ratio. The *age structure* provides the share of population underlying the following age classes: 0 to 4, 5 to 7, 8 to 9, 10 to 14, 15, 16 to 17, 18 to 19, 20 to 24, 25 to 29, 30 to 44, 45 to 59, 60 to 64, 65 to 74, 75 to 84, 85 to 89, 90 and over. In the spatial context, the OA boundaries are published including the unique OA census *code* (Office for National Statistics, 2016a). The OA boundaries are a feature class of polygons provided as a *shapefile* format. Additionally, the OAs are provided and used as a population weighted centroid (Office for National Statistics, 2016b). The study area consists of 22,092 OAs, with a minimal population of 101 and a maximal population of 3,407. The average population per OA in the study area is 311 and the median is 307. The total population of the study area is 6,878,432.

3.4.4 Road Network

The Ordnances Survey (OS) publishes the *OS open roads* dataset twice a year licensed under the Open Government License. The *OS open roads* is a road network dataset covering the Great Britain. It consists of three separate datasets: the road links, the road nodes and the motorway junctions.

First, the road links, provided in *shapefile* format, represent the edges of roads in the network. The line feature of the road links characterises the generalized carriage way of the road. The road links always connect two road nodes and have the same road attributes for the whole feature. The road links start/end when they cross another road, excepting roads links crossing over another road (e.g., at a bridge). Each single road link is classified using the following attributes: The *Identifier* represents a unique road link ID and the attribute *Name* stands for a non-unique road name. The attributes *start Node* and *End Node* defines the two roads nodes in-between the road link. The attribute *Form of Way* classifies the road link and distinguishes between the levels listed in Table 3.4. The attribute *Road Function* defines the function of a road link and gives information about the road class using the levels listed in Table 3.5. Finally, the length attribute gives information about the length of the road link in meters.

Second, the road nodes stand for the nodes of the road network and are therefore the spatial geometry for the start and end point of road links. The point feature represents a junction, roundabout, change in attribution, or the end of a road. Third, the motorway junctions are point features and represent the junction between motorways sections. They appear when the motorway’s names change. The roads and the motorway junctions have a unique *ID*, which match with the *Start Node* and *End Node* of the road attribute. The *OS open road* does not include route restrictions information, such as one-way roads, width and height restrictions and turn restrictions.

Table 3.4: OS open roads: *Form of Way* (Ordonance Survey, 2018, p. 23)

Code	**Description**
Single carriageway	A road consisting of one carriageway with traffic in one or both directions. There may be more than one lane in any particular direction.
Dual carriageway	A road consisting of two separate carriageways with separate flow directions. The carriageways are partitioned by physical features, such as a barrier and/or verge.
Slip road	A link that provides exit from or entry to another link.
Roundabout	A method of controlling traffic flow by allowing vehicles from a particular direction priority.
Collapsed dual carriageway	The geometry of the dual carriageway has been collapsed where they are running parallel and is less than a defined distance apart, resulting in a single line representing both carriageways of a dual carriageway.
Guided busway	A specially constructed or modified route for passenger road vehicles that have been built or adapted to be steered by external means. Typically, along guided busways, a raised kerb acts upon small wheels protruding from the sides of the modified vehicle. This classification is only for the specific cases where buses run along specifically designed tracks or channels that remove the need for steering.
Shared use carriageway	Roads that have been altered for use principally by pedestrians but may provide some access for certain types of vehicle.

Table 3.5: OS open road: *Road Function* (Ordonance Survey, 2018, p. 23)

Code	**Description**
Motorway	A multi-carriageway public road connecting important cities.
A road	A major road intended to provide large-scale transport links within or between areas.
B road	A road intended to connect different areas, and to feed traffic between A roads and smaller roads on the network.
Minor road	A public road that provides interconnectivity to higher classified roads or leads to a point of interest.
Local road	A public road that provides access to land and/or houses, usually named with addresses. Generally, not intended for through traffic.
Local access road	A road intended for the start or end of a journey, not intended for through traffic and will be openly accessible.
Restricted local access road	A road intended for the start or end of a journey, not intended for through traffic and will have a restriction on who can use it.
Secondary access road	A road that provides alternate/secondary access to property or land not intended for trough traffic.

4 METHODS

This study made use R 3.5.2 (R Core Team, 2018) and ArcGIS 10.6 (ESRI, 2018) software. The specific algorithms used are explained in detail in this chapter.

4.1 Data Preparation

The OS open road network includes all the roads in the UK – whether for cars, buses, or pedestrians. In this study, the network is defined as roads that can be used for car traffic. The long-distance trips that patients travel in the context of this study are usually taken in a personal vehicle. Consequently, the relevant roads include the road segments where the *Road Function* attribute is *A Road, B Road, Motorway, Minor Road, Local Access Road,* or *Local Road*. Additionally, the road segments where the attribute *Form of Way* is either a *Guided Busway* or a *Shared Use Carriageway* are excluded. The extent of the road is defined using the bounding box of the study area with an extra distance of 10 km to avoid edge effects (Gil, 2017).

The subset of the *OS open road* network is topologically corrected with the topological error tool of ArcGIS. All of the self-intersected road segments and isolated islands are excluded using this tool. Undershoots and overshoots are corrected by hand in the network building interface. The topologically correct network is converted into a network dataset layer of ArcGIS in which network analyses take place. New nodes are generated in the network dataset, based on the corrected edges of the *OS open roads*, so that the original *OS open roads road junctions* are no longer utilised. The network dataset layer connects all of the streets together to form a network in which the travel impendence is defined as the distance in meters. The road network does not have any restriction related to turns at crossings and driving direction, so it is possible to take every road in both directions and to turn from every road segment into every connected road segment.

4.2 Current Situation Analysis

The current situation is analysed based on different statistics for clinics and patients based on oximeter pick-up data. The aim of the current situation analysis is to understand the current situation of spatial accessibility, which is necessary in order to suggest improvements later on. Firstly, some general statistics give an overview of the clinics and patients and their spatial distribution. Secondly, statistics about the distance between the patient's home and the clinic show the importance of distance in oximeter testing.

4.2.1 General Overview

The clinics have different operating periods; while some clinics were operating for the entire oximeter data survey period (2013 to 2018), some started their service during the survey period. The oldest and the most recent appointment date was calculated for every clinic and illustrated in a Gantt chart with yearly time steps. The analysis assumed that the clinic started its operation at the date of the first oximeter pick-up at the clinic. All the clinics were operating as a pick-up facility until the end of the data survey, so the end of the survey was defined as the last pick-up appointment for all facilities.

The different clinics were compared according to the number of oximeter pick-up appointments. Due to the different opening periods, the average number of yearly pick-up appointments per clinic was calculated for all the attended and no-show oximeter pick-up appointments. The start date and the end date of the oximeter data survey and the opening dates of new clinics were not necessary at the beginning or end of the year. The yearly opening time was, therefore, weighted according to the number of opened days per year and not according to the entire year (e.g., if a clinic opened on 1 June 2014, which is the 152nd day of the year, and was operating until the end of the year, the year is weighted as 152/365 = 0.42 years). If a clinic was operating for the whole year, the year was weighted with 1. The opening date of the clinic or the start date of the oximeter survey was determined using the first pick-up appointment of each clinic. The end date of the survey was defined as the last pick-up appointment in all the clinics, as all the clinics were operating until the end of the survey.

Additionally, some descriptive statistics about the patients give information about the patients' tendencies in clinic choice. A bar chart illustrates the proportion of patients that were visiting the RSSCCSS or other clinics. Furthermore, a boxplot shows the number of pick-up appointments per patient for patients that showed up. Finally, a line chart compares the number of tests per patient with visiting the RSSCCSS at least once (Section 5.1).

The study area includes 98% of the scheduled oximeter pick-up appointments in the oximeter data survey. To understand the spatial distribution, hexagons with a diameter of 6 km, overlaid on the study area, determined the home location of every scheduled pick-up appointment (2013 to 2018). A resolution of 6 km fits twice into the large cities – including their suburbs (e.g. Cambridge, Peterborough, Luton and Norwich) – of the study area; this resolution can therefore show cities with their population density. Hexagons have advantages in terms of their readability (Birch et al., 2007), because the hexagons are not orientated in the horizontal and vertical lines to which the human is sensitive (Coppola et al., 1998). Hexagons have lower edge effects bias compared to quadrates and, therefore, have a more natural shape (Krebs, 1989). Compared to quadrates, hexagons have the advantage of being closer to the shape of a circle than a quadrate and tend to be less ambiguous (Birch et al., 2007).

4.2.2 Oximeter Distance Statistics

4.2.2.1 OD Distance Matrix

The origin destination distance matrix between the patients' postcodes and the existing RPH facilities was calculated using the Network Analyst extension of ArcGIS. This origin destination distance matrix gives information about the travelling distance in the road network between the home postcode (origin) and the facility (destination). The distance was calculated for every unique postcode in which a minimum of one patient lived. The method assumes that everyone takes the shortest driving path to the facility, as calculated using Dijkstra's algorithm (ESRI, 2019). The nearest facility to each patient was calculated using the OD distance matrix.

4.2.2.2 Service area of the clinics

For the 21 RPH oximeter pick-up facilities operating during the survey period – including one hospital, seven outreach clinics, and 13 GPs – the service area was calculated using the service area algorithm of Network Analyst in ArcGIS. For the service area, the distance from every node of the network to the nearest clinic was calculated. The distances were classified into 10 km distance classes and illustrated as polygons on a map. This calculation helps to determine the regions with a lack of accessibility through derivation. These nested polygons are called isochrones and indicate areas of equal travel time to any of the clinics operating at the time (Figure 5.10).

4.2.2.3 Distance Statistics

As Parkin (1979) demonstrated, distance is an indicator of whether a patient is likely to attend an appointment. Therefore, the correlation between attended pick-up appointments and the travel distance was calculated using the point-biserial correlation coefficient, which allowed a correlation between a discrete and a continuous variable to be calculated (Bonett, 2007). In this case, the product moment correlation between the discrete variable *attended* and the continuous variable *travel distance* from the patient's home to the clinic was calculated.

Furthermore, all of the pick-up appointments where the distance from home to the clinic was within defined distances were mapped to get an overview of the regions with a lack of accessibility. Accordingly, all the pick-up appointments where a patient's home location was greater than a defined distance to the clinic are illustrated in Figure 5.10.

4.2.2.4 Quantiles of Catchment

Each facility has a catchment within which the patients are coming to the facility to pick up an oximeter. For each clinic, the distance quartile from the patients' homes to the clinic was calculated to get information about the spatial distribution of the patients' home locations. Based on these calculations, every pick-up home location was assigned to a quartile of the catchment. For every quartile, the convex hull polygon of the respective patient's home was calculated. The polygons were nested and, therefore, had to be clipped with the subjacent quartile so that the polygons did not overlap (e.g., the 50% quartile only included the patients' homes lying within a distance of 25% to 50% and was, therefore, clipped with the 25% quartile convex hull polygon). The results are illustrated on a map (Figure 5.9) showing the four nested polygons of the quartiles. Additionally, the convex hull of the upper whisker was calculated to get information about outliers.

4.3 OSA risk

4.3.1 Risk Factors

The introduction gives an overview of the risk factors associated with OSA. The individual risk factors are used to estimate the risk of OSA in the study area. The risk group is calculated using the risk factors age and overweight. In this section, the reasoning for including or excluding the individual risk factors in the risk model is clarified.

4.3.1.1 Relevant Factors

Age: The prevalence of OSA rises with advancing age; therefore, age is an important risk factor (Bixler et al., 1998). For women, the prevalence rises after menopause (Young et al., 2002). The median age for women's natural menopause is 54, but this varies depending on different health factors (Dratva et al., 2009). Consequently, age is an important risk factor and is included in the risk model. For this study, the risk of age was defined as the population older than 65 so that menopause is likely finished in women and the overall OSA prevalence is at its highest.

Overweight: Obesity is a major risk factor of OSA (Martinez & Faber, 2011), with the prevalence increasing as weight increases (Young et al., 2004). It is, therefore, essential to include this risk factor into the risk model. The risk factor of obesity (a BMI of 30 kg/m^2 or higher) is only available on the level of CCG (NHS, 2018a), while the health risk factor of being overweight (a BMI of 25 kg/m^2 or higher), including obesity, is published on the level of LAD (Public Health Profiles, 2018). The risk model uses the risk factor overweight instead of the risk factor obesity, because having a higher spatial resolution is crucial for a spatially distributed risk estimation.

4.3.1.2 Excluded health factors

Alcohol: Alcohol has only a short-term effect (Young et al., 2004) and is, therefore, not relevant for calculating long-term OSA risk.

Sex: Men have a greater OSA prevalence than women and sex is, therefore, an important risk factor (Martinez & Faber, 2011). The risk calculation used aggregated data on the level of census 2011 OA. On these aggregated levels, the sex ratio has a low range and a leptokurtic kurtosis of around 50% percent. This risk factor is thus not useful for a spatially distributed risk estimation.

Diabetes type 2: Diabetes type 2 is associated with obesity and is, therefore, not an independent risk factor (Al-Goblan et al., 2014). Additionally, the provided diabetes data aggregates type 1 and type 2 diabetes. In the OSA context, only type 2 is a relevant risk factor (British Lung Foundation, 2015).

Smoking: Literature is not able to show the correlation between OSA and smoking with high significance (Wetter et al., 1994). Therefore, this factor has insufficient supporting evidence to include it into the risk model.

Hypertension: Hypertension is not a risk for OSA; rather, OSA is a risk factor for hypertension (Young et al., 2002). Therefore, estimating OSA on the basis of hypertension is inappropriate.

4.3.2 Risk Model

The two risk factors overweight and age were used to calculate the OSA risk on the geographical level of OA. The two risk factors are not on the same spatial unit. While the risk of age above 65 can be determined from the census 2011 OA (Office for National Statistics, 2011b), the risk of overweight is on the geographical level of LAD (Public Health Profiles, 2018). The two risk factors have to be on the same spatial unit to determine the total OSA risk score. Therefore, the overweight prevalence on the level of OA was deducted from the overweight on the level of LAD. All of the OAs within a LAD were assigned the overweight prevalence from the LAD. The spatial distribution of overweight prevalence stayed, therefore, on the geographical level of a LAD, but every OA had information regarding the corresponding overweight prevalence. Both risk factors were classified from 1 to 5, where 5 is the highest risk band and 1 the lowest risk band. The prevalence of OSA increases with age and weight; therefore, the risk band 5 represents the highest population-weighted quintile of population older than 65 and overweight. The lowest risk band of 1 represents the lowest population weighted quintile of the population older than 65 and overweight. These five levels were determined using the population weighted quintiles of every risk factor on the level of OA. The population weighted quintiles were determined based on the OAs all over the UK and are shown with their risk bands Table 4.1. Each OA was allocated to one of the risk classes based on the risk quintiles. The total OSA risk score of each spatial unit (e.g., OA) was calculated using a model in which each classified risk factor (e.g., overweight and age) was summed and divided by the number of factors – in this case, two. In other words, an OA with a 22% share of the population older than 65 (risk class equals 4) and 58% overweight prevalence (risk class equals 2) had a total OSA risk of (4 + 2) / 2 = 3. The OSA risk determination was highest with the total OSA risk score 5 and lowest with the risk score 1.

Two different risk scores were calculated – first, the total OSA risk score and second, the relative risk score. The total risk score is the risk score of the two risk factors, as described above. The relative risk score is the total risk score relative to the average risk score all over the UK, where the average risk score is the population weighted average risk on the level of OA. The population weighted average risk score in the UK equalled 2.99. The relative risk was therefore the total risk at the OA minus the average risk all over the UK. The result of the formula distributed the risk in positive and negative values, where positive values are above the average risk and negative values are below the average risk.

The ecological fallacy underlay the risk determination due to having used aggregated data. The ecological fallacy appeared when the risk calculated on the level of an aggregated group was applied for the individual risk. The risk was determined on the aggregated level, which does not mean that all the individuals in this region had the same risk. The individual differences were not taken into account (Freedman, 1999; Mendoza et al., 2013).

The risk estimations are illustrated on map (Figure 5.12). The OAs are illustrated using hexagons of 6 km in diameter. Therefore, all the OAs were matched to the hexagons within which they are lying. The population weighted average total risk score was calculated for every hexagon and afterwards converted into the relative risk score.

Table 4.1: Risk classes

Quintile	**> 65 population (%)**	**Overweighed population (%)**	**Risk class**
0 - 20 %	0 - 8.18	40.47 - 57.24	1
20 - 40%	8.18 - 12.71	57.24 - 60.94	2
40 - 60%	12.71 - 17.41	60.94 - 63.44	3
60 - 80%	17.41 - 23.61	63.44 - 66.08	4
80 - 100%	23.61 - 96.75	66.08 - 74.95	5

4.4 Location Allocation

Two kinds of LAPs were applied – first, the ordinary *P*-median problem without any additional restrictions and second, the conditional *P*-median problem. The *P*-median and the conditional *P*-median LAP were applied on ArcGIS Desktop using the Network

Analyst extension (ESRI, 2019). Both *P*-median problems were applied for the entire study area. They both used the prepared OS open roads network with an extra margin of 10 km around the study area (details in Section 4.1) and employed the same three demand scenarios: Patients Demand, Census Demand, and Risk Demand. Table 4.2 and Table 4.3 summarise the different scenarios.

The optimal solution was determined using the vertex substitution heuristic of Teitz and Bart (1968) and metaheuristics to improve the results of the vertex substitution heuristic (ESRI, 2019).

Table 4.2: Different demand scenarios. In white: The ordinary *P*-median scenarios. In grey: The conditional *P*-median scenarios.

Scenarios	**Candidate facilities**	**Required facilities**	**Demand nodes**	**Total Demand**
Patients Demand	4,708	-	17,392	23,970
Census Demand	4,708	-	22,092	6,678,432
Risk Demand	4,708	-	22,092	20,736,073
Census Demand	4,686	22	17,392	23,970
Census Demand	4,681	27	22,092	6,678,432
Risk Demand	4,681	27	22,092	20,736,073

4.4.1 Demand Scenarios

4.4.1.1 Patient Demand Scenario

The demand in the Patient Demand Scenario was based on the patients' postcodes in the oximeter survey data. The 23,970 patients resided in areas associated with 17,392 different postcodes. Each postcode was weighted according to the number of residential patients. About 72% of the postcodes had just one patient residing in them, and 18% of the postcodes had two patients. The included post codes had a residential range between 1 and 101 patients, where the maximum represents the postcode of a prison.

4.4.1.2 Census Demand Scenario

In the Census Demand Scenario, the demand was represented by the population weighted centroids of the census 2011 OAs. There were 22,092 OAs in the study area, where 6,678,432 persons reside. The average population per OA in the study area was 311 and the median was 307. The minimum population of an OA in the study area was 101, while the maximum population of an OA in the study area was 3,407.

4.4.1.3 Risk Demand Scenario

The Risk Demand Scenario used the determined risk score population. For each of the 22,092 OAs, the determined total risk score was multiplied with the census population. The population weighted total risk score was, therefore, the demand input of this scenario. The total population weighted risk score of the study area was 20,736,073, with an average of 938.6 per OA. The minimal population weighted risk score per OA was 130 and the maximum 5,970.

4.4.2 Ordinary *P*-median

The ordinary *P*-median had three inputs: demand, candidate facility, and number of facilities to locate. The demand inputs were weighted based on the scenario introduced in Section 4.4.1. The candidate facilities were all part of the existing health facilities in the study area, which were potential oximeter pick-up partners of the RPH and included the previously mentioned GPs, hospitals, clinics, pharmacies, and current RPH oximeter pick-up facilities. Consequently, there were 4,708 candidate facilities in the study area, including all the current pick-up facilities and external facilities. The candidate facilities in the study area consisted of 1,072 GPs, 2,137 clinics, 1,336 pharmacies, 155 hospitals, the seven current outreach clinics, and the Manea which is scheduled to open in summer 2019. The candidates of the different demand scenarios are listed in Table 4.3. For all three demand scenarios, the demand weighted average distance was calculated for each P of facilities to determine a trade-off between the P facilities and the demand weighted average distance. Incrementally increasing the number of facilities led to a decrease in the average weighted distance. A good trade-off was, therefore, at a knee point in a line plot between the number of facilities and the average weighted distance. The knee point was at the position where the P facilities sufficiently improved the average weighted distance compared to the $P = 1$ solution, and an additional $(P + 1)$ facility just marginally improved the average weighted distance. To determine the knee point, the *P*-median problem was applied for $P = 1$ through $P = 30$ facilities. So, the *P*-median solution was calculated 30 times, successively adding facilities, one by one. The knee point with a good trade-off between the demand average weighted distance and the P facilities was then determined visually where diminishing returns were apparent.

Table 4.3: Candidates listed by the different demand scenarios. In white: The ordinary P-median scenarios. In grey: The conditional P-median scenarios.

Scenarios	**Hospital**	**Clinics**	**GPs**	**Pharmacies**	**Outreach Clinics + Manea**	**Total Candidates**
Patients Demand	155	2,137	1,072	1,336	8	4,708
Census Demand	155	2,137	1,072	1,336	8	4,708
Risk Demand	155	2,137	1,072	1,336	8	4,708
Census Demand	154	2,137	1,059	1,336	-	4,686
Census Demand	149	2,137	1,059	1,336	-	4,681
Risk Demand	149	2,137	1,059	1,336	-	4,681

4.4.3 Conditional P-median

The conditional P-median, where optimal facilities were located with respect to the current existing facilities, had four inputs: demand, existing facilities, candidate facilities, and number of facilities to locate. The demand inputs were weighted based on the scenarios introduced in Section 4.3.1. The existing facilities and candidate facilities differed for the three demand scenarios. For the Patients Demand Scenario, the existing facilities were the current oximeter pick-up facilities of the RPH and its partners. Table 4.3 shows the different candidate types for all the demand scenarios. There were 21 RPH facilities at the time, consisting of one hospital, 13 GPs, and seven outreach clinics. The hospital RSSCCSS at the time, which was located in Papworth, was scheduled to move about 22 km east to Cambridge in summer 2019, so the new location in Cambridge was defined as the existing location of the RSSCCSS. An additional sleep clinic called Manea was scheduled to open in summer 2019; therefore, this clinic was also included as an existing facility. In total, there were 22 current facilities consisting of the new location of the RSSCCSS, Manea, the 13 GPs, and the seven outreach facilities. The candidate facilities were the 4,686 remaining facilities (the 22 current facilities were excluded). For the Census Demand Scenario and the Risk Demand Scenario, an additional five external facilities, on top of the current 22 RPH facilities (the existing facilities from the conditional P-median with Patients Demand), were defined as existing facilities. These external facilities were all clinics offering sleep diagnostics and operating independently from the RPH. In total, there were 27 current facilities consisting of the new location of the RSSCCSS, the Manea facility, the 13 GPs, the seven outreach facilities, and the five external sleeping centres. The candidate facilities were the 4,681 remaining facilities (excluding the 27 current facilities). For adding P facilities to the current Q facilities, the demand weighted average distance was calculated to determine a trade-off between the P facilities and the demand weighted average distance. The conditional P-median was calculated from $P = 22$ through $P = 40$ facilities for the Patients Demand Scenario and from $P = 27$ to $P = 40$ facilities for the Census Demand Scenario and the Risk Demand Scenario.

5 Results

5.1 Current Situation

5.1.1 General Overview

The oximeter pick-up facilities of the RPH had been operating during different time periods, as the Figure 5.1 shows. The facilities are labelled by short name, with full names given in Table 3.1. All the clinics had been operating until the end of the oximeter data survey in 2018, although the facilities had opened their services at different points in time within the study period. Ten facilities had been operating during the entire oximeter data survey and, thus, since 2013 or even before. In 2014, three facilities started their service; in both 2016 and in 2018, four facilities started their services, respectively. In 2018, there were 21 operating oximeter pick-up facilities coordinated by the RPH.

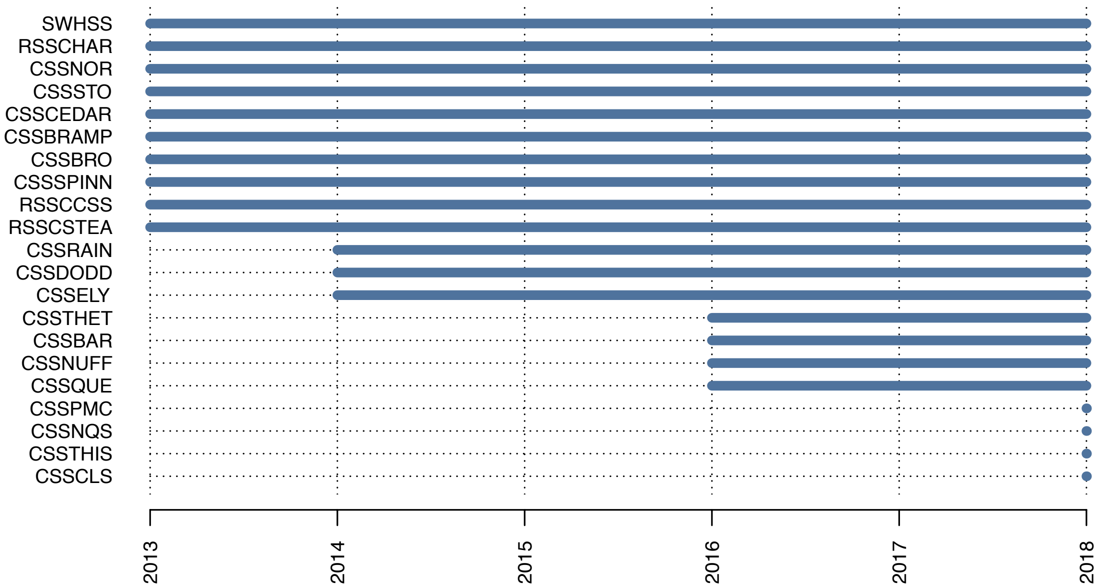

Figure 5.1: Opening period per facility

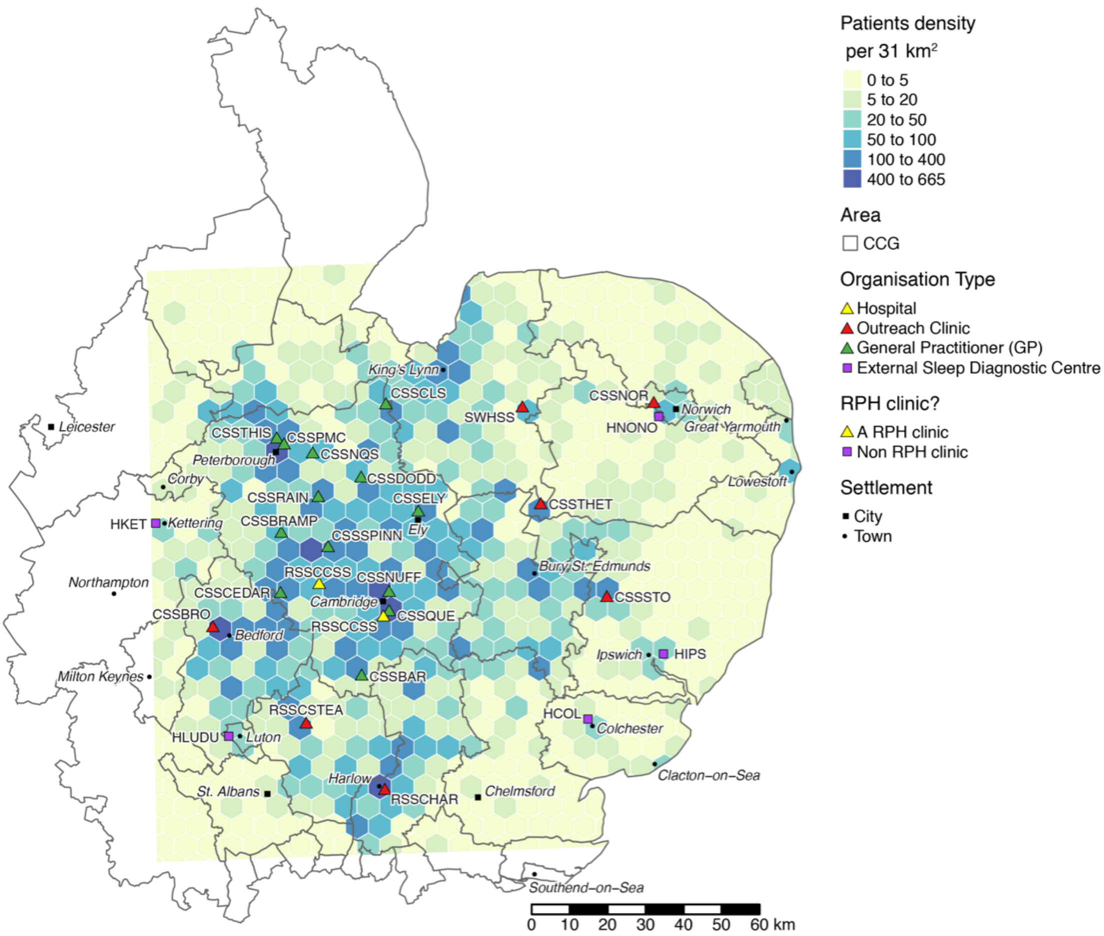

Figure 5.2: Spatial distribution of current OSA-facilities and patients

Figure 5.2 shows the spatial distribution of oximeter pick-up facilities in the study area and gives information about their type. There are four different types of facilities illustrated on the map. Firstly, the hospital RPH, with its sleep centre RSSCCSS, situated in Papworth. The map shows a second hospital with the same abbreviation (RSSCCSS) in Cambridge, lying east of the original RSSCCSS, where the RSSCCSS was scheduled to move to in summer 2019. Secondly, 13 partner GPs of the RPH which were all located in the Cambridgeshire and Peterborough CCG. Thirdly, seven outreach clinics were situated around the Cambridgeshire and Peterborough CCG in the shape of a letter U, and none of them lay within the Cambridgeshire and Peterborough CCG. Fourth, five external sleep diagnosis centres, which operated independent of the RPH and were responsible for sleep diagnosis in the outer region of the study area. These external centres were located next to large cities – namely, Norwich, Ipswich, Colchester, Luton, and Kettering. The Table 9.7 in the appendix match the short names of the map to the official name of the external facilities. The hospital in Kettering was the only external sleep diagnostic facility that lay within a CCG adjacent to the Cambridgeshire and Peterborough CCG in the Nene CCG. Additionally, the hexagon's colour gives information about the patient density, where darker colours indicate a high patient density. As the map shows, patients doing oximeter testing at any of the 21 RPH facilities were living all over the study area. The majority of CCGs in the study area did not have any hospital providing diagnostic sleep tests; hence, patients were likely visiting the RPH. Major cities (Cambridge, Peterborough) and towns (e.g. Bedford, King's Lynn, and Harlow) tended to have greater patient density, while density decreased in rural areas and moving towards the coast. Patient density was highest in the Cambridgeshire and Peterborough CCG where the RSSSCCSS is located.

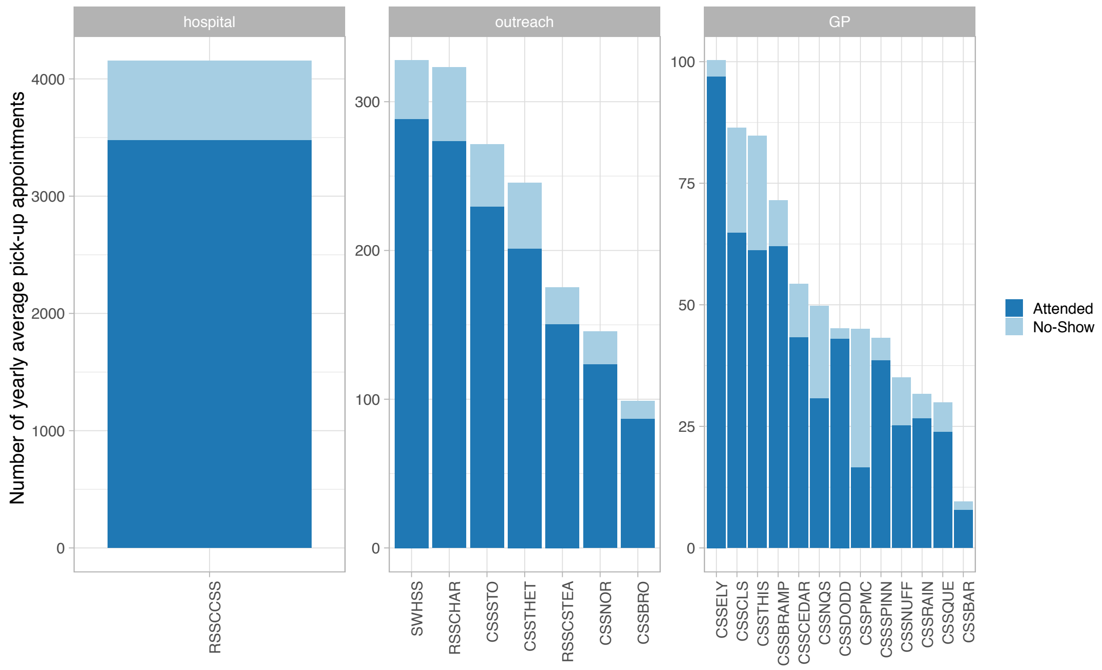

Figure 5.3: Scheduled pick-up appointments per facility

Figure 5.3 shows the average yearly oximeter appointments per facility grouped by the facility type. The yearly average was calculated according to the operating period per clinic. The main clinic RSSCCSS had 4,157 scheduled yearly pick-up appointments on average, of which 3,480 (83.7%) were attended by the patient. Relative to all the yearly average pick-up appointments, 64.6% of the average yearly pick-up appointments occurred at the RSSCCSS. Comparing facility types, GPs had the lowest average number of scheduled pick-up appointments per year, with a maximum of 100 and a minimum of 10 pick-up appointments. The outreach clinics had, on average, between 99 and 328 scheduled pick-up appointments per year. The hospital had the highest average number of pick-up appointments per year with 4,157. Exceptionally, the GP CSSELY, with an average of 100 scheduled pick-up appointments, was the only facility to have more scheduled pick-up appointments than the outreach clinic CSSBRO, with 99 scheduled pick-up appointments. CSSBRO thus had the lowest number of scheduled pick-up appointments of all the outreach clinics. In terms of no-show appointments, the clinic with the highest no-show percentage was CSSPMC, where 63% of the yearly average pick-up appointments were no-shows. CSSPMC had its first pick up on 2018-04-10 and, therefore, had only 18 scheduled pick-up appointments within the study period, of which seven were attended appointments (which is an average yearly scheduled pick up of 44.99 with an average yearly show-up of 16.59). All four clinics that opened in 2018 (CSSNQS, CSSPMC, CSSTHIS, CSSCLS) had a yearly no-show rate greater than 23% and were the facilities with the highest no-show rate. By facility type, the no-show rate showed only small changes – the hospital had a 16.3% no-show rate, outreach clinics 14.5%, and GPs 13.3%. It is, therefore, expected that the no-show rate of these four clinics that opened in 2018 will decrease with a longer operating time.

Figure 5.4 shows the proportion of patients that picked up an oximeter at the RSSCCSS or other clinics. Of these patients, 57.1% visited only the RSSCCSS and no other facility. The second highest proportion of patients (28.5%) never picked up an oximeter at the RSSCCSS and just visited other clinics. A small percentage (7.6%) of patients picked up an oximeter at different clinics and at the RSSCCSS. Surprisingly, 6.7% of the patients never attended any scheduled pick-up appointment.

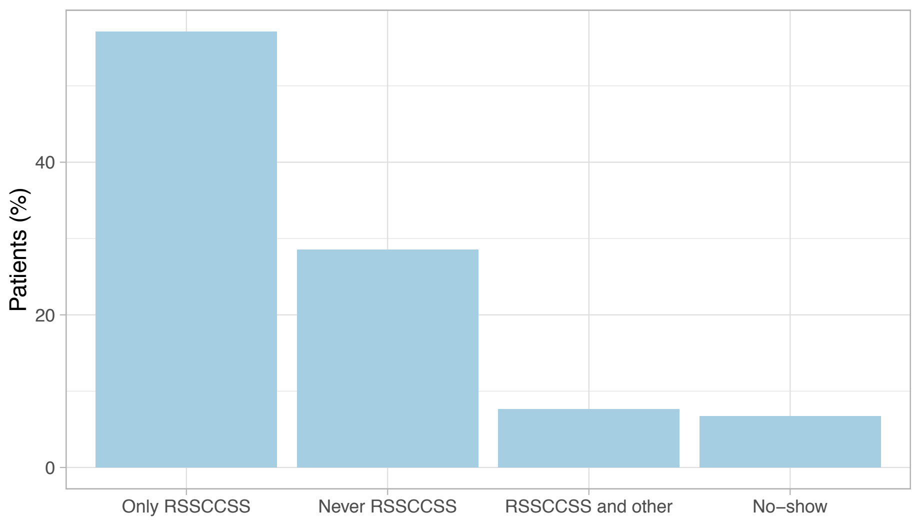

Figure 5.4: Patients tendencies in facility choice

Figure 5.5 shows the number of oximeter tests compared to patients going to the RSSCCSS at least once. Of all the patients picking up at least one oximeter, 70% went to the RSSCCSS. Patients who had more than one oximeter test are more likely to visit the RSSCCSS at least one time.

Figure 5.6 shows the number of attended oximeter pick-up appointments per patient as a boxplot. Half of the patients tested just once with an oximeter, and more than a quarter did two or more oximeter tests. The boxplot shows a minimum of zero attended pick-up appointments, which represents patients in the oximeter data who did not attend their scheduled pick-up appointment. The maximal number of attended pick-up appointments was a patient who attended 17 such appointments. There were 1,391 outlier patients that underwent more than four oximeter tests; thus, the average number of attended pick-up appointments per patient was 1.63, which was higher than the median.

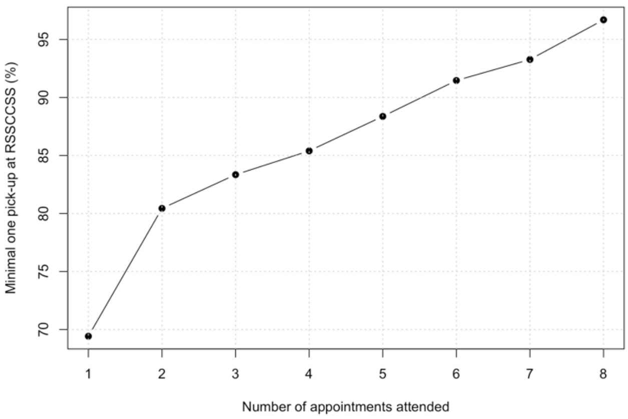

Figure 5.5: Percentage of patients visiting the RSSCCSS at least once

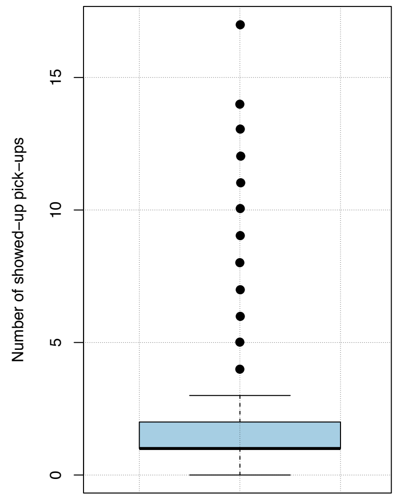

Figure 5.6: Number of oximeter pick-up appointments per patient

Figure 5.7 compares the patient's home locations to the population in the study area. Each 31 km^2 hexagon compares the patient density to the population density and gives information about the share in percentage. Every patient was included just once with the first registered postcode given for the patient. The quadrat's colour gives information about the patient-population ratio, where darker colours indicate a higher percentage in patient-population ratio. The map shows a core region in the Cambridgeshire and Peterborough CCG in which the patient-population ratio was mainly greater than 1%, indicating that a large number of patients in the core area had been oximeter tested. The hexagon with the maximal patient-population percentage (6.6%) had 23 patients living in it and a residential population of 348. This 6.6% hexagon was in a rural area in the north-east of Ely. Urban areas next to the RSSCCSS like Cambridge, Bedford, and Peterborough had a patient-population ratio below 1%, which indicated that oximeter testing demand was lower in urban areas. The rural areas between Cambridge and Peterborough included hexagons with the highest patient-population ratio in the study – – between 1% and 6.6%. The patient-population ratio decreased moving away from the RSSCCSS, especially towards the coasts in the east and the suburbs of London in the south.

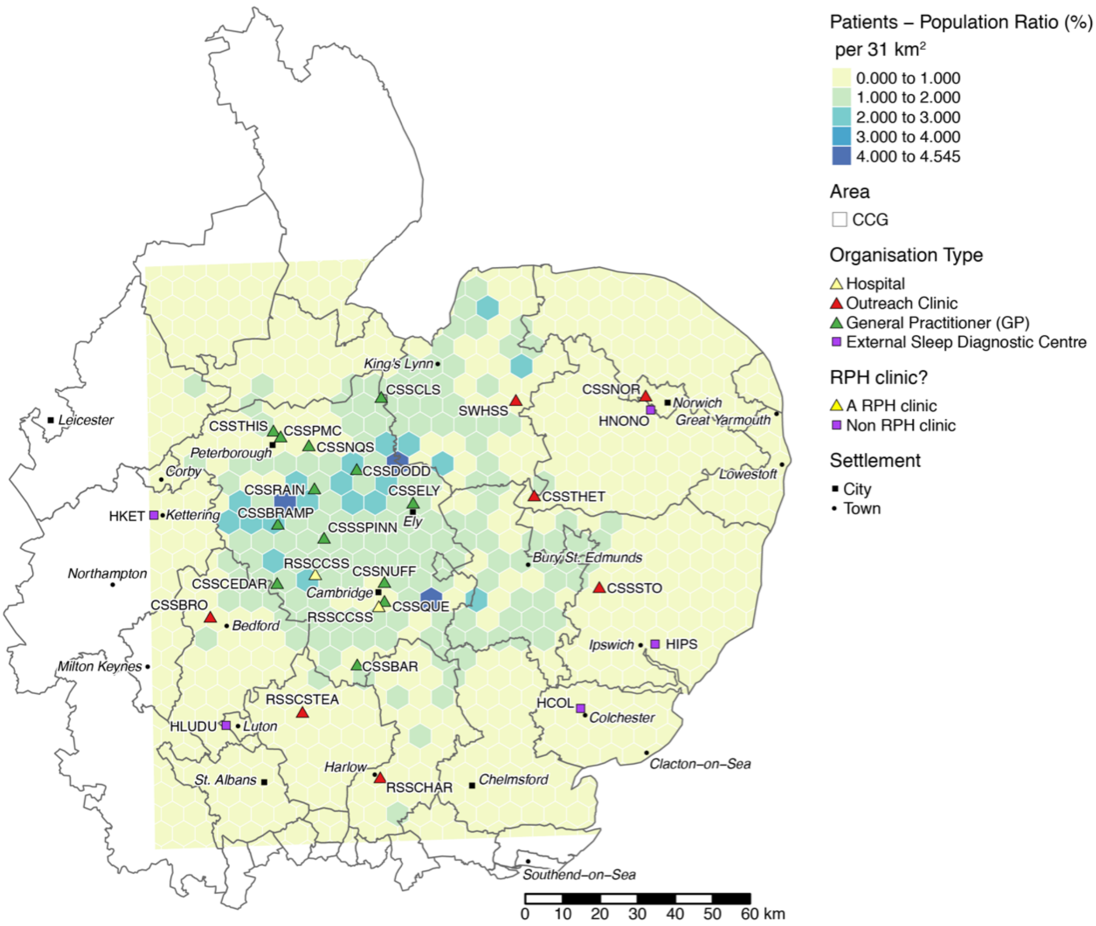

Figure 5.7: Hexagons comparison between the patient's home location and the population as a percentage.

5.1.2 Distances analysis

Figure 5.8 shows the impact of distance from a patient's home to the facility on attendance and no-show, grouped by facility type. The boxplots demonstrate that patients had similar distances from their home to the clinic for attended and no-show pick-up appointments. Overall, the average distance for no-show pick-up appointments was 33.8 km compared to 32.7 km for attended pick-up appointments. The hospital RSSCCSS was the facility with the highest median distance (37 km) from patients' homes and had many outliers of oximeter pick-up appointments with a long travel distance. The RSSCCSS had patients from all over the study area, was the clinic with 69% of scheduled oximeter pick-up appointments, and had a whisker range distance of between 0 km and 100 km. The clinic types show a trend in distance: The distance was highest for the clinic type hospital with a median distance of 38.4 km (average: 39.4 km; standard deviation: 21.1 km). Second furthest were the outreach clinics, with a median of 19.6 km (average: 20.6 km; standard deviation: 15.4 km), and third furthest were the GPs, with a median of 6.9 km (average: 8.0 km; standard deviation: 7.8 km). Worth noting are the figures for CSSNOR, which was the nearest facility for patients in Norwich itself and in the coastal areas of Great Yarmouth and Lowestoft. This clinic had an extensive catchment area which caused the largest interquartile range of between 10 km and 42 km.

With regards to clinic type, the different clinic types had similar no-show ratios (hospital: 83.7%; outreach clinics: 85.5%; GPs: 86.7%), even though the average distance was greater for hospitals (39.4 km) than for outreach clinics (20.6 km) and GPs (8.0 km). Consequently, there was no significant correlation between the travel distance and the probability of showing up at a pick-up appointment (correlation was 0.018 with a p-value less than 0.001). Accessibility in terms of travel distance alone was thus a negligible factor in understanding the reason for no-shows in the context of oximeter pick-ups in this study.

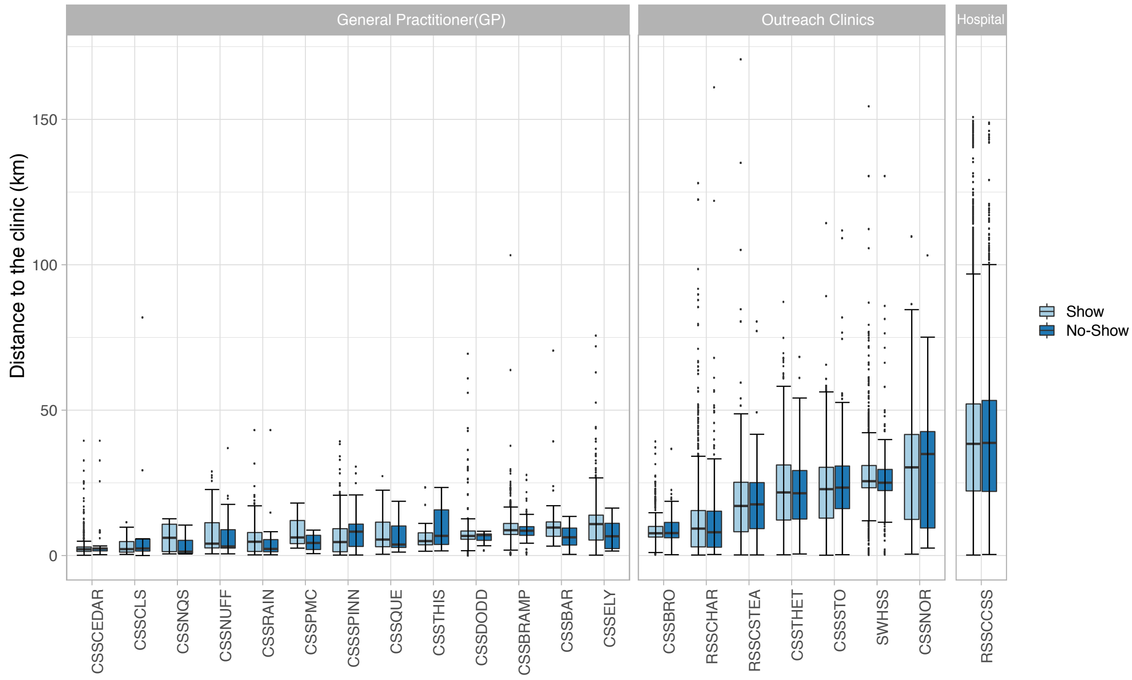

Figure 5.8: Actual distances from patient's home to the facility by facility type.

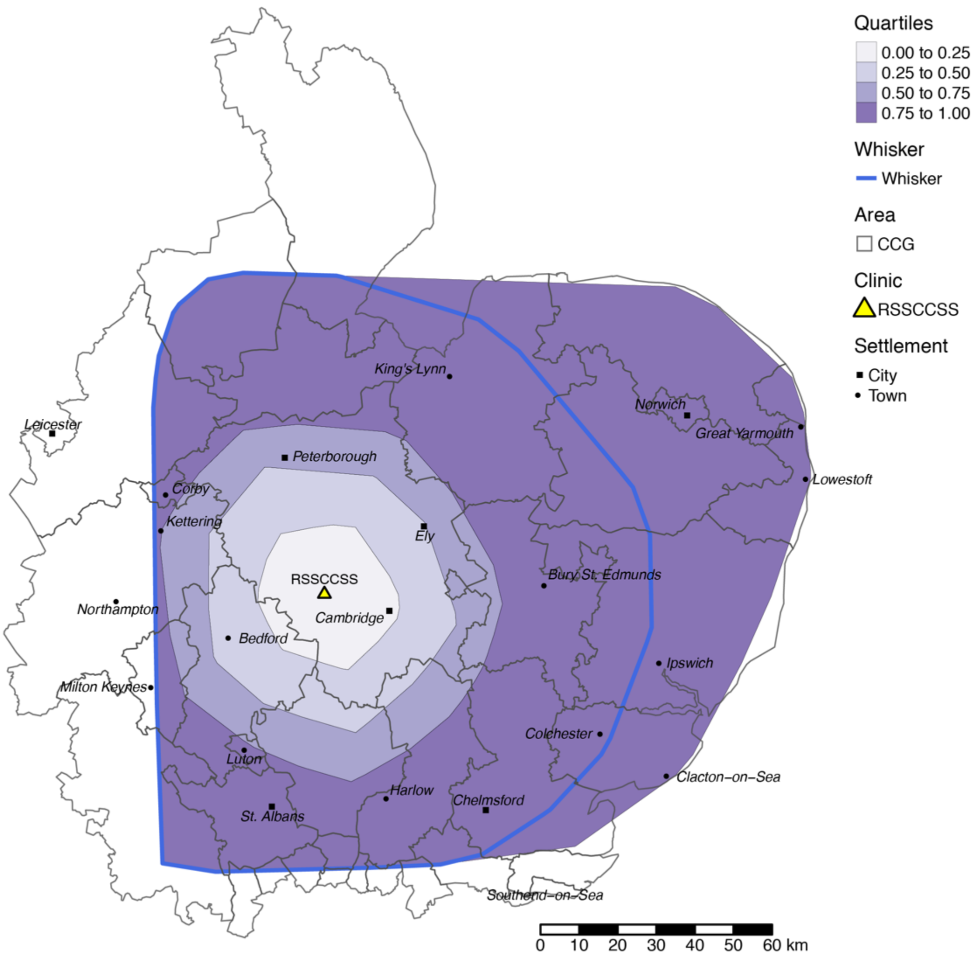

Figure 5.9: Patients home distribution in the RSSCCSS catchment area.

Figure 5.9 illustrates the convex hull of the patients who visited the RSSCCSS during the oximeter survey, illustrated by quartile distances from a patient's home to the RSSCCSS as nested polygons. The quartiles correspond to the following distances: 0% equals 0.1 km, 25% equals 22.2 km, 50% equals 38.4 km, 75% 52.1 km, and 100% equals 150.8 km. The whisker, which is 1.5 times the interquartile range of a boxplot, lies at a distance of 97.0 km, meaning that the patients had a long-distance journey. About 1% of the pick-up journeys had a greater distance than the whisker of 97.0 km. In the north, south, and west, the highest quartile's polygon falls along the border of the study area, so that the polygon is a straight line. In the east, patients living along the entire coast were coming to the RSSCCSS. The lower three quartiles are shaped as circles around the RSSCCSS. The area of the highest quartile's polygon is larger than the area of the three lowest quartiles' polygons together. Norwich, Lowestoft, and Ipswich were the only towns/cities in the study area with a patient density greater than 20 patients lying outside the whisker.

Figure 5.10 shows the service area of the 21 RPH oximeter pick-up facilities categorised as current during the study. The current facilities served 44.7% (10,202 km^2 of the 22,812.26 km^2) of the area with less than 20 km travelling distance. The map reveals the following areas with a lack of accessibility: A north-south direction band between the CSSLS and SWHSS and between CSSELY and CSSTHET of distances greater than 30 km. To the south of this band, there were regions with an accessibility distance of greater than 50 km. The closer the patients lived to the coast, the worse the accessibility became – especially in the regions in the south of Lowestoft. The north-west and the south-west regions of the study area had the worst accessibility, with a distance of more than 60 km to the nearest clinic. The best accessibility was in the Cambridgeshire and Peterborough CCG, where 92.0% of the area had a travel distance of less than 20 km to the nearest facility.

Figure 5.11 shows all patients' home locations for all pick-up appointments, where the distance from a patient's home to the facility they visited is higher than the defined distance threshold. The distance is defined as the network distance between locations, assuming that everybody takes the shortest path. As the map shows, patients having a long journey mostly went to the RSSCCSS; hence, the map > 50 km shows a circle around the RSSCCSS within which the patients had an accessibility distance of less than 50 km. There was a wide range of travel distances (0.2 km to 150.8 km) for pick-up appointments, where 1.1% of pick-up journeys were greater than 100 km. About

25% of the attended pick-up appointments were at the nearest pick-up facility from the patient's home. For the RSSCCSS, where 69% of the oximeters were picked up, 97% of the patients had passed the nearest pick-up facility to their home to reach the RSSCCSS. In comparison, 80% and 71% of the pick-up appointments were at the nearest clinics when either GPs or outreach clinics, respectively, were utilised. This indicates that patients were willing to attend the main hospital, RSSCCSS, even though this involved a long-distance journey. A quarter of patients had a journey of over 45.9 km, which is greater than the 30 km that patients were willing to travel (Yen, 2013). Furthermore, the map > 50 km shows that a high number of patients in the rural areas between the core RPH area and the outer areas in the east had travel distances greater than 50 km. The average patient's travel distance would decrease to 12.3 km (standard deviation: 9.9 km) if all the patients picked up their oximeters at the nearest facility; this would constitute a reduction of over 60% compared to the study's average travel distance of 32.9 km. Under the perfect scenario, where every patient visits the nearest facility, no patient would have to travel more than 60 km with the current geographical distribution of facilities.

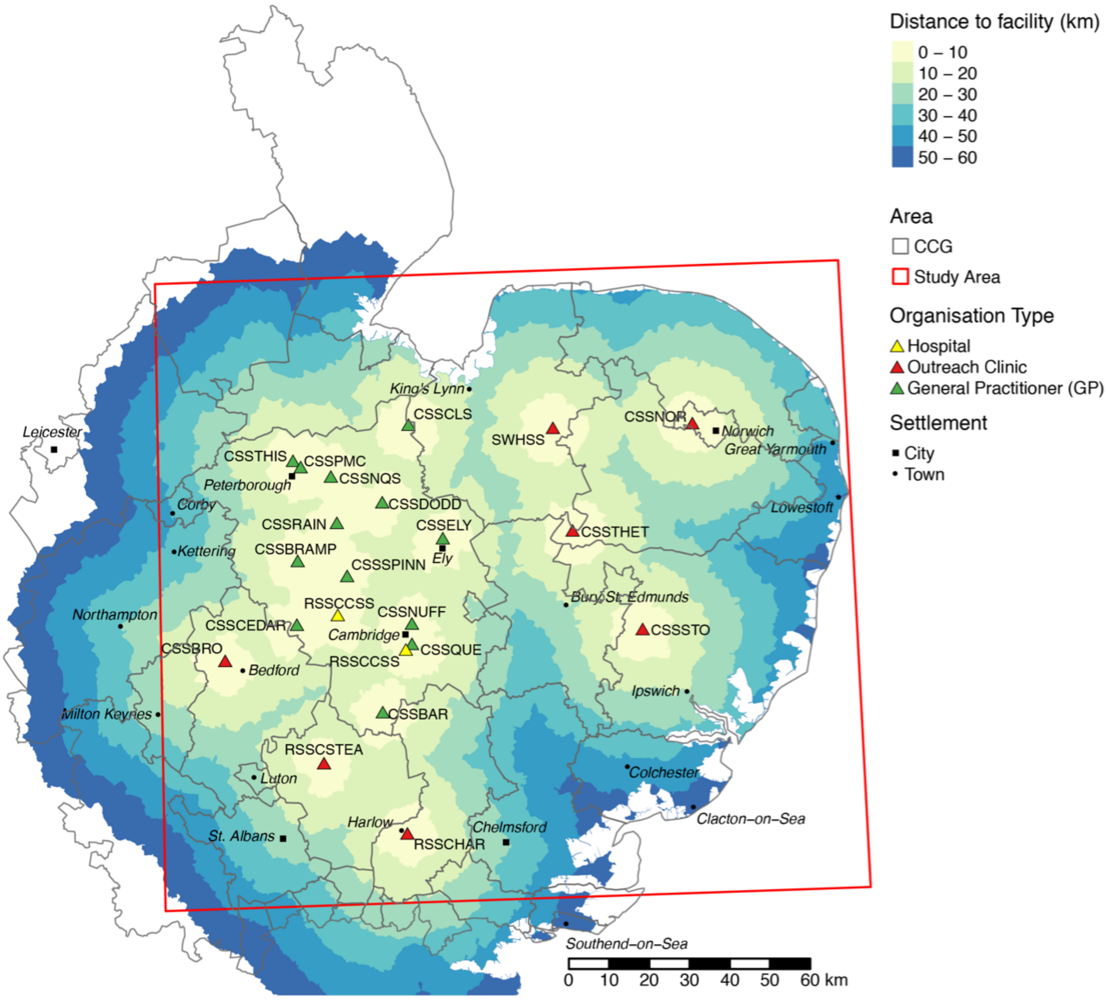

Figure 5.10: Service Area of the current RPH facilities

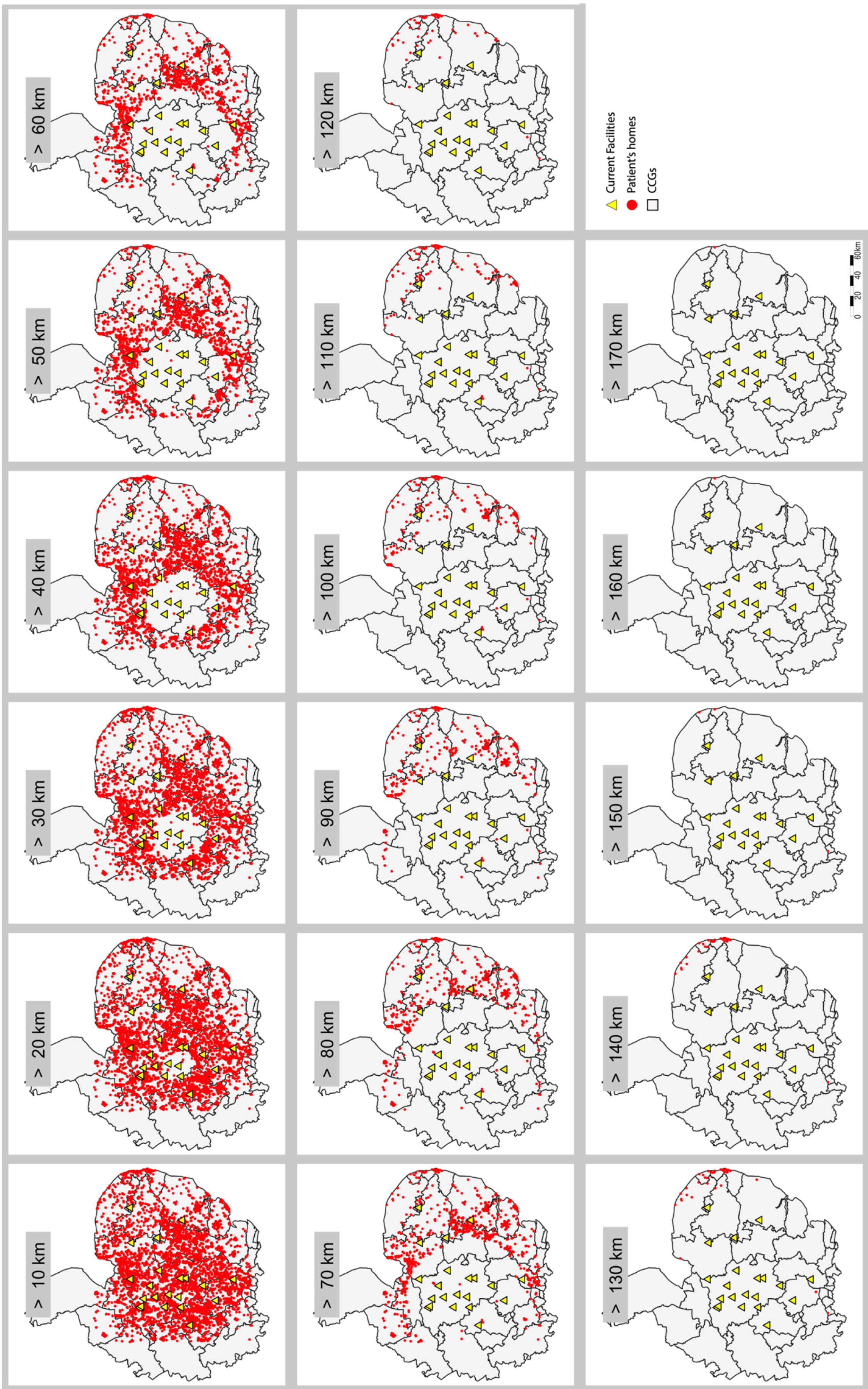

Figure 5.11: Patient distribution by actual distance to facility.

5.2 OSA-risk

Figure 5.12 shows the average relative OSA risk score in 31 km^2 hexagons. The relative risk score per hexagon, which was determined based on the risk on the level of an OA, shows an unequal distribution of risk in the study area. The average relative risk per hexagon is between the scores -1.99 and 2.01, where negative scores indicate low OSA risk and positive scores indicate a high OSA risk. The map reveals that the risk is lowest in the areas around the city of Cambridge (especially in the south), in the boroughs of London (e.g., St. Alban), at the north-eastern coast around Ipswich, and around the city of Norwich. High-risk regions are along the coast, especially in the north of King's Lynn and in the east around Great Yarmouth, Lowestoft, and Clacton-on-Sea. Additional high-risk regions are in the rural areas between Cambridge and Peterborough and in the region to the north of Ely.

On the geographical level of OA, the average population weighted total risk score in the study area is 3.01 (standard deviation: 0.99), which is 0.02 higher than the average population weighted total risk score of 2.99 (standard deviation: 1.05) over the entire UK. The minimal total risk in an OA of the study area is 1 and the maximal is 5. The population weighted average relative risk per OA in the study area is 0.02 (weighted standard deviation: 0.99) and, consequently, marginally higher than the average for the UK.

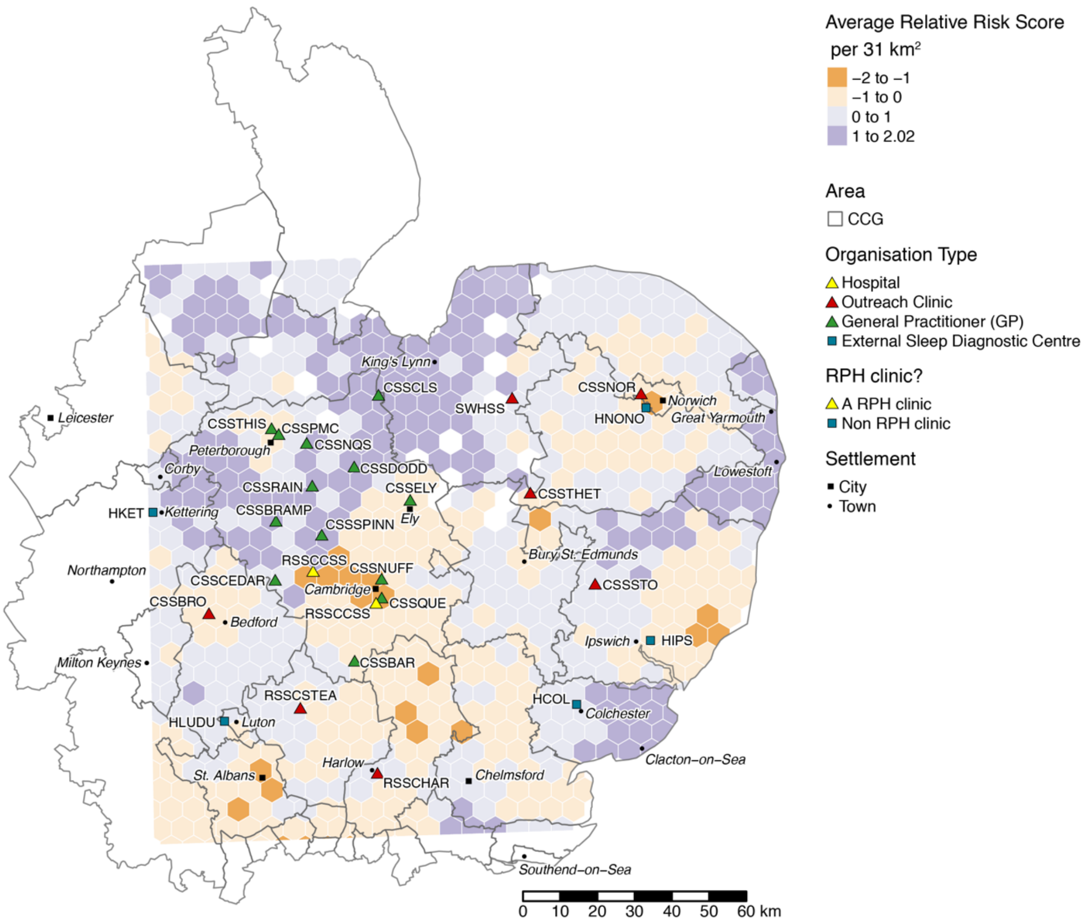

Figure 5.12: Average relative OSA risk per 31 km^2 hexagon

5.3 Location Allocation

5.3.1 Ordinary P-median

The ordinary *P*-median was calculated for the three different demand scenarios. A proper *P* was determined, detecting a knee point at the trade-off curve shown in Figure 5.13. Figure 5.13 illustrates the trade-off curves for the demand weighted average distance on the y-axis and the number of facilities (*P*) on the x-axis. As expected, the demand weighted average distance decreases with locating each additional facility.

The green curve represents the trade-off curve for the Patient Demand Scenario. For $P = 1$ to $P = 10$, the curve is steepest, which indicates greatest improvement of the demand weighted average distance. From $P = 10$ to $P = 30$, the curve decreases marginally, indicating that each additional facility does little to improve the accessibility in terms of travel distance. The ideal knee point is, therefore, at $P = 10$ facilities, where the demand weighted average distance is 13.7 km. For $P = 12$, the demand weighted distance is 12.4 km and equals the current accessibility of 12.4 km.

Keeping the number of currently located facilities ($P = 21$), the demand weighted average distance would be 9.0 km choosing the optimal locations. Compared to the situation at the time of the study, where the demand weighted average distance is 12.4 km, $P = 21$ with optimised configuration reduces the demand weighted distance by 3.4 km.

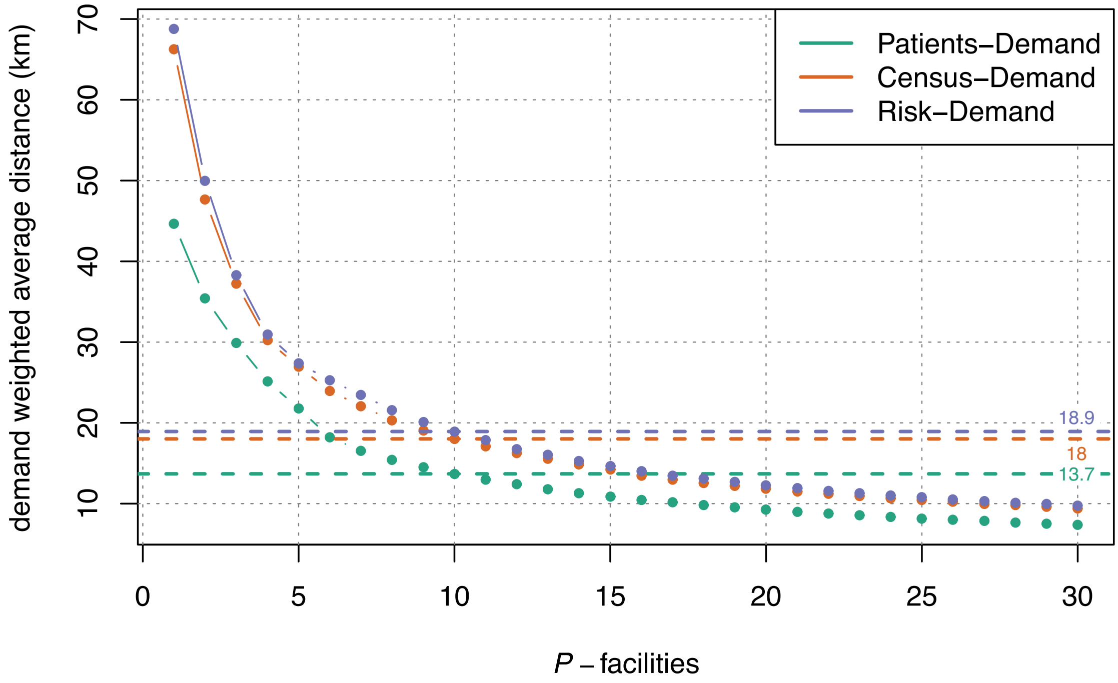

Figure 5.13: Ordinary P-median trade-off curves

The orange curve shows the demand weighted average distance for the Census Demand Scenario for $P = 1$ to $P = 30$. As with the Patient Demand Scenario, the trade-off curve for Census Demand shows only marginal improvements in minimising demand weighted average distance after $P = 10$ facilities. The demand weighted average distance at $P = 10$ is 18.0 km. The current 27 facilities (consisting of 22 RPH facilities, including Manea, and five external clinics) had a demand weighted average distance of 18.8 km; hence, the $P = 10$ solution slightly improves the accessibility, with fewer facilities overall.

The purple curve represents the Risk Demand Scenario and has, like the other demand scenarios, a knee point at $P = 10$ facilities, where the demand weighted average distance is 18.9 km. The arrangement of the 27 facilities in the study had a demand weighted average distance of 19.0 km; consequently, the $P = 10$ solution for the Risk Demand Scenario improves the accessibility by 0.1 km.

When comparing the three scenarios, they all show a knee point at $P = 10$ where the demand weighted average distance is lowest for the Patient Demand Scenario. For the entire curve, the Patient Demand Scenario has the shortest demand weighted average distance, the Risk Demand Scenario the greatest, and the Census Demand Scenario is in-between.

In the next three sections, the optimal facility configuration of the detected knee point (P =10) for each demand scenario is compared to the current facility configuration on a map, as at the time of the study. The names of the optimal locations, the postcodes, and the calculated demand are presented in tables in Appendix 1.

5.3.1.1 Patient Demand Scenario

Figure 5.14 compares the $P = 10$ solution, where the trade-off is optimal, with the current 21 oximeter pick-up facilities of the RPH. Six of 10 facilities were located in or next to towns where RPH facilities were operating (e.g., Harlow, Bedford, Cambridge, Ely, Peterborough, and Norwich). In King's Lynn and Bury St. Edmunds, additional facilities are located to improve the accessibility in the area. Furthermore, between King's Lynn and Peterborough, the ($P = 10$)-median solution suggests a facility in the village Wisbech, where the facility CSSCLS was located. In the Cambridgeshire and Peterborough CCG, the $P = 10$ solution suggests five (i.e., fewer) facilities compared to the current 14 existing facilities.

Figure 5.14 shows that the facility in the western part of the Cambridgeshire and Peterborough CCG has an especially high demand (3,138 patients) and can replace the five surrounding existing facilities. In the south-east, next to the towns Colchester, Ipswich, Chelmsford, and Clacton-on-Sea, the $P = 10$ suggests no facility to be located, because only a small number of patients in the area are referred to RPH facilities. The minimal demand is at the facility in Norwich, with 623 patients, which is the only facility with less than 1,000 patients. The maximal demand is at the clinic located in Cambridge with 3,902 patients, where six of the ten facilities have high demands greater than 2,590 patients.

5.3.1.2 Census Demand Scenario

Figure 5.15 illustrates the facility configuration for the $P = 10$ solution, where the knee point is detected, and compares it to the current OSA facility locations at the time of the study. The current 27 facilities are the new RSSCCSS in Cambridge, Manea, the seven outreach clinics, the 13 GPs, and the five external hospitals. The 10 optimal clinics are distributed all over the study area. These clinics are distributed in a circular shape around the Cambridgeshire and Peterborough CCG, with one clinic inside the CCG as hub. Notably, four clinics were located in the southern part of the study area where the boroughs of London have a high population density. The additional facility inside Cambridgeshire and Peterborough CCG is located in Cambridge, which would replace all the clinics in the southern part of the CCG. Some optimal clinics are located next to a city (e.g. Norwich, Cambridge, Ipswich, King's Lynn, Luton and Chelmsford) and some clinics are located near to an existing clinic (e.g., Norwich, Cambridge, Ipswich, and Luton). The Census Demand Scenario has a population range between 276,438 and 956,639, where the facility with the maximum demand is the southernmost clinic on the map and the one with the minimum demand is in King's Lynn.

5.3.1.3 Risk Demand Scenario

Figure 5.16 illustrates the facility configuration for the ($P = 10$)-median solution and compares it to the locations of the current OSA facilities at the time of the study. The 10 optimal clinics are distributed all over the study area in a circular arrangement around the Cambridgeshire and Peterborough CCG, with one clinic inside the CCG as a hub. Again, the high population density in the boroughs of London seems to support locating a greater number of clinics in the southern part of the study area. The optimal facility inside the Cambridgeshire and Peterborough CCG is located in Cambridge and would replace all of the clinics in the southern part of the CCG. Some clinics are located near an existing clinic (e.g. Norwich, Cambridge, Ipswich, Luton and Chelmsford). The $P = 10$ solution of population weighted Risk Demand has a range between 1,115,849 and 2,961,607, where the clinic with the maximum demand is located in the north of Luton and the clinic with the minimum demand in King's Lynn.

The P-median with the Census Demand Scenario and the Risk Demand Scenario has similar knee points at $P = 10$. Compared to the P-median problem with the Census Demand Scenario, most of the optimally located clinics in the Risk Demand Scenario are in similar locations. The main difference between the Census and Risk Demand Scenarios is the shifting of three facilities. First, the facility located in Ipswich in the Census Demand Scenario moves south towards Colchester in the Risk Demand Scenario. The high-risk region around Clacton-on-Sea and the low-risk regions around Ipswich cause a shift of the optimal location in a southern direction. Second, the facility in Luton moves towards the north in the Risk Demand Scenario because the OSA risk in the north of Luton is greater than the risk in the south of Luton. Third, the clinic between Bedford and Kettering moves towards Kettering in the Risk Demand Scenario. This is due to the high-risk region in Kettering and the low-risk area in Bedford.

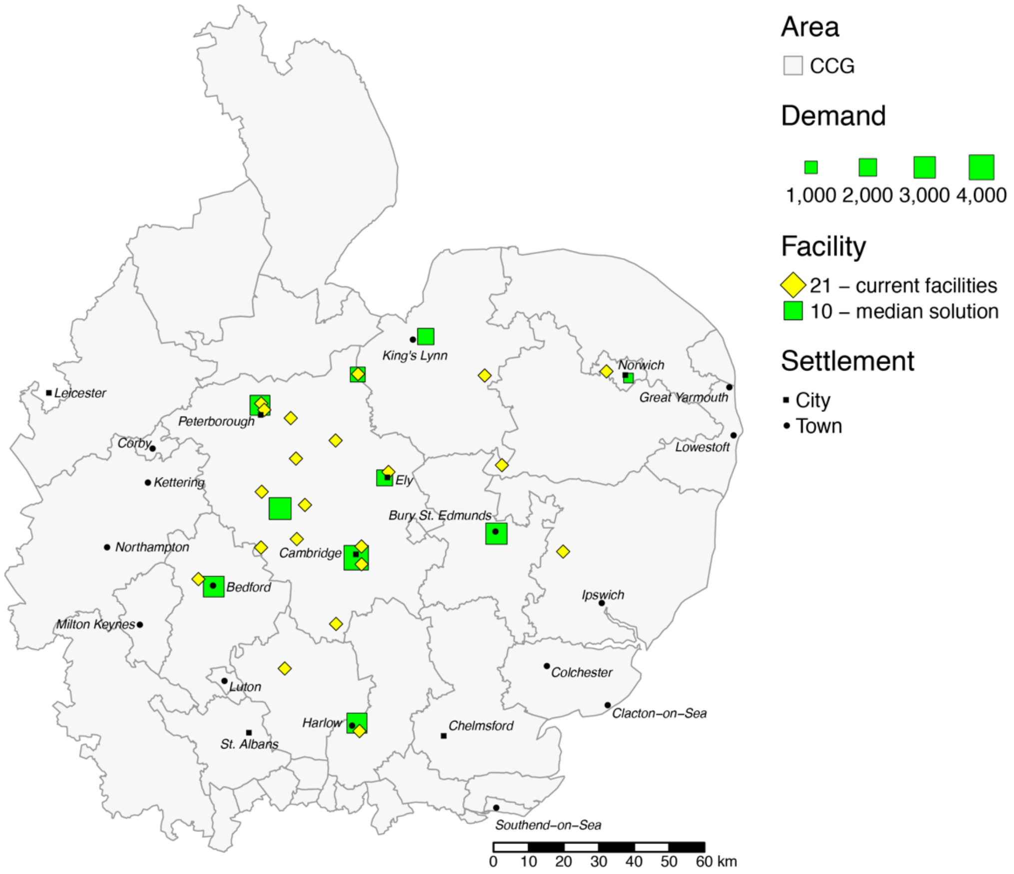

Figure 5.14: (P = 10)-median solution for the Patient Demand Scenario

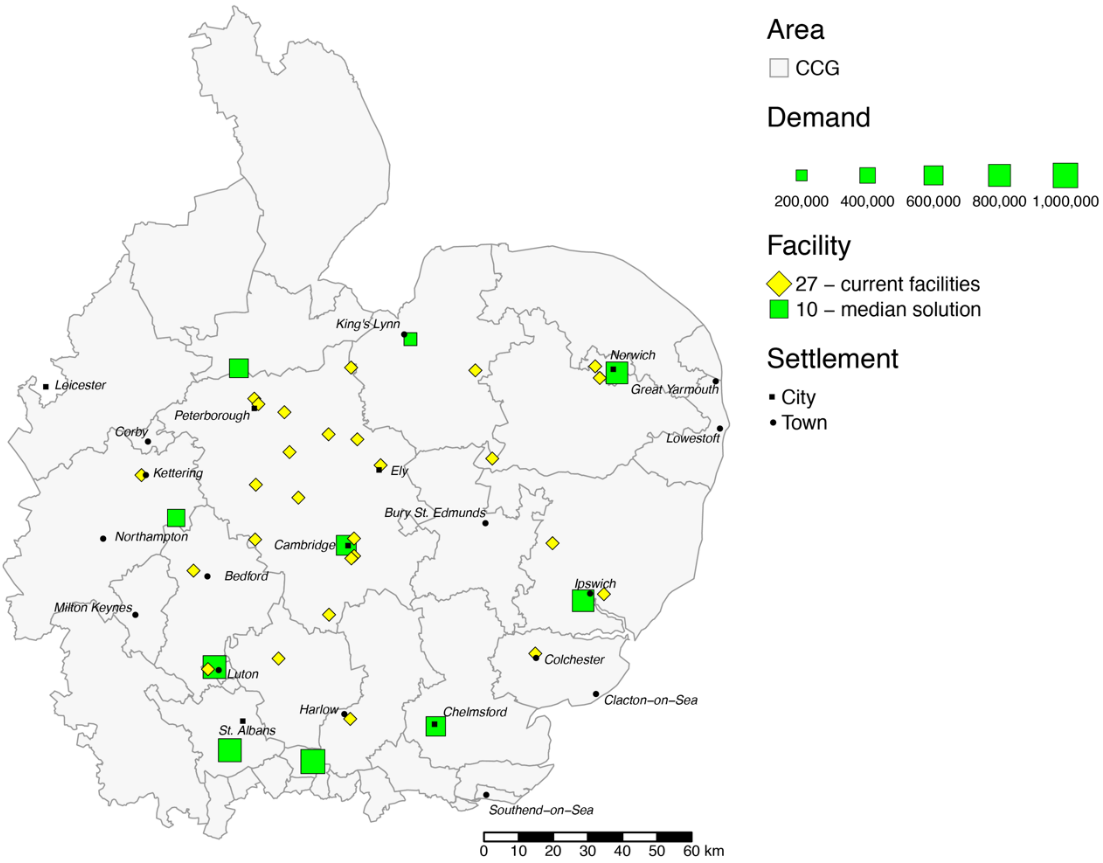

Figure 5.15: (P = 10)-median solution for the Census Demand Scenario

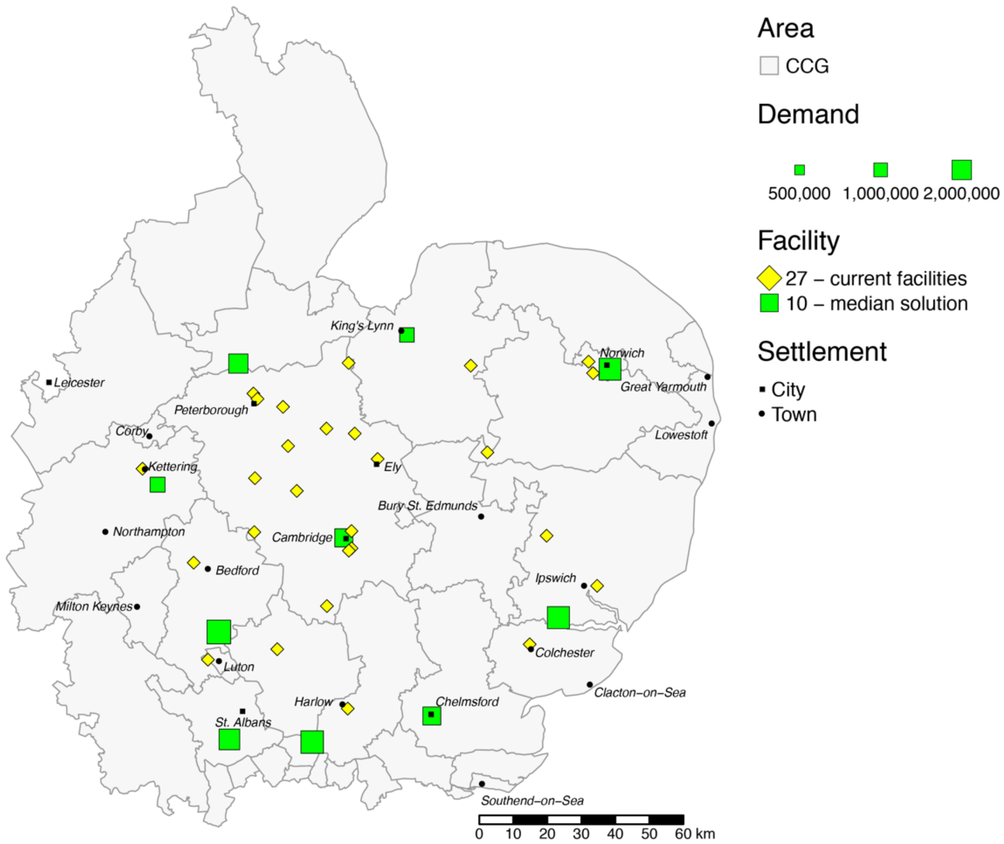

Figure 5.16: (P = 10)-median solution for the Risk Demand Scenario

5.3.2 Conditional *P*-median

The conditional *P*-median was calculated for the three different demand scenarios. The (*P,Q)*-median solution was determined using a trade-off curve (shown in Figure 5.17). Figure 5.17 shows the trade-off curve for the conditional (*P,Q)*-median analysis between the demand weighted distance on the y-axis and the number of facilities (*P,Q*) on the x-axis.

The green curve shows the Patient Demand Scenario, which represents the (*P,Q* = 22)-median curve where *Q* = 22 represents the current facilities at the time of the study (defined as the RSSCCSS at its new location, Manea, the 13 GPs, and the seven outreach facilities) and has a demand weighted average distance of 12.5 km. The Figure 5.17 shows an improvement in distance when locating an additional facility (*P*), where 23 on the x-axis represents adding one additional facility (*P* = 1, *Q* = 22), and 40 implies adding 18 facilities (*P* = 18, *Q* = 22). For each (*P,*22), the curve shows the minimal demand weighted average distance, which is the optimal solution in accessibility for locating the defined *P* facilities in addition to the 22 existing facilities. A suitable knee point of the curve is at 29 facilities, with a demand weighted average distance of 8.9 km. In this solution, seven additional facilities from the 4,686 candidates are located in addition to the 22 existing facilities, which is the (*P* = 7, *Q* = 22)-median solution. Compared to the existing 22 facilities, where the demand weighted distance was 12.5 km, the (*P* = 7, *Q* = 22)-medians improves the accessibility by 3.6 km.

The orange curve shows the distance improvement for each additional facility (*P*) in the Census Demand Scenario, where 28 on the x-axis stands for adding one additional facility to the set of *Q* = 27 existing facilities (*P* = 1, *Q* = 27), and 40 implies adding 13 facilities (*P* = 13, *Q* = 27). *Q* = 27 current facilities includes the RSSCCSS at its new location, Manea, the 13 GPs, the seven outreach facilities, and the five external oximeter hospitals in the study area. The curve has a knee point at 32 facilities, where the demand weighted average distance of the (*P* = 5, *Q* = 27)-median solution is 12.3 km. Compared to the existing 27 facilities, where the demand weighted distance was 18.8 km, the average travel distance reduces by 5.9 km.

The purple curve in Figure 5.17 shows the trade-off for the conditional (*P,Q)*-median analysis between the demand weighted distance and the number of facilities (*P*). The demand weighted average distance for the *Q* = 27 existing facilities is 19 km. The distance shows only marginal improvement after (*P* = 5*, Q* = 27)-median, at which point the demand weighted average distance is 12.6 km, with a total of 32 facilities.

Compared to the current 27 facilities at the time of the study, the demand weighted average distance decreases from 19.0 km to 12.6 km, which is an improvement of 6.4 km.

The comparison of the three scenarios shows that the curve of the Patient Demand Scenario has the shortest demand weighted average distance. The Census Demand Scenario and the Risk Demand Scenario both show a similar demand weighted average distance, where the Risk Demand Scenario distance is always slightly greater than that of the Census Demand Scenario. With 29 facilities at the knee point, the Patient Demand Scenario has fewer facilities in total than the Census Demand Scenario and the Risk Demand Scenario, with 32 facilities each.

In the next three sections, the facility configuration of the detected knee point of each demand scenario is demonstrated on a map. The names, demand, postcode, and facility type of the *(P,Q)*-solution can be looked up in the table presented in Appendix 1.

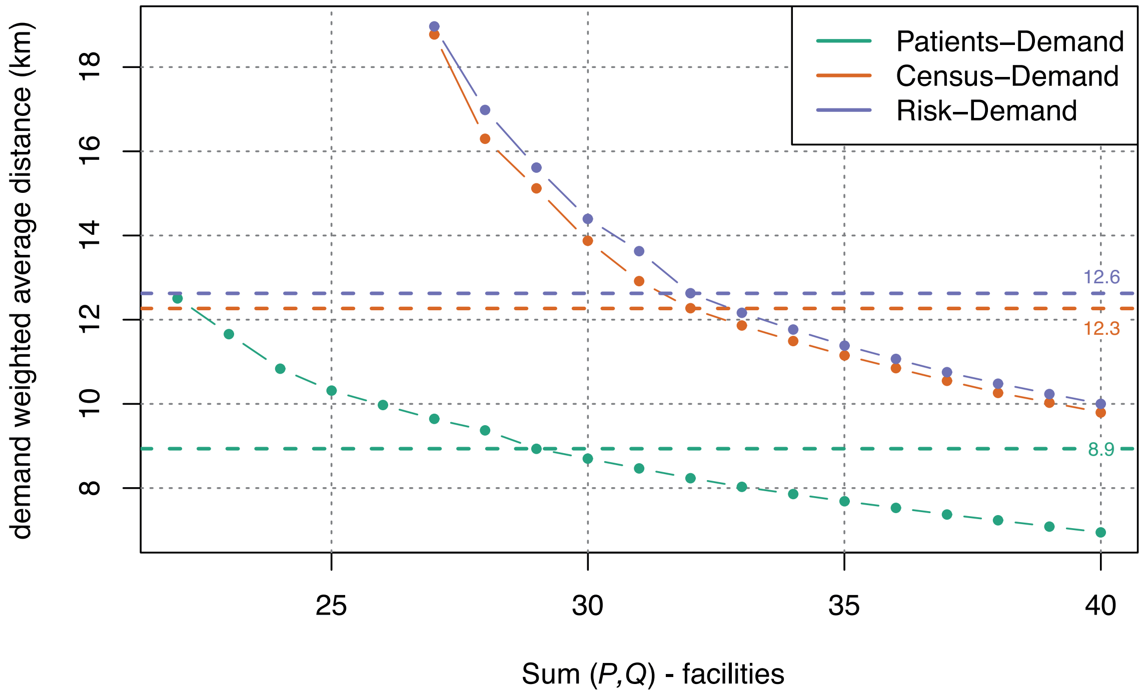

Figure 5.17: Conditional *(P,Q)*-median trade-off curves

5.3.2.1 Patient Demand Scenario

Figure 5.18 illustrates the ($P = 7$, $Q = 22$) medians on the map. An additional facility is located in King's Lynn, where there is a high demand of 1,382 patients. Four additional facilities are located in the north-south directed band, where there was a notable lack of spatial accessibility (presented in Figure 5.10). In Bedford, the ($P = 7$, $Q = 22$) median suggests an additional facility, although an existing facility is operating next to it.

Because of the poor location of the clinic in Bromham, the ($P = 7$, $Q = 22$)-median solution suggests an additional clinic in Bedford. There are current and additional clinics with short distances in-between (e.g., in/next to Peterborough [1.8 km], Cambridge [1 km], and Bromham/Bedford [5 km]). Regarding demand, the seven additional facilities would have between 625 patients and 1,333 patients, which is a higher number than the eight current facilities with the lowest demand. The maximal demand is at the additional clinic in Bedford, with 1,750 patients, and the minimal demand is at Manea clinic, with a demand of 104. Five current clinics have a demand of less than 307 patients (i.e., CSSPMC, CSSRAIN, Manea, CSSBRO, and the new RSSCCSS), likely caused by spatial proximity to other facilities.

5.3.2.2 Census Demand Scenario

Figure 5.19 show the facility configuration for the conditional ($P = 5$, $Q = 27$) solution for the Census Demand Scenario. The five additional facilities surround the current facilities located towards the centre of the study area. Three additional facilities in the south would have a demand greater than 470,000 people caused by the high population density in the boroughs of London. An additional clinic in Lowestoft and an additional facility in the north of Peterborough improve the accessibility in the outer regions. The core region of the map has an oversupply of existing clinics, so the individual existing clinics have lower demand. Overall, the existing facilities have a lower demand compared to the new facilities in this Census Demand Scenario. The five additional clinics all have a demand greater than 200,000, while 10 of the current facilities have a demand of less than 200,000, and nine current facilities have demand of less than 100,000. For the Census Demand Scenario, the current facilities have a lower demand compared to what the additional facilities have. The maximum demand of 778,678 is at the clinic in Watford, to the south of the study area, and the minimum demand of 3,959 is at the Manea clinic, positioned between Ely and King's Lynn.

5.3.2.3 Risk Demand Scenario

Figure 5.20 shows the facility configuration for ($P = 5$, $P = 27$)-median solution. The five additional facilities surround the existing facilities located toward the centre of the study area. Three additional facilities are located in the south of the study area, where the boroughs of London have high population density. Even though the risk in this area is low (as Figure 5.12 shows), the Census Demand is so high that the risk weighted Census Demand needs additional facilities. Furthermore, two additional facilities are located in Lowestoft and in the north of Peterborough. Regarding demand, the clinic with the minimal population weighted Risk Demand is the clinic Manea located in the village Manea between the Ely and King's Lynn with a demand of 16,848. The maximal population weighted Risk Demand is the southernmost clinic of the study area with a demand of 1,949,4230. The five additional facilities are in the top 12 of the 32 clinics in terms of demand in this scenario, and 14 of the current facilities have a demand below 400,000.

The results of the conditional *P*-median in the Census Demand Scenario and Risk Demand Scenario are similar; they both have the same knee point at ($P = 5$, $Q = 27$) medians. Furthermore, looking at the map, both scenarios have located the additional facilities in the same areas. The only minor difference is the demand at the facilities. In the Risk Demand Scenario, the clinic in Chelmsford has a similar demand as the two clinics in the suburbs of London. In the Census Demand Scenario, however, the clinic in Chelmsford has less demand compared to the two clinics in the suburbs of London. This is caused by the risk gradient in the south, where Chelmsford lies within a higher-risk region than the suburbs of London (Figure 5.12). Similar characteristics are displayed for the clinic in Colchester, where the demand in the Risk Demand Scenario is relatively high compared to the Census Demand Scenario, due to the high-risk regions in Clacton-on-Sea.

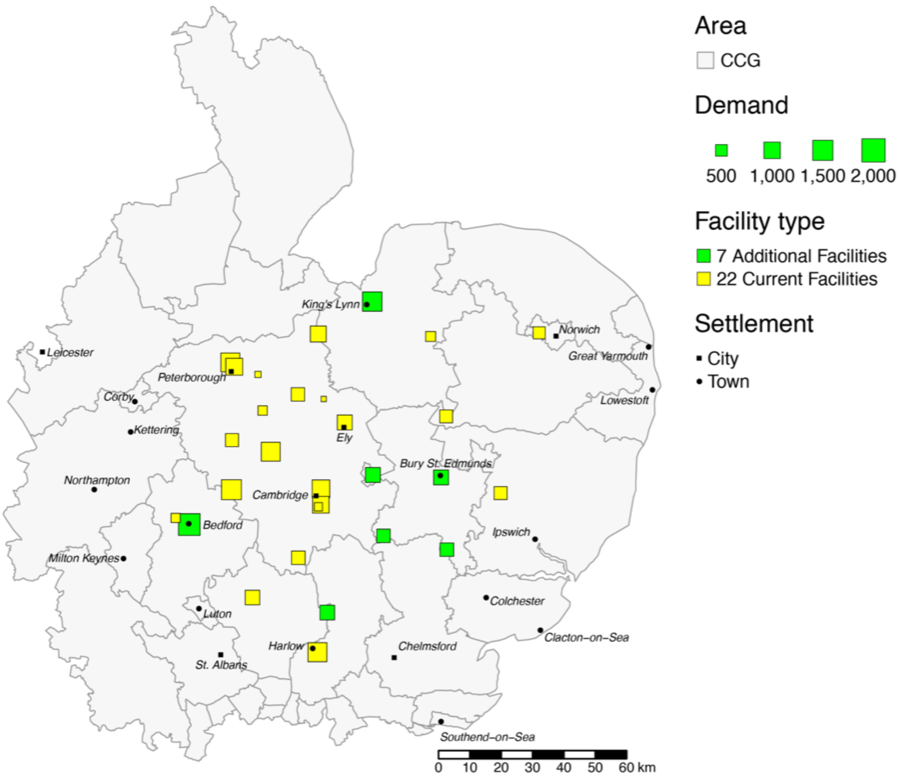

Figure 5.18: Conditional (P = 7, Q = 22)-median solution for the Patient Demand Scenario

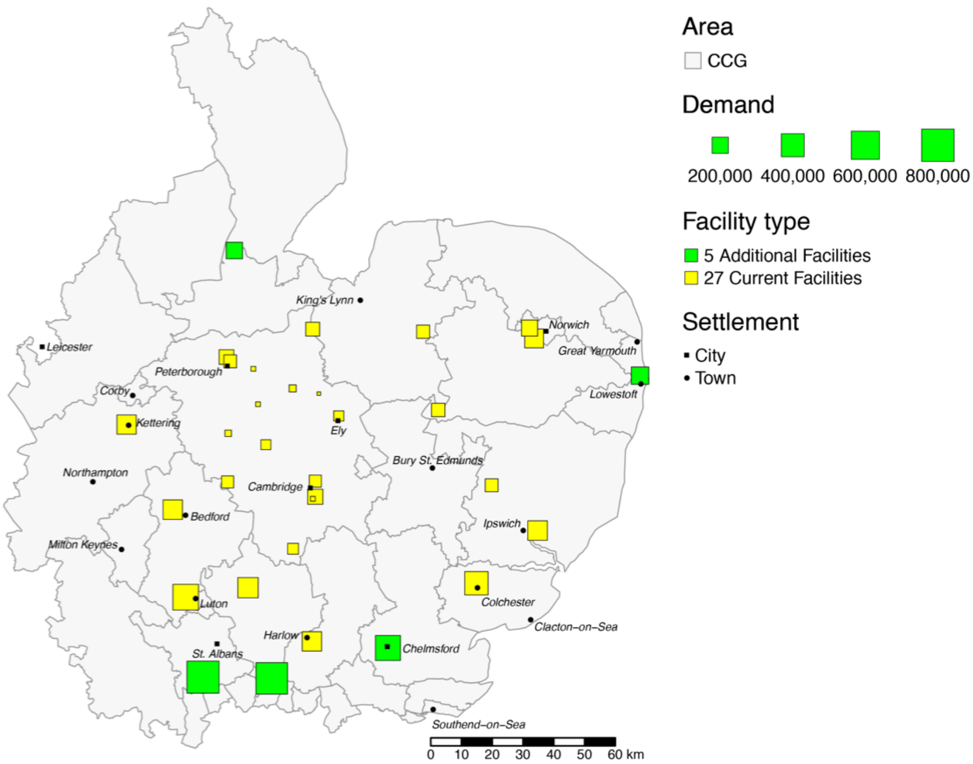

Figure 5.19: Conditional (P = 5, Q = 27)-median solution for the Census Demand Scenario

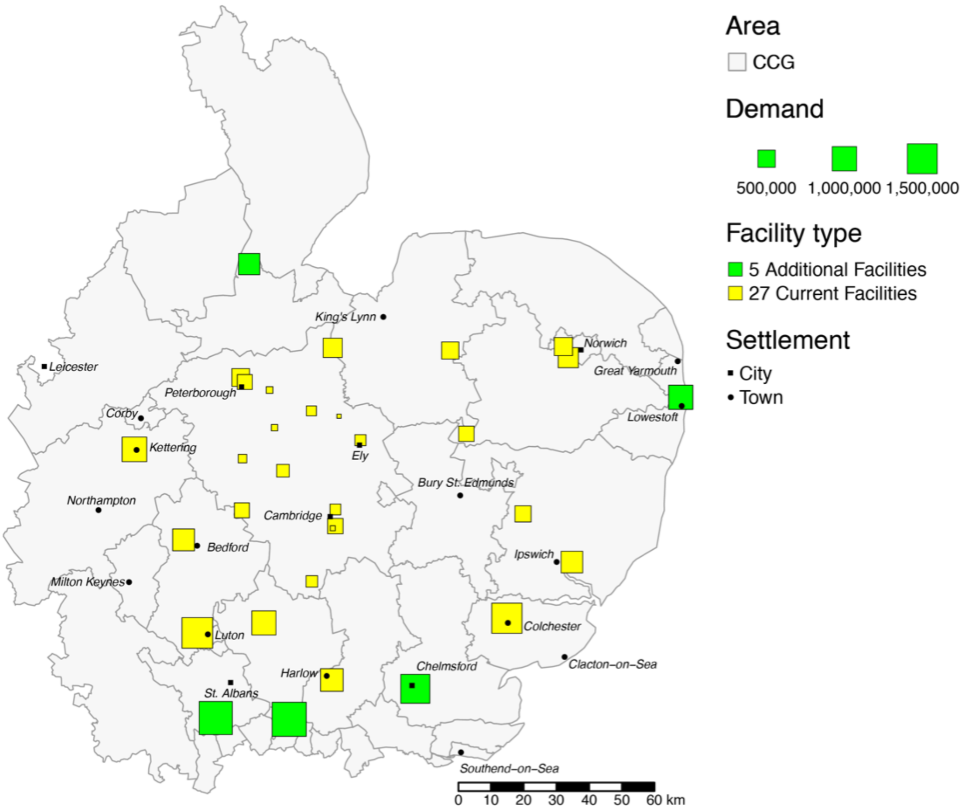

Figure 5.20: Conditional (P = 5, Q = 27)-median solution for the Risk Demand Scenario

6 DISCUSSION

This study had two main objectives: first, to get an overview of the current situation related to accessibility and the trends among RPH patients' facility visits during the period covered by the study. Using historical patient data, the study highlighted the regions with a lack of accessibility and analysed statistics about patients and clinics. The second objective was to provide a solution to improve the spatial accessibility in the RPH catchment area by applying different location allocation models with varied demand scenarios. The optimal number and configuration of facilities was determined using the *P*-median and the conditional *P*-median LAPs. The *P*-median and the conditional *P*-median were calculated for the three different demand scenarios – namely, the Patient Demand, Census Demand, and Risk Demand Scenarios. The different demand scenarios were compared to determine the strengths and weaknesses of each scenario.

6.1 Current Situation

The current situation provides information about patient trends in terms of clinic visits and spatial aspects, such as the patients' home distribution and the actual travel distances to the clinic visited, during the study period.

Hypothesis 1.1: A large number of people pick up at the nearest pick-up facility.

The study has shown that 25% of the pick-up appointments did not take place at the nearest facility. This is especially the case for the patients visiting the RSSCCSS, where over 60% of the pick-up appointments took place and where 97% of the patients passed by smaller pick-up facilities to pick up an oximeter at the RSSCCSS. The patients were visiting the RSSCCSS from the entire study area, so that patients going to the RSSCCSS had a large interquartile range of distances between 22 and 52 km (Figure 5.8). However, for GPs and outreach clinics, the catchment area was smaller than that of the RSSCCSS, so that the patients were more likely to visit the nearest outreach clinics or GPs. For GPs, the ratio of pick-up appointments at the nearest clinic was 80%, while the ratio for outreach clinics was 71%; these figures were far greater than the RSSCCSS, which was the nearest pick-up location for just 2% of patients (Chapter 5.1).

A clear pattern thus exists of patients visiting the main hospital RSSCCSS despite provision of the same oximeter devices at all clinics. There might be several explanations for this pattern. The OSA experts are operating within the hospital, hence the patients may have preferred to visit the hospital (McLafferty, 2003). This explanation is reinforced by the fact that patients with more pick-up appointments were more likely to pick up at RSSCCSS (Figure 5.5). It is reasonable to assume that patients with serious or complex OSA were undergoing oximeter testing at the hospital when more than one oximeter test was needed. Therefore, it would also be reasonable to assume that those patients needed the care and advice of OSA experts rather than general clinic staff. Additionally, the coupled scenario was the most common scenario and always involved picking up an oximeter at the RSSCCSS. Patients having a positive oximeter result always had an appointment at RSSCCSS, independent of the pick-up clinic and pick up scenario. It is likely that patients undergoing two or more oximeter tests (46% had more than one scheduled oximeter pick-up) went directly to the RSSCCSS because they likely had another appointment after initial testing (Figure 5.9). Another reason for the trend of picking up at the RSSCCSS might be misinformation from the referring GP, who may have been uninformed about other pick-up facilities and always sent the patients directly to the hospital. The referring GPs might not have been informed about the fact that all the clinics provide the same service. For travel cost reduction, the uncoupled scenario, with pick-up appointments at the nearest facility, should be applied – especially for the first oximeter pick-up where the test is the most likely to be negative. For diagnosed patients doing a second oximeter test, the coupled scenario is more reasonable because an additional appointment is likely to take place.

It is promising that 80% and 71% of patients were visiting the nearest facilities (Section 5.1) when they visited a GP or an outreach clinic, respectively, especially compared to a resent tuberculosis service study which found that 61% of patients visited the nearest service provider (Smith et al., 2017). Consequently, the spatial accessibility seems to be an important factor for patients choosing GPs and outreach clinics as OSA pick-up facilities.

Regarding distances, the patients had an average journey of 32.9 km, which is quite similar to the result of a study by Yen (2013), which shows that patients were willing to travel approximately 33 km. For the existing OSA facilities, the actual travel distances had a huge distance range, as Figure 5.6 shows. This can potentially be explained by the fact that patients have different opinions regarding a threshold distance which they would travel (Cabrera-Barona et al., 2017). Furthermore, patients might have different social backgrounds; hence, the patient's distance barrier varies and the travel distances, therefore, have a huge range (Buzza et al., 2011). In the optimal solution, where all the patients visit the nearest facility, the average distance is 12.3 km and is, therefore, significantly lower than the distance the patients actually took. Visiting the nearest facility, 90% of patients would have a travel distance below 25 km. This is higher than the results of Lovett et al. (2002), who showed that 90% of patients have a journey time of less than 10 min. This difference is caused by the number of facilities offering health services. The 1,073 GPs in the study area offer better accessibility in term of distance than the 22 OSA facilities.

Hypothesis 1.2: People living far from a pick-up facility are more likely to be a no-show.

The study has shown that the no-show instances for pick-up appointments are not related to the distance to the clinic. The different clinic types have similar no-show rates (hospital: 83.7%; outreach clinics: 85.5%; GPs: 86.7%), even if the average distance is greater for hospitals (39.4 km) than outreach clinics (20.6 km) and GPs (8.0 km) – as Figure 5.8 and Section 5.1.2 show. This study considered no-shows for oximeter pick-up appointments and not for a proper medical appointment and might, therefore, have different results than the previous literature, which showed an association between no-showing and distance in the East of England (Haynes & Bentham, 1979; Parkin, 1979). However, the current study did not distinguish between different social classes and age subgroups, for which Parkin (1979) was able to find negative dependencies. Investigating different age groups separately might be able to uncover trends (Buzza et al., 2011; Watt et al., 1993). The idea of accessibility is more complex than just looking at the aspect of spatial accessibility. Further investigation with a more complex accessibility definition (Penchansky & Thomas, 1981) might be able to find the additional reasons for no-shows in health care. Although this study was not able to find a negative impact on the attendance rate of oximeter pick-ups, accessibility in term of journey distance is an important accessibility barrier (Syed et al., 2013). Future health planning should, therefore, always consider the accessibility in terms of distance.

Hypothesis 1.3: The share of oximeter-tested people is higher for areas close to a facility than those far from a facility.

The registered patient density was linked to the highest population, in the Cambridgeshire and Peterborough CCG, and decreased with additional distance from the RSSCCSS (Figure 5.7). The RSSCCSS was the most significant clinic in terms of number of visits (Figure 5.3) and had a large catchment area (Figure 5.9), so that the distance from the RSSCCSS had an impact on patients' population density. Smaller facilities, such as GPs and outreach clinics, had a slight effect on the patient-population ratio (Figure 5.7). For instance, CSSNOR in Norwich had a patient-population density in the surrounding region of less than 1%; hence, the CSSNOR clinic did not increase the patient-population ratio of the surrounding area. Consequently, the patient-population ratio in Norwich was low due the vast distance to the RSSCCSS and the small impact of GPs and outreach clinics. For GPs and outreach clinics, the study was not able to show a decrease in patients' population density by distance. The hypothesis is, therefore, confirmed for the facility RSSCCSS, while for GPs and outreach clinics the hypothesis is rejected. The pattern of decreasing patient numbers by distance is supported by previous literature (Haynes & Bentham, 1979). However, the current study shows that the patients' distribution is a more complex pattern, where not only the distance from the facility is relevant. The literature shows that different clinic types and patients from different social backgrounds affect the distribution of patients (Buzza et al., 2011; McLafferty, 2003; Parkin, 1979; Watt et al., 1993). Additional factors, such as the clinic type and the characteristics (rural/urban) of the areas, affect the patient density. In the Cambridge and Peterborough CCG, the patient-to-population ratio in rural areas tended to be higher than in urban areas (Figure 5.7). In the context of the disease OSA, the results seem reasonable since the risk estimation shows higher risk in rural areas than in urban areas (Figure 5.12).

This study demonstrates the complexity of defining health facility catchment areas. Even though the patient-to-population ratio decreased with increasing distance from the RSSCCSS, it reached the zero mark only at a vast distance from the RSSCCSS. While 98% of the patients lived in the catchment, the zero-percent areas were found outside the catchment. Patients were free to choose the hospital and were sometimes willing to pass other facilities to get to the preferred health facility. A considerable number of patients continued visiting the RSSCCSS even though there were OSA experts in other hospitals and clinics (here called external clinics). One of the major difficulties in health care planning is to define the catchment area for a health facility when patients display complex behaviours in choosing the facility. In future research, the RPH's oximeter data includes more detailed information about the patient – like age, sex, referral GP, and health characteristics (BMI, smoking, alcohol consumption, and hypotension) – from which potential trends might be detected.

6.2 OSA Risk

The risk determination for the study area, which used the two factors age and overweight, indicates regional variation of OSA risk. The general picture on the level of an OA is similar to the result of the recent risk determination on the level of CCGs by Steier et al. (2014). Rural areas tend to be the high-risk regions, so the prevalence is expected to be high, while urban areas have a lower risk and an expected lower OSA prevalence (Figure 5.12). The number of elderly people ratio is greater and growing more rapidly in rural areas, so the OSA risk determination is higher in rural areas than in urban areas (Walford & Kurek, 2008; Stockdale, 2011). In comparison to Steier et al.'s (2014) results, however, the greatest improvements in risk estimation is the reduction of OSA risk characteristics and doing risk estimation on a more fine-grained geographical unit. The fine-grained risk calculation has the advantage that risk factors have a higher range in prevalence; hence, the risk estimation is more meaningful. This study showed how factors from the differing spatial resolutions can be matched to the lowest spatial unit where risk factor data exists and can then be used to calculate a risk model. Using fine-grained spatial units allows more possibilities in geographical epidemiology applications. One such possibility is incorporating the risk estimates into a LAP, which this study suggests.

6.3 Location Allocation

The current situation analysis showed that problem areas with poor accessibility exist in the study area (Figure 5.10, Figure 5.11). The study suggested different solutions involving reducing and redistributing of the existing 21 oximeter facilities or adding additional facilities to improve accessibility. The ordinary *P*-median solution determined the optimal number of facilities and their optimal configuration based on the accessibility for which all current facilities have to be rearranged. Furthermore, the conditional *P*-median provides solutions for improving the accessibility by locating additional facilities to those operating during the study period.

Hypothesis 2.1: The number of facilities is currently not optimal.

From the perspective of having an optimal number of facilities, the ordinary *P*-median solutions for all three the scenarios suggested reducing the number of facilities to 10 facilities (Section 5.3.1). These 10 facilities provide a similar accessibility as the existing 21 facilities. A reduction in facilities reduces the OSA diagnosis costs for the healthcare system, while ensuring the same level of accessibility for patients. Realising the ordinary *P*-median solution in practice, however, would require a great deal of effort, and would generate costs for redistribution, and might not be feasible. On the other hand, siting and opening an additional clinic using the conditional *P*-median seems more feasible. The conditional *P*-median shows that the number of facilities was too high in the core region of the study area and too low in the areas lacking in accessibility (see Chapter 5.1). The oversupply of clinics in the core region caused a small demand in clinics (Figure 5.19, Figure 5.20). In the peripheral areas, adding only a small number of additional facilities considerably improves the accessibility for the patients living there (Figure 5.18). A slight adjustment of the number of facilities in the different regions of the study area improves the overall accessibility for the patients a great deal, which should, in turn, positively affect patient screening rates. Adjusting the number of facilities is in the health system's economic interests due to savings in clinic operating costs and delivering better accessibility. These improvements could also potentially reduce the number of undiagnosed patients (Leger, Bayon, Laaban, & Philip, 2012; Rejón-Parrilla et al., 2014). From the patient's perspective, diagnosed patients have reduced health costs (Kapur et al., 1999). Furthermore, with CPAP therapy, treated patients enjoy improved quality of life (Batool-Anwar et al., 2016).

Hypothesis 2.2: There is a mismatch between the current pick-up locations and the optimal pick-up locations, suggesting the need for a redistribution of pick-up locations.

The ordinary *P*-median LAP showed the optimal location for different demand scenarios and compared these to the current situation. The different demand scenarios for ordinary *P*-median showed different optimal locations (Section 5.3.1). The Patient Demand Scenario showed that facilities in large cities (e.g. Cambridge, Peterborough, Bedford, Norwich, and Harlow) are located in the same city as the current facilities; hence, the current arrangement of facilities is near optimal, but would still require some reconfiguration to achieve the optimal reduction in average travel distance (Figure 5.14). It is surprising, however, that the ordinary *P*-median for the Patient Demand Scenario suggests a facility in Norwich which competes against an existing external sleeping centre in the same city (Figure 5.14). Patients visiting the RPH facility in

Norwich are making a sub-optimal decision regarding accessibility because, if they have a subsequent appointment at the RSSCCSS as a result of a positive oximeter test, this will result in a longer travel distance. The RSSCCSS is the only facility from the RPH providing appointments; all the GPs and outreach clinics just operate as oximeter pick-up facilities. If patients would instead go to the external sleep clinic centre in Norwich instead, they would get a similar service with lower travel costs.

The NHS should organise the planning and coordination of facilities all over the UK; or, conversely, the local CCGs should take into consideration the external clinics in the UK health planning. This is the only way the clinics can be located in an optimal configuration all over the UK, avoiding redundancies of locations in the health service planning. Patients' home location, which is a factor that has been frequently used in recent literature (Meskarian et al., 2017; Smith et al., 2017), leads to such a redundant facility as Figure 5.14 shows for the city of Norwich. The Census Demand and Risk Demand Scenarios improve this problem. For the defined study area, these two demand scenarios show a mismatch between the current facilities and the optimally located facilities (Figure 5.19, Figure 5.20). The current sleep clinics in the study area do not provide OSA diagnosis in the southern peripheral areas (e.g., Boroughs of London), where most of the facilities in the scenarios are being placed (Figure 5.19, Figure 5.20). For the Cambridgeshire and Peterborough CCG, the study has shown the difficulty of health care planning. The conditional *P*-median showed that the current facilities can provide good access to OSA diagnosis in core areas, thus no additional facility is located in these areas. However, adding a few additional facilities in the other parts of the study area significantly improves the overall accessibility for all the scenarios. The best locations for facilities are mostly in large cities and towns. Towns are the optimal location for the Risk Demand Scenario, although the OSA risk tends to be higher in rural areas (Figure 5.12). The population weighted Risk Demand remains higher in urban areas than in rural areas, but is still strong enough to slightly shift the facility location to the higher-risk areas (Comparing Figure 5.19 and Figure 5.20).

Additionally, this study was able to show the improvement in spatial accessibility by adding an additional facility. The conditional *P*-median with the Census Demand Scenario reduced the demand weighted average distance by 35% (from 18.8 km to 12.3 km). The spatial accessibility reduction is similar in comparison to Mohan's (1983) hospital study around Durham, which was able to reduce the average distance by between 32.7% and 49.8%, depending on the scenario. It can thus be concluded that a conditional location allocation model can provide solutions that improve the spatial accessibility in health care.

6.4 Strength and Limitations

6.4.1 Current Situation

The situation at the time this study showed that patients' home and pick-up appointment data can be used for an accessibility study. The problem areas for spatial accessibility can be determined from the patients' home locations, and the data is sufficient to get an overview of the trends in patients' clinic choice. Other health providers in other study areas with similar data about the registered patients can also apply this analytical approach to their application area. One limitation is that the study was just able to show the pattern in clinic visits but could not explain the patients' motivation behind their choice of clinics. Further research should investigate the motivation of patients in choosing which clinic they visit. Accessibility includes more than just spatial accessibility (Penchansky & Thomas, 1981); nevertheless, it might be an important factor, especially for older, immobile patients. An additional limitation is the distance analysis which just considers the accessibility by car in an undirected street network and, therefore, does not account for accessibility by public transport. It is likely that the optimal locations identified might be non-optimal in terms of travel by public transport. It is, moreover, assumed that patients always travel from home to the clinic to pick up an oximeter. In practice, the patient might combine the pick-up journey with other activities at other places, such as working or shopping.

6.4.2 Risk Model

The risk determination falls into the ecological fallacy due to using aggregated data which do not take individual differences into account (Freedman, 1999; Mendoza et al., 2013). The strength of the risk determination is the regional variation in the risk on a low geographical level. The study showed that a spatial risk model should only include independent risk factors having a high spatial variation. The risk factor *sex* would not improve the risk determination due to the low deviation. Furthermore, the study showed how general health factors from different spatial units can be combined into a risk model. Using the risk determination approach, the different regions can be compared and classified, even if the prevalence of the disease remains unknown.

6.4.3 Location Allocation Model

One strength of the location allocation model is the determination of the optimal location based on candidate facilities (hospital, GPs, clinics, and pharmacies) which could all operate as a pick-up facility. The candidate facilities operating at the time of the study are able to store and supply oximeters, thus they could extend their service with the oximeter pick-up service with marginal investments. An additional strength of the model is the use of the *P*-median LAP, which can determine a suitable number of facilities and which does not have the issue of allocating too many facilities that appears in other location allocation approaches (Daskin & Dean, 2005). The *P*-median is especially strong in the Patient Demand Scenario, where the patients are unevenly distributed in the study area. The *P*-median is one of the best location allocation models in health care planning and provides effective solutions (Fo & da Silva Mota, 2012). A main limitation is the assumption that patients always travel from home to clinic and back and do not combine the trip with other duties such as shopping or working. The location allocation model assumes that all the patients go to the nearest facility, which is not the case in the research data for this study. The location allocation equally considers all the candidate facilities in the *P*-median problem. As the analysis in this study shows, the clinic type is the key factor in a patient's choice to visit the facility. Depending on facility type, the patients are willing to travel longer (for hospitals) or shorter (GPs and outreach clinics) distances. The model is limited in differentiating clinic types and might be improved with a hierarchical location model (Sinuany-Stern et al., 1995). Thus far, the location allocation model did not take the clinic capacity into account. Even if all the candidate facilities can operate as a pick-up facility, they may have a limited capacity to do so, which the model should take into account. Furthermore, the study does not propose the number of oximeters that should be stored in a pick-up facility to satisfy Patient Demands. While it is outside the scope of this study, the oximeter stack per facility should be estimated based on historical oximeter data to make the system as efficient as possible.

The different demand scenarios each have strengths and weaknesses. The strength of facility location planning based on the patient's demand is that the locations can be applied even if the facilities' catchment is difficult to define. This study showed that patient data is useful for health planning, even if it is not designed for research (Gordis, 2013, p. 55). Patient data is especially useful for studies where the study area is difficult to define. Utilising patient data in health care optimisation has been done in previous research so that the clinics are located based on the historical demand (Meskarian et al., 2017; C. M. Smith et al., 2017). The Patient Demand has limitations in locating the facilities based on the entire population because it is not necessarily representative. The patient-population density might change based on the supply of clinics and is, therefore, not representative (e.g., an additional clinic in the south of the study area might increase the patient-population ratio in the south). The study showed that the patient density decreases with additional distance from the RSSCCSS; the patients' demand for the location allocation model will give little consideration to the regions far from the RSSCCSS. The weakness of the location allocation model using a Patient Demand Scenario is the strength of the Census Demand Scenario. The *P*-median provides a solution in which the total population has the best accessibility, which might better take a consistent population into account. This study provides a framework for improving the Census Demand using estimated risk as input. The Risk Demand Scenario improves the determination of optimal facilities. In regions with a risk gradient, the facility's location is shifted to the high-risk regions. The strength of this Risk Demand Scenario lies in the combination of risk and Census Demand (population weighted risk), so that the facilities are just slightly shifted to the risk, but the entire population is still considered. This solution still locates the clinics in the cities and not in the rural high-risk regions, and it improves the location allocation model with Census Demand. The total population is only a rough approximation of the demand, assuming homogenous health needs (Mohan, 1983). The current study was able to improve this approximation using the idea of a risk-based demand. The Risk Demand is able to determine an unevenly distributed OSA demand to improve the homogenous Census Demand.

In practice, it is crucial for the RPH to define a proper catchment area for which they want to provide OSA health care services. The study area is appropriate for the current situation analysis, but has limits in the LAP. For the current analysis, including 98% of the patients reduces the outliers and allows a representative study area to be defined. For the location allocation model, the study area includes catchment areas of other OSA health providers so that the study area can be defined differently. The Census and Risk Demand Scenarios suggest facilities in the boroughs of London, where the population density is high. The patients in the boroughs of London might be London orientated, and they can rapidly reach the city by public transport. The RPH catchment definition needs to integrate other OSA health institutions in planning service provision so that the regions are not covered by multiple different institutions that introduce redundancies or inefficiencies.

6.5 Recommendations for Practice

The current study has conducted an analysis of historical OSA patient data and examined the problem of OSA health care accessibility and the configurations of facilities for the first time. Other organisations providing OSA health services should similarly analyse their facilities in a spatial accessibility context to discover accessibility patterns in their area. The study provided a framework for improving the problem of accessibility using an OSA risk-weighting approach in a location allocation model. The current study shows how a risk approach can improve the limitation found by Mohan (1983), who has explained that the total population is a rough approximation of health demand. The population is heterogeneous, has different health and social characteristics, and, consequently, an uneven health demand. The OSA risk weighting can be applied in all countries with a census survey that includes information about the age of the population. This study just focused on optimising facilities in terms of location and travel distance. In practice, all the access dimensions have to be considered to find a suitable facility. For instance, the optimal location of the *P*-median might not be acceptable; hence, the facility should not be chosen as an optimal location. In the case where an optimal facility location is sub-optimal in terms of other access dimensions, the facility should be excluded from the list of candidate facilities, and the *P*-median algorithm should be applied once more to determine the optimal facility location. For the UK, a nationwide location allocation analysis would avoid the bias of study area definition and might improve the OSA diagnostic system, reduce the number of undiagnosed OSA cases, reduce OSA-related car accidents, and potentially decrease health care costs (British Lung Foundation, 2015; Garbarino et al., 2015; Rejón-Parrilla et al., 2014).

7 CONCLUSION

7.1 Major Findings

This study showed how patient data can be used in health geography to analyse the current situation and to provide solutions for improving the problem of accessibility. The study analysis of a historical OSA patient survey made the following key findings:

1. Patients were distributed all over the study area and were willing to pass other oximeter faculties to reach the RSSCCSS. For smaller clinics (e.g., GPs and outreach clinics), the patients commonly visited the nearest facility. The patient density was highest next to the RSSCCSS and decreased with increasing distance from the RSSCCSS (Figure 5.2). Depending on their home location, patients suffered from poor accessibility to OSA health facilities (Figure 5.11). Poor accessibility regions in the study area were in the north, along the coast, in the south-east, and in the south. The existing pick-up facilities were, consequently, non-optimally located and can be improved by shifting their location around (Figure 5.14).
2. The RPH facilities had an uneven number of oximeter pick-up appointments per year, depending on the facility type, with GPs having the lowest number, outreach clinics the middle, and the RSSCCSS the highest number of pick-up appointments (Figure 5.5). The pick-up no-show rate was similar for all the clinic types and was worst for recently opened facilities (Figure 5.8).
3. Over half of the patients were tested with an oximeter only once. Patients undergoing more than one oximeter test were more likely to visit the RSSCCSS (Figure 5.5).

The OSA risk estimation was able to determine the spatial variation of risk on the geographical level of an OA. Rural areas are likely to be high-risk regions, while urban areas are likely to be low-risk areas (Figure 5.12). Using two equal weighted risk factors in the risk determination delivers similar results as the risk model of Steier et al. (2014), with five risk factors. The study showed that, in a spatial distributed model, the data from the lowest spatial unit should be included and data having a small value range (e.g., gender) should be excluded.

The location allocation analysis showed the differences among optimal facilities when using different demand scenarios (Section 5.3). All the location allocation results improved the situation at the time of the study – either by reducing the number of clinics with equal accessibility as in the current situation or by adding additional facilities to improve the distance accessibility. In the Cambridgeshire and Peterborough CCG, there was a high clinic density; hence, a fewer number of facilities can reduce service costs with just marginally poorer accessibility for patients. In the outer region, new facilities need to be located to improve the accessibility. The Risk Demand Scenario improves the *P*-median problem compared to the Census Demand Scenario (Section 5.3.1.3). The facility locations are shifted towards the higher-risk regions. However, even if the estimated risk is higher in rural areas, the optimal facility locations are mainly in towns and cities. For RPH, it is crucial to define an appropriate catchment area for which the RPH wants to provide OSA services. Especially for the boroughs of London, where the Census and Risk Demand Scenarios would locate additional facilities, the RPH needs to decide on including or excluding the regions, giving due consideration to the fact that people might be London orientated and not Cambridge orientated.

7.2 Future Work

In the present study, the analysis was unable to explain the impact of different health characteristics on patients' tendencies related to clinic choice, not showing up for appointments, and the number of oximeter tests undergone. Future work might focus on the detailed patient characteristics which are included in historical oximeter surveys and generate more diverse findings. Furthermore, patient questionnaires at appointments might give insight into the motivation beyond clinic choice and could assist in further analysis of the different dimensions of access.

In the context of the location allocation analysis, future studies might focus on demand forecasts and an extended location allocation model. With regards to forecasts, the Risk Demand Scenario might be extended using risk forecasts. Obesity and age are both characteristics which will likely grow in prevalence in the future; hence, the Risk Demand will change (Agha & Agha, 2017; Walford & Kurek, 2008). For an extended location allocation model, the current location allocation model can be improved by differentiating among the clinic types – for instance, using a hierarchical location model (Sinuany-Stern et al., 1995). Additionally, the model can be optimised by different optimisation heuristics which might provide different optimal solutions (Daskin & Maass, 2015). In health planning, location allocation models with a Risk Demand Scenario should be applied for other diseases using routinely provided health and census data. Furthermore, it would be interesting to apply the same analysis in other study areas to confirm the findings of this study.

One objective for more research would be to examine the impacts of the optimal facility configuration compared to the current facility configuration. It is crucial for optimal facility planning to determine whether the optimal facility configuration has a positive impact on patient satisfaction. There are many hypotheses in literature which can be tested to compare an optimal RPH facility configuration to the current sub-optimal facility configuration – for example, increasing the rate of diagnosis, reducing health care costs, reducing the number of accidents due to daytime sleepiness, or improving patient satisfaction with OSA services.

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9 APPENDICES

APPENDIX 1 LOCATION ALLOCATION PROBLEM

The tables give information about the optimal facilities of the location allocation analysis. Each table include information about the name, town/city, postcode, facility type and demand. Each of the six tables represents one location allocation scenario.

Table 9.1: Ordinary (P = 10)-median solution for the Patient Demand Scenario

Organisation Name	**Organisation Type**	**City**	**Postcode**	**Demand Weight**
Boots	Pharmacy	Norwich	NR2 1LD	623
BPAS Bedford	Clinic	Bedford	MK42 0AH	2,807
Cambs and Peterborough Referral Support Services - Fenland Area	Clinic	Wisbech	PE13 1HG	1,446
Cambs and Peterborough Referral Support Services - Huntingdon Area	Clinic	Huntingdon	PE29 3TN	3,138
Cuh At Turning Point	Clinic	Bury St. Edmunds	IP33 1HE	2,945
Gft Davies and Co.	Pharmacy	Cambridge	CB2 1LA	3,902
Graham Young Chemist (2007) Ltd	Pharmacy	Peterborough	PE1 3HA	2,590
Lloyds Pharmacy	Pharmacy	Ely	CB7 4HF	1,667
Nuffield House Doctors Surgery	GP	Harlow	CM20 3AX	2,638
The Queen Elizabeth Hospital	Hospital	King's Lynn	PE30 4ET	1,730

Table 9.2: Ordinary (P = 10)-median solution for the Census Demand Scenario

Organisation Name	Organisation Type	City	Postcode	Demand Weight
Boots	Pharmacy	Norwich	NR2 1LD	780,532
Boots	Pharmacy	Rushden	NN10 0QE	493,578
Bridge Street Medical Centre	GP	Cambridge	CB2 3LS	655,751
Chelmsford and Essex Centre	Clinic	Chelmsford	CM2 0QH	622,085
Dr Mohammed Abedi	GP	Enfield	EN3 4DE	956,639
LloydsPharmacy	Pharmacy	NA	LU3 2NJ	856,933
LloydsPharmacy Inside Sainsbury's	Pharmacy	NA	PE30 4LR	276,438
Pinewood Surgery Ipswich	GP	Ipswich	IP8 3SL	777,235
St Albans Road	Clinic	Watford	WD25 9FG	874,427
Well Market Deeping - Rainbow Superstore	Pharmacy	Peterborough	PE6 8EA	584,814

Table 9.3: Ordinary (P = 10)-median solution for the Risk Demand Scenario

Organisation Name	Organisation Type	City	Postcode	Demand Weight
Bridge Street Medical Centre	GP	Cambridge	CB2 3LS	1,737,581.5
C and H (Barton) Ltd	Pharmacy	Barton-le-Clay	MK45 4LL	2,961,607
Chelmsford and Essex Centre	Clinic	Chelmsford	CM2 0QH	1,715,604.5
Constable Country Rural Medical Practice	GP	Colchester	CO7 6RT	2,580,029.5
Dr Spencer And Partners	GP	Kettering	NN15 5PU	1,178,901
LloydsPharmacy Inside Sainsbury's	Pharmacy	NA	PE30 4LR	1,115,849
St Albans Road	Clinic	Watford	WD25 9FG	2,266,078.5
Unit 5 St John's Row	Clinic	Norwich	NR1 3DD	2,526,187
Well Enfield - 644 Hertford Road	Pharmacy	Middlesex	EN3 6NA	2,688,684
Well Market Deeping - Rainbow Superstore	Pharmacy	Peterborough	PE6 8EA	1,965,551

Table 9.4: Conditional (P = 7, Q = 22)-median solution for the Patient Demand Scenario: In white: (Q = 22) current facilities. In grey: (P = 7) additional facilities.

Organistaion Name	Organisation Type	City	Postcode	Demand Weight
Alconbury and Brampton Surgeries	GP	Huntingdon	PE28 4EQ	634
Bishops Stortford Chiropractic Clinic	Clinic	Bishop's Stortford	CM23 2DH	814
Boots	Pharmacy	Sudbury	CO10 2EA	680
BPAS Bedford	Clinic	Bedford	MK42 0AH	1750
Bromham	outreach	Bromham	MK43 8JT	307
Cathedral Medical Centre	GP	Ely	CB6 1DN	825
Cedar House Surgery	GP	St Neots	PE19 1BQ	1453
Clarkson Surgery	GP	Wisbech	PE13 3AN	958
Clock Pharmacy	Pharmacy	King's Lynn	PE30 4EA	1382
Cuh At Turning Point	Clinic	Bury St. Edmunds	IP33 1HE	824
Doddington Medical Centre	GP	March	PE15 0TG	665
Granta Medical Practices Barley Surgery	GP	Barley	SG8 8HY	681
Harlow	outreach	Harlow	CM18 6LY	1,340
Manea	hospital	Manea	PE15 0GN	104
New Papworth	hospital	Papworth	CB2 0QQ	254
Norwich	outreach	Norwich	NR5 0GB	538
Nuffield Road Medical Centre	GP	Cambridge	CB4 1GL	1,170
Park Medical Centre	GP	Peterborough	PE1 2UF	1,063

Organistaion Name	Organisation Type	City	Postcode	Demand Weight
Rainbow Surgery	GP	Huntingdon	PE26 1SA	326
Spinney Surgery	GP	St Ives	PE27 3TP	1,323
Stevenage	outreach	Stevenage	SG1 5RD	786
Stowmarket	outreach	Stowmarket	IP14 1NL	623
Swaffham	outreach	Swaffham	PE37 7HL	369
Tesco Instore Pharmacy	Pharmacy	Haverhill	CB9 0BQ	675
Tesco Stores Ltd	Pharmacy	Newmarket	CB8 7AH	832
The New Queen Street Surgery	GP	Peterborough	PE7 1AT	147
The Queen Edith Medical Practice	GP	Cambridge	CB1 8PJ	1,023
Thetford	outreach	Thetford	IP24 1JD	620
Thistlemoor Medical Centre	GP	Peterborough	PE1 3HP	1,320

Table 9.5: Conditional *(P* = 5, *Q* = 27)-median solution for the Census Demand Scenario: In white: (*Q* = 27*)* current facilities. In grey: *(P* = 5) additional facilities.

Organisation Name	**Organisation Type**	**City**	**Postcode**	**Demand Weight**
New Papworth hospital	hospital	Papworth	CB2 0QQ	17,443
Ipswich Hospital	External Hospital	Ipswich	IP4 5PD	289,959
Colchester Hospital	External Hospital	Colchester	CO4 5JL	412,839
Luton and Dunstable Hospital	External Hospital	Luton	LU4 0DZ	500,394
Norfolk and Norwich hospital	External Hospital	Norfolk	NR4 7UY	271,346
Kettering general Hospital	External Hospital	Kettering	NN16 8UZ	282,180
Manea	Outreach	Manea	PE15 0GN	3,959
Lincoln Co-Op Chemists Ltd	Pharmacy	Spalding	PE11 4ST	207,904
Thetford	outreach	Thetford	IP24 1JD	136,871
Healthfare Pharmacy	Pharmacy	enfield	EN1 1YY	751,747
Swaffham	outreach	Swaffham	PE37 7HL	133,805
Cathedral Medical Centre	GP	Ely	CB6 1DN	78,486
Harlow	outreach	Harlow	CM18 6LY	285,349
Alconbury and Brampton Surgeries	GP	Huntingdon	PE28 4EQ	31,465
Park Medical Centre	GP	Peterborough	PE1 2UF	127,909
Clarkson Surgery	GP	Wisbech	PE13 3AN	145,339
Nuffield Road Medical Centre	GP	Cambridge	CB4 1GL	110,522

Organisation Name	Organisation Type	City	Postcode	Demand Weight
The New Queen Street Surgery	GP	Peterborough	PE7 1AT	18,459
Spinney Surgery	GP	St Ives	PE27 3TP	73,914
Cedar House Surgery	GP	St Neots	PE19 1BQ	110,598
The Queen Edith Medical Practice	GP	Cambridge	CB1 8PJ	174,002
Doddington Medical Centre	GP	March	PE15 0TG	38,125
Rainbow Surgery	GP	Huntingdon	PE26 1SA	16,756
Thistlemoor Medical Centre	GP	Peterborough	PE1 3HP	163,613
Norwich	outreach	Norwich	NR5 0GB	195,657
Avenue Clinic	Clinic	Watford	WD17 3NU	778,678
Stevenage	outreach	Stevenage	SG1 5RD	311,964
Chelmsford and Essex Centre	Clinic	Chelmsford	CM2 0QH	477,337
Granta Medical Practices Barley Surgery	GP	Barley	SG8 8HY	89,589
Stowmarket	outreach	Stowmarket	IP14 1NL	125,429
Bromham	outreach	Bromham	MK43 8JT	285,944
Oulton Ooh Base	Clinic	Lowestoft	NR32 3AZ	230,850

Table 9.6: Conditional $(P = 5, Q = 27)$-median solution for the Risk Demand Scenario: In white: $(Q = 27)$ current facilities. In grey: $(P = 5)$ additional facilities.

Organisation Name	Organisation Type	City	Postcode	Demand Weight
Alconbury and Brampton Surgeries	GP	Huntingdon	PE28 4EQ	124,245
Avenue Clinic	Clinic	Watford	WD17 3NU	1,837,463
Bromham	outreach	Bromham	MK43 8JT	801,912
Cathedral Medical Centre	GP	Ely	CB6 1DN	208,643.5
Cedar House Surgery	GP	St Neots	PE19 1BQ	379,684.5
Clarkson Surgery	GP	Wisbech	PE13 3AN	619,849.5
Colchester hospital	External Hospital	Colchester	CO4 5JL	152,6824
Doddington Medical Centre	GP	March	PE15 0TG	165,809
Granta Medical Practices Barley Surgery	GP	Barley	SG8 8HY	223,613
Harlow	outreach	Harlow	CM18 6LY	861,326.5
Healthfare Pharmacy	Pharmacy	Enfield	EN1 1YY	1,949,429.5
Ipswich hospital	External hospital	Ipswich	IP4 5PD	786,772
Kettering general hospital	External hospital	Kettering	NN16 8UZ	1,019,183.5
Lincoln Co-Op Chemists Ltd	Pharmacy	Spalding	PE11 4ST	753,474
Luton and Dunstable hospital	External Hospital	Luton	LU4 0DZ	1,575,714.5
Manea	outreach	Manea	PE15 0GN	16,848
New Papworth	hospital	Papworth	CB2 0QQ	42,393.5

Organisation Name	Organisation Type	City	Postcode	Demand Weight
Norfolk and Norwich hospital	External hospital	Norfolk	NR4 7UY	681,717.5
Norwich	outreach	Norwich	NR5 0GB	557,147
Nuffield Road Medical Centre	GP	Cambridge	CB4 1GL	195,850.5
Oulton Medical Centre	Clinic	Lowestoft	NR32 3AZ	984,063.5
Park Medical Centre	GP	Peterborough	PE1 2UF	376,383
Rainbow Surgery	GP	Huntingdon	PE26 1SA	689,44.5
Spinney Surgery	GP	St Ives	PE27 3TP	266,897.5
Stevenage	outreach	Stevenage	SG1 5RD	974,292.5
Stowmarket	outreach	Stowmarket	IP14 1NL	437,951.5
Sutherland Lodge Surgery	GP	Chelmsford	CM2 7PY	140,8517
Swaffham	outreach	Swaffham	PE37 7HL	494,875
The New Queen Street Surgery	GP	Peterborough	PE7 1AT	76,309
The Queen Edith Medical Practice	GP	Cambridge	CB1 8PJ	394,524.5
Thetford	outreach	Thetford	IP24 1JD	399,121
Thistlemoor Medical Centre	GP	Peterborough	PE1 3HP	526,294

APPENDIX 2 EXTERNAL OSA HOSPITALS

The study considers externals sleep diagnostic centres. They are all hospitals providing sleep diagnostic for other OSA clinics in the East of England. The table matches the used short name to the entire name and the post code.

Table 9.7: Currently operating external sleep diagnostic centres in the study area.

Short Name	Official Name	Postcode
HNONO	NORFOLK AND NORWICH UNIVERSITY HOSPITALS NHS FOUNDATION TRUST	CO4 5JL
HIPS	IPSWICH HOSPITAL NHS TRUST	CO4 5JL
HCOL	COLCHESTER HOSPITAL UNIVERSITY NHS FOUNDATION TRUST	CO4 5JL
HLUDU	LUTON AND DUNSTABLE UNIVERSITY HOSPITAL NHS FOUNDATION TRUST	LU4 0DZ
HKET	KETTERING GENERAL HOSPITAL NHS FOUNDATION TRUST	NN16 8UZ

DECLARATION

Personal declaration: I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

Sign: L. Hubler

Loris Christian Hubler, 30.06.2019