

# Stadia and Sporting Events in London, Use of GPS Data to analyse Spectators Behaviour

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University College London

MSc Smart Cities and Urban Analytics

The Bartlett Centre for Advanced Spatial Analysis

Module ID CASA0010

Submitted 30th August 2019

Word count: 11,893

This dissertation is submitted in partial requirement for the MSc in the Centre for Advanced  
Spatial Analysis, Bartlett Faculty of the Built Environment, UCL

## **Abstract**

Mobile phones evolved into sophisticated sensors, capable of monitoring and recording individual behavioral data, which collectively help to identify urban trends. Recognizing their capabilities, the study was designed to get an understanding of the spectators' behaviour at event stadia across London. The literature has seen numerous studies in the spatio-temporal and socio-economic processes occurring during large-scale events. While Computer Scientists and Urban Analysts explored human's mobility and crowd-behaviour, Economists and Geographers researched humans' behaviour and interest. As such, previous research have given little attention to the analysis of spectators at large-and small-scale sporting events.

This study examined the spectators flows for each event, their arrival, departure and dwell time as well as their origin, i.e home location and travel distance. Moreover, different from most geodemographic studies, this paper investigated the demographic profile of events' spectators regarding the classification of residential neighbourhoods used for market segmentation. This novel approach allows the identification of the socio-economic profiles of spectators to an extent that would not have been possible through traditional survey methods. Transport planners and sporting event managers will benefit from the results and the extended discussion to gain further insight into the attitudes and interests of their sport spectators.

## **Declaration of Authorship**

I, Aude Vuillomenet, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. It is 11,893 words in length.

Signed:

Date:

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## List of Abbreviations

CDR	Call Data Records
DBSCAN	Density-Based Spatial Clustering Algorithm with Noise
EPL	English Premier League
FA	English Football Association
GPS	Global Position System
NFL	National Football League (American Football League)
UEFA	2018 FIFA World Cup Qualification
UCL	UEFA Champions League
UEFA	2018 FIFA World Cup Qualification

## Acknowledgements

*"What I think I've been able to do well over the years is play with pain, play with problems, play in all sorts of conditions."* - Roger Federer

This thought could not reflect better my year at CASA and the past months I have been working on my final master's thesis. I played with points, I played with numbers and words that patient, critical and supportive guides throw to me. I thank them for their remarkable training and inspiring exercises.

To begin, I would like to thank my professors at CASA. Jens Kandt for his exceptional views and careful considerations of the digital urban processes. He learnt me to take a social and critical approach to the development of cities, their policy and governance. Sarah Wise for her endless enthusiasm for loops, ternary operators, prototypes and agents. She gave me the confidence to become familiar with these concepts and allows me to explore an entirely new world. Hannah Fry and Thomas Oléron Evans for their ardent passion to point out striking patterns in cloudy images. Elsa Arcaute for her simple and natural approach to the exciting fields of systems, networks and complexity. Steve Gray for his infinite resources and excitement to short acronyms. Without his indulgence, SQL, API, NodeJS, HTML, CSS, DOMs and all their fellow friends would have remain a mystery for me. He allowed me to turn my head around and take a look behind my screen. Finally, Adam Dennett for his cheerful and absorbing engagement with spatial analytics. He woke up my interest in geography and continuously nourished my curiosity to information science. CASA have challenged myself and certainly shaped my future movements and interactions.

Moreover, I wish to thank the support of Movement Strategies, especially Daniel Stockdale, Christian Tonge and Steve Gwynne. Their guidance, critical comments and unusual questions provided me with a unique opportunity to derive valuable insights in the data and perform meaningful analyses.

Finally, I thank the Bartlett baristas, the Student Center staff, my family and friends for giving me energy, providing calm, releasing doubts and sharing smiles over the course of the year.

Thank you very much to all of you.

# 1 Introduction

## 1.1 Motivation

Sporting events play a major role in urban regeneration, city marketing and community engagement. The sports stadia are not only an architectural element of cities but a cultural place where entertainment happens and large audiences gather (Kool, 2016). These stadia attract a significant number of spectators and understanding their behaviour is essential to create conditions for memorable and safe experiences (Pettersson and Getz, 2009). Moreover, the development of football stadia into multi-facility areas, incorporating shopping centres, restaurants and hotels lead to changes in event consumption and are now a central element for cities economy and marketing (Kool, 2016). According to Bouchet et al., (2011), the transformation of these sporting sites contributed to the diversification of spectators. To answer their interests, it is crucial for sport-marketing practitioners to identify their behaviour. Conversely, these events can have some negative impacts on the local residents, such as traffic congestion, overcrowding, urban disorder and noise pollution (Bale, 1990; Xu and Gonzalez, 2016). In order to mitigate any problems that arise, event planners and government officials need better knowledge about how spectators travel to the venue as well as when they arrive and leave the event area (Xu and Gonzalez, 2016).

The spatial and temporal study of visitors is well established in order to acquire insight into how human activities unfold (Pettersson and Getz, 2009). While past research used methods such as in-depth interviews, event diaries or participant photographs, recent years have seen growth in research using smartphone data and location-aware sensors to capture events attendance and visitors flows (Wirz et al., 2012). Their main drawbacks are, however, their unstable signal acquisition and difficult but necessary processing (Shen and Stopher, 2014). In parallel to urban planners and spatial analysts, socio-economic researchers investigated event attendees according to their individual characteristics. Their research aimed to segment spectators according to their demographic and/or psychographic factors to develop target marketing measures, and as a result increase sport spectatorship (Kotler and Gertner, 2002). While traditional studies use customers interviews, advances in technology have given access to large and rich datasets. Digital contents produced by customers on online platforms such as TripAdvisor, Meetup or Foursquare are now getting large attention in light of providing intelligence on customers' profiles (Ahani et al., 2019;

Zhang et al., 2015). Both academic fields highlight that having a deeper understanding of spectators can aid forecasting impacts and overall potential of events (Getz and Page, 2016).

## 1.2 Research Aims and Questions

The overall goal of this thesis is to bridge the geospatial and social schools of research to gain novel perception of sports spectators. At first, this study aims to explore the spatial and temporal dimensions of spectators during sporting events, using Global Positioning System (GPS) data. The second section aims to test if this source of data can be used to characterize visitors according to their geographic and demographic profile. This research has the intention of delivering valuable insight to event planners and government officials. The following three research questions are addressed:

- Can GPS data give an accurate measurement of stadium event attendances?
- Is there a temporal and spatial difference in spectator behaviours regarding the event and venue characteristics?
- Is it possible to use GPS data to gain insight into the demographic profile of the event attendees?

## 1.3 Research Contribution and Scope

Research on visitors' movements and the spatio-temporal processes occurring during events has significantly increased in recent years. (Pettersson and Zillinger, 2011; Phithakkitnukoon et al., 2015; Siła-Nowicka et al., 2016). However, the study of spectators during sporting events using GPS data remains rare in the academic literature. Previous research has focused either on tourists' mobility in cities or crowd-behaviour during large-events, giving little attention to the analysis of people's trajectories and their behaviour for sporting events (Getz and Page, 2016). This study aims to fill this gap, bringing new insights on spectators mobility and events catchment area.

The dataset used for this research consists of GPS smartphones data from September 2017 to January 2018. The data covers sportings events (2018 FIFA World Cup Qualification (UEFA), UEFA Champions League (UCL), English Premier League (EPL), National Football League (NFL) and rugby games) across four stadia in London (London Stadium, Twickenham, Vicarage Road and Wembley). The aim of the study is to assess whether these various events in the different stadia create changes in spectator behaviour.

When compared to traditional data collection methods, such as field surveys and questionnaires, GPS technology gives the opportunity to provide insight into spectators' movements at a granular spatio-temporal scale, for lower cost and large coverage (Palmer et al., 2013; Wirz et al., 2012). The primary GPS data are obtained by a second-party that collects location of smartphone users after they have given permission for data sharing while using specific applications. Stadia are selected based on the following two criteria: they are located in/near London and hosted major sports events within the temporal window of the dataset .

- London Stadium was rebuilt to host the London 2012 Olympic Games and has now a 60,000 seats capacity. The stadium is home to West Ham United playing in EPL.
- Twickenham Stadium is the world's largest stadium dedicated to rugby. Home to England Rugby, it can seat up to 82,000 people.
- Vicarage Road Stadium located in Watford is a small stadium with a capacity of 22,200 seats. The stadium is home to Watford Football club playing in EPL.
- Wembley Stadium is the National stadium and hosts the England Football team and FA Cup Final as well as NFL games. It was the temporary home of Tottenham Hotspur Football club between August 2017 and March 2019. The stadium has 90,000 seats, thus being the second largest sports stadium in Europe. It is assumed that the stadium contribute to one third of the economy of the local area (Deloitte 2018). The season 2017/18 at Wembley saw a record number of events hosted. It was also the first time that a football team took residency at the stadium.

The remainder of the paper is organised as follows. Chapter two starts with a review of earlier studies on large-scale events in cities, followed by a discussion concerning the spatial and temporal scales of events. It finishes with a brief description of the application of new technologies to analyze spectators movements. In chapter three, the dataset is presented and the pre-processing steps for the analyses are described. The chapter four discusses thoroughly the methodological framework for this study. Last but not least, chapter five presents the results. Chapter six concludes underlining the implications of this study for event organizers and suggesting future directions of research.

## 2 Literature Overview

Cities, Sports, People are the three ingredients of this research. To set the scene, the following literature review discusses the interactions of these three intertwined entities. Organized into three parts, it first introduces the history behind cities spaces and their cultural values. This section particularly focuses on the role of Football in cities, explaining the importance of stadium and spectators. The second part explored geo-demographics and human's mobility patterns. Here special attention is given to recent research made on people movements at cultural events. Third, the development of new data sources, their benefits and disadvantages to capture travel behaviour and activity is debated.

### 2.1 Urban Space and Cultural Events

World Expos, Olympics Games, World Cup, Biennials, Fashion Shows are all major, one-off events for which cities compete to be the organizers. Cities devote extensive attention to these events, viewing them as opportunities to present their cultural values, redevelop their urban spaces and foster their local economies. Lynch (1960) argued that cities build their image through the assemblage of three components: identity, structure and meaning. These are expressed in urban spaces, which are seen as the product of social processes and individual values (Henri Lefebvre, 1974). These spaces are moreover shaped by human activities, which utilized them with specific purposes (Harvey, 2006; Soja, 1980). Batty (2002) defined them as clusters of "spatial events": characterized by their time and their events, they express individuality in duration, intensity, volatility and location. Batty's thinking contrast with the previous appreciation of urban spaces as spaces with clear contours and fixed geography (Wirth, 1938). His approach is supported by Amin and Thrift (2002), who argued that in the contemporary, mobile and connected cities, spaces become boundless: "extending their footprint everywhere, they generate flows and form networks that take the form of commuters, tourists, media or lifestyles." Consequently, when trying to understand cities, it is indispensable to view them as a plural system and understand the relationships between their components (Sheppard, 2015).

### 2.2 Large-scale Events

Large-scale events taking place in cities have become an essential part of urban marketing and branding. Cities have historically promoted themselves through their architecture, gastronomy, history, and more recently through sport (Anholt, 2002). In the past,

World Fairs and Exposition were a central pivot in embracing ideas about the relations between nations, the advancement of science, the form of cities or the place of art in society (Anderson, 1983). Hallmarks of previous fairs such as the Crystal Palace (London, 1852), the Parc de la Ciutadella (Barcelona, 1888) or the Eiffel Tower (Paris, 1889) remain of the greatest importance and still attract numerous visitors to those cities. However, as observed by Malecki (2004) and McCallum et al. (2005), those fairs have progressively seen a decline of importance, while sports mega-events have become prevalent in the metropolitan agendas. The Olympic Games described by Shoval (2002) as the "greatest show on earth" are regarded by cities government as a unique opportunity to leverage economic growth, sustain urban redevelopment, foster community attachment and increase life satisfaction and are nowadays one of the most employed means by cities to capture international attention as well as financial investment. However, these large-scale sports events are accompanied by negative effects for the local residents. Scholars pointed out the increase in taxes and real estate prices, the problems of traffic congestion, noise, pollution and overcrowding (Bale, 1990; Hall, 2006, 2004; Kim et al., 2015; Nauright, 2004; Waitt, 2003). In order to mitigate these troubles, Richelieu (2018) stressed the need for local government and sports organizers to capture the behaviour of spectators, understand their habits and characteristics.

### 2.2.1 Sport Events

Though there is a multitude of cultural and sports events, football is considered to be the most popular sport, defined by Bale (2000) as a "representational" sport. Drawing on approaches from human geography, football clubs are intrinsically linked to a place, which is represented by the club stadium. Bale (2000) affirmed that football club supporters viewed their club stadium beyond a simple functional space, but as "a family member", with who memories and strong friendships are built.

The football playgrounds have evolved considerably since the new millennium. Globalization processes illustrated by an increasing consumption society and growing demand for entertainment turned football stadia into multi-purpose areas (Lee, 2000). First, several cultural amenities can now be found around a stadium such as restaurants, merchandising shops, dedicated football team's museum, as well as larger facilities including hotels, fitness and crèches. Moreover, the playgrounds are not anymore reserved to footballers but open to musicians or preachers, hosting large music venues or religious activities (Kool, 2016). Furthermore, the architectural features of stadia have hold particular fascination and are viewed with the potential of becoming iconic elements of a city. Richard

Caborn, ex-UK sports minister and Asif Burhan, British football commentator illustrated this perfectly when speaking about Wembley (Ames, 2017): "The main thing was to make sure it was a showpiece.", "It's become our Eiffel Tower. Whenever there's a big event in the news we look to the arch and see what colour it is. It's like a symbol of our country now."

The abundant literature on the economic, commercial and social dimensions of football stadia and sports events has highlighted the important role that both elements played in cities. However, there is a major gap in research engaging with the specificity of events sites as well as with the difference between large- and small-scale sporting events. Another drawback of previous approaches lies in the global consideration of spectators. As proposed by Gibson (1998) who classified sports tourists into three distinct categories, there is a need to understand the spectators' groups that dominate in the use of stadia. Moreover, the relative spatial isolation of football playgrounds mentioned by Kloosterman (2014) invites cities governments and events organizers to gain quantitative and qualitative insight of spectators behaviours to support efficient planning and provide effective infrastructures. Finally, reviews of event-tourism literature confirm the near absence of consideration of event attendees and event organizational ecology, although management of event portfolios is an emerging topic (Getz and Andersson, 2016). There is, therefore, a demand to investigate the behaviour of spectators attending various sporting events at different venues.

## 2.3 Geo-Demographics

Being able to understand and estimate people interests is crucial for the strategic planning of transportation networks, the allocation of public expenditure or the delivery of specific goods. As a result, spatial interaction models, also named "demand-supply interaction or origin-destination models" have been used in a variety of ways such as to predict the movement of people or determine the attractiveness of retail locations. Important progress in the use of geospatial data has been seen with the integration of geodemographic information. Geodemographic is defined by Goss (1995) as the ability to aggregate and geo-reference consumer characteristics and behaviour information. Moreover, Sleight (2004) described geodemographic as methods used to classify different neighbourhoods according to the characteristics of their residents. Law (2016) summarized geodemographic principles such that: (1) people from the same neighbourhood are more likely to present similar characteristics and (2) neighbourhoods can be categorized through the characteristics of their population, even though they are geographically distant from each other.

The heterogeneity and complexity of human behaviours and attitudes have asked for new ways of considering geodemographics analyses. As a consequence, Longley et al. (2013) argued that finer factors were necessary to define realistic population segments. They proposed to use multiple datasets, such as mobility, temporal, and spending data. Their effectiveness and suitability have since been exemplified in various studies. Two of particular interests are the one conducted by Longley et al. (2008) to measure citizens engagement with communication technologies and the second carried by Calabrese et al. (2010) to define the living place of people according to various types of events. Those studies suggest that essential elements for geodemographic studies are awareness of individuals mobility, as well as their homes and workplaces.

### 2.3.1 Market Segmentation

With respect to geodemographic research, economist and business have studied consumer habits and preferences to answer specific consumers' needs and increase their revenues (Hooley and Saunders, 1993). Over the last 20 years, sports marketers observed globalisation and diversification of sporting events. Since Hu (1996) stated that "one of the most important issues of tourism and leisure marketing is to understand the visitors' travel and leisure patterns and to know where they come from, the later enables the marketer to more closely match a product or service to the needs of the target market", numerous studies engaged in profiling sport spectators (Bae, 2004; Bouchet et al., 2011; Lee, 2000; Saayman and Uys, 2003; Tapp and Clowes, 2002). The most common approaches to categorize customers in these past research can be summarized as follows:

- (1) Demographic variables (gender, age, education, occupation)
- (2) Socio-economic variables (income, spending patterns)
- (3) Psychographic variables (reasons for attendance)
- (4) Geographic variables (travel behaviours)

Similarly to customer segmentation research, studies have examined the factors affecting spectators attendance (Bae, 2004; Bird, 1982; Byon et al., 2010; Kim et al., 2013). Throughout the diverse sport studies such as baseball, basketball, football or golf, researchers found that the five most common variables to explain attendance were:

- (1) Game performance (athletes individual skills, league standing)
- (2) Promotional dimension (advertising, publicity, entertainment)

- (3) Socio-demographic profile (age, gender, education, occupation)
- (4) Facility convenience (stadium quality, accessibility)
- (5) Schedule convenience (schedule of games)

Overall, the main shortcomings of these studies reside in their small samples' size. Generally, these research use survey of spectators at one single event. Their conclusions are drawn from a specific context and thus, lack a wider approach. Bae (2004) concluded his research by suggesting that future investigations engage with minor and major league games and explore the differences between spectators attending those games.

## 2.4 Human Mobility

Understanding human's mobility play a major role in demographic studies. Both information allows answering questions as diverse as how and by whom urban spaces are used, how cities grow and where social and cultural capital is located and distributed (Balcan et al., 2009; Bettencourt et al., 2007; González et al., 2008; Wilson and Bell, 2004). In the long-standing tradition of human mobility studies, multiple strategies have been applied to record how and when people move from a specific place or to measure how long and at what time they visit certain areas.

The movement of large numbers of people over short periods of time is an ever-growing feature of cities, and the spatial problems that these movements generate are increasingly important. As pointed out earlier, it is thus crucial to understand humans' location and movement to plan the distribution of facilities, the provision of transportation services and the design of events area (Siła-Nowicka et al., 2016). Earlier works used time-space diaries, interviews or travel surveys, thus having the serious disadvantages of self-reported inaccuracies and small sampling rates size, being moreover time-consuming and poorly dynamic (Palmer et al., 2013; Shen and Stopher, 2014). With the emergence of connected devices capturing real-time position information, considerable progress has been made in the exploration of travel behaviour and crowd density (Calabrese et al., 2011). This collection of data, called 'big data' are generally captured from three different sources: smartcards (e.g. Oyster card on the London underground, retail centre loyalty card or bank card), smartphones or roadside sensor data (Kitchin, 2013).

#### 2.4.1 Travel Trajectories

As previously discussed, human movement is embedded into geographical space, where individuals move from one place to another, attributing particular importance to each of these locations. Home is often viewed as the most important place, while the working place is ranked second (Oldenburg, 1989). Both locations are places at which individuals spent a significant amount of time and at which regular activity takes place (Xu et al., 2015). It is believed that home and workplaces play a major role in determining the so-called “third places”, which are places at which individuals practice their leisure activities and socialise with others (Siła-Nowicka et al., 2016). While early works focus mainly on commuting trips aiming at finding similar patterns (González et al., 2008), new studies have engaged with non-commuting trips such as tourist journeys. For instance, Phithakkitnukoon et al. (2015), used GPS data to analyze vacation trips of Japanese. As a result, they learnt about tourists’ behaviour, their top destinations, their modes of transportation, their trip distances as well as their time spent at destinations. Furthermore, De Cantis et al. (2016) investigated space-time activities of cruise passengers in the city of Palermo. Both studies strengthened geodemographic research and the so-called ‘mobilities’ paradigm, which considered people’s lifestyles as key determinants of people movements and flows (Castells, 1996; Sheller and Urry, 2006).

#### 2.4.2 Crowd Dynamics

With respect to transport planners, event organizers also need to understand the spatial movements of humans. Festivals and city mass events are of critical importance to individual safety as they gather an extremely large number of visitors in confined spaces (Helbing and Johansson, 2013). To study crowd behaviour and thus design spaces allowing for optimal crowd flow-density and efficient evacuation in case of emergency, researchers have commonly used a combination of heterogeneous sources such as video records, field observations, computer simulations, and laboratory experiments (Moussaïd et al., 2018). With the rise of smartphones and its embedded GPS sensor, several researchers changed their approaches of crowd monitoring. To illustrate this development, two studies are worse citation. The first carried by Zimmerman et al. (2016), researched the social and mobile traces of spectators of the world-famous music festival in Roskilde, Denmark. The second conducted by Garcia et al. (2017) investigated the crowd densities and dynamics of festival visitors in California. Both studies provide great business intelligence and demonstrate the enormous potential of GPS data to understand the utilization of spaces.

## 2.5 Smart Devices - Smart Data

In support of travel behaviour research, mobile phone data have been the most widely used data source. These can be viewed as a massive data stream that reports real-time location and displacement of the users carrying the device (Xie et al., 2013). Cellular network-based data, as for instance Call Data Records (CDRs), smartphone sensor-based data illustrated by GPS, Wifi or Bluetooth, and social-media network data such as geo-reference posts or pictures from users of Twitter, Instagram, Facebook or Flickr are all examples of mobile phone data (Guo and Ma, 2015; Kitchin, 2013; Wang et al., 2018).

GPS data are passively generated by smartphones applications. A data point is created by a GPS device when it receives the signal of at least three satellites. This signal allows determining the position of the device on earth in location coordinates (longitude, latitude) as well as the timestamp of the device location. GPS technology shows the benefits of higher spatial resolution compared to CDRs. Major benefits of the GPS technology lie in the autonomous, constant as well as accurate time and positional recording of individual movement. Nevertheless, GPS modules show drawbacks regarding signal loss and signal noise, as well as the tedious processing of their recorded data (Shen and Stopher, 2014). Being aware of the advantages and disadvantages of GPS, the careful experiment designed by Blanke et al. (2014) allowed them to use such data to acquire fine-grained understanding of crowd dynamics at the largest Swiss event (Züri Fäscht).

## 2.6 Summary

The aforementioned literature review discusses the importance of sporting events for cities and the potential of new datasets to analyze these on a high-granular spatial-temporal scale. The chapter draws attention to studies that explored spectators behaviour, illuminating their efforts to segment events customers according to their demographic characteristics and interests. Moreover, it points out to research exploring human's movements and their use of spaces and signals the gap in the literature, investigating the geographic extent of small and large sporting events. To conclude, sporting event attendees are highly diverse and capturing their behaviour would benefit multiple actors. The prior studies have however been subjected either to human mobility or spectators segmentation and thus exploring how smartphone data can be employed to gain insight into the spatial and temporal behaviour of event attendees is welcomed.

## 3 Data

In light of the previous literature, this section gives an overview of the GPS dataset and discusses the pre-processing steps to pinpoint spectators behaviour for different sporting events in London.

### 3.1 GPS Data

This study had access to two anonymized GPS datasets covering the period between September 2017 and January 2018. The first consists of 12,153,272 records and contains the entire timestamps of GPS users for the day at which a game took place. The second includes 4,027,519 records, which correspond to the first daily individuals timestamp for the 5 months of the study period. In total, 89,209 GPS users are covered, having the following variables: user\_id, timestamp, longitude and latitude coordinates. These data were collected by a secondary party using software development kit (SDK) technology, which records users' smartphones position via the integrated GPS module. However, before information on the users' location can be retrieved, users should, first, have installed the application used by the company and, second, agreed to its terms asking access to their data. These applications are available on any iPhone or Android devices.

#### 3.1.1 GPS Data Cleaning

The dataset shows a high variation in the frequency of GPS records per user. While the most active user has 3,876 GPS records for a day, yet a median of 60 GPS records per user per day. These fluctuations are caused by smartphone battery level and version, operators signal strengths, as well as users' mobility and environment situation. For instance, some GPS modules record location data only if the GPS user position changes. This means that if a user remains stationary, their device will not generate any new record and thus the trajectory will consist of a small number of GPS points (Calabrese et al., 2014). Moreover, the accuracy of a position depends highly on the GPS signal strength. In an urban canyon, in crowded places or inside buildings, the signal might be lost or weakened due to multipath noises (Shen and Stopher, 2014). Finally, battery death will fail to record a complete trajectory, the recorded section might, therefore, be inadequate to research users' home or destination (Bohte and Maat, 2009).

To avoid biased results or wrong conclusions, it is essential to understand the quality of the dataset and accordingly perform necessary cleaning steps. Bohte and Maat (2009) and Zhou et al. (2017) proposed several principles to remove missing trips and inaccurate coordinates. These can be summarized as follows: (1) GPS record need to be complete, which means timestamp, longitude, latitude and user\_id are available; (2) GPS data coordinates are located in the corresponding geographic study area; (3) GPS trajectory points have unique timestamp; (4) GPS trajectory points are continuous; (5) GPS points do not have an instantaneous speed higher than 60m/s; (6) GPS trajectories consist of at least 4 points. These six principles were applied to this study dataset.

### 3.1.2 GPS Data Trajectories

GPS trajectories consist of chronologically time-ordered points, which when assembled one after the other represent the travel path of a user. Extracting meaningful information from GPS traces is essential to learn about human activities. Thus, numerous mobility-researchers have engaged with various methodologies to distinguish between stops and moves, and identify significant stops such as home, work or leisure places.

Kang et al. (2015) summarised the identification of stop locations as a "basic clustering problem", such that regions are separated from each other according to their characteristics. Standard clustering algorithms such as k-means or hierarchical are not quite adequate to apply to GPS traces. One problem resides in the need to specify the number of clusters in advance. Another is the inclusion of all trajectories coordinates to a cluster, such that points describing the GPS user movement are considered as "stop" rather than "move". To overcome the limitations of these standard algorithms, new clustering methods have been developed. For instance, Kang et al. (2015) applied a time-based clustering algorithm. Clusters of GPS coordinates are created along a time axis and coordinates which are under a certain time threshold are removed. Similarly, (Gong et al., 2018) employed a temporal and entropy DBSCAN (DBSCAN-TE) followed by support vector machines (SVMs) to distinguish between activity (shopping, work) and non-activity (traffic congestion, waiting for green lights) points. These studies underline the importance to tune the clustering thresholds parameters (distance, number of records, time) according to the research aims. Thus, it is crucial to consider the following questions: What is the size of an important place? How frequently and how long should a place be visited to be considered as important?

Regarding the distance threshold, if a large value is chosen, the final cluster will likely consist of several smaller important places. As an example, Wembley stadium area is composed of the actual football stadium, diverse food and drink bars as well as nearby shopping facilities, where a spectator may spend various time in each of these places but globally a long time in the area. On the contrary, if a small value is applied, the final cluster will more clearly point to specific places such as a specific restaurant. Moreover, the minimum number of points and timespan of a cluster, are further measures worse considering to discern important places such as home from less significant places such as a coffee shop or a bus stop (Kang et al., 2015).

Parallel to the development and use of specific algorithms, some researchers established simplified rules to estimate significant-stop locations. For instance, Krumm et al. (2013) considered the start- and end-point of trajectories as home, while Phithakkitnukoon et al. (2012) viewed points recorded during night hours as records indicating GPS users' home. However, as mentioned by Zhou et al. (2017) these rules are arbitrary and subjective, and required the awareness of the researched region. Consequently, many researchers decided to turn towards hybrid methods to detect important locations of GPS subjects.

As pointed out by Shi and Pun-Cheng (2019), the considerable body of literature that has been published to gain knowledge from GPS trajectories mostly deal with the development of new algorithms. However, there have been few attempts to pre-define thresholds to detect GPS points clusters. Thus the choice of the clusters' radius, distance to other clusters, time length or minimum number of points is left to researchers trials and common sense and varies from study to study. Bermingham and Lee (2018) questioned the multiple clustering approaches, due to the choice of sensitive parameters selection that highly influence the quality of stop clusters and suggest to add a probability parameter to improve the current clustering methods.

### 3.1.3 Statement of Ethics

Studying people's mobility using position signals sent by smartphones can lead to ethical considerations. As an example, New York City is currently considering banning telecommunication companies from selling mobile location data to marketers of other businesses (Mays, 2019). In contrast to self-recorded travel diaries, where individuals can omit information on the places they visit, the use of GPS technology does not allow participants to revise their routes and activities. Therefore, it is crucial to get the agreement of the

participants on the use of their shared data for studies and also to ensure that throughout the research, their anonymity remain (Pettersson and Zillinger, 2011). In this research, both datasets are composed of anonymised records, which do not contain any individuals personal information. The findings also grouped the individual's home to England districts and London wards. Finally, the datasets can only be accessed through a password secured Google Account.

## 3.2 Data Pre-processing

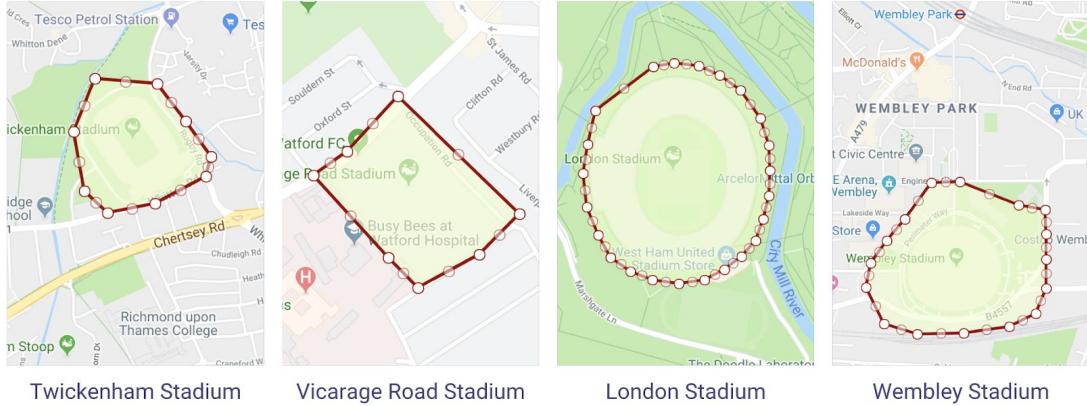
The previous section has reviewed the data handling and mining methodologies to extract information from GPS data, thus highlighting that cleaning procedures need to be chosen according to the data available and the research purposes. Considering the aim of this study, the cleaning steps suggested by Bohte and Maat (2009) and, Zhou et al. (2017) as well as simplify home detection method proposed by Krumm et al. (2013) were chosen to identify the home and start location of each spectator.

The next section describes the processes to identify the sporting event attendees out of all GPS data available.

### 3.2.1 Extracting Event Spectators

First, it was essential to identify the spectators from the non-spectators within the GPS users. The two most obvious criteria to define events spectators is to consider the spatial and temporal qualities of their GPS data. While the spatial measure filters spectators by examining their location at the time of an event, the temporal measure filters individuals according to their dwell time. The spatial measure is based on the stadia geography boundaries, which consist of a close geometry shape enclosing the stadium such that other nearest facilities are disregarded. The temporal criterion considers the average dwell time of each individual. Individuals spending less than 45 minutes in the stadium were excluded from the analyses. This choice was made according to the duration of a football or a rugby game, having half of 45 minutes for the first, and 40 minutes for the second. Hence, assuming that spectators will attend at least one-half of the games. A final procedure to identify GPS users as spectators was to exclude individuals with GPS points recorded 4 hours before the beginning and/or 2 hours after the end of a game inside the stadia geography boundaries. These individuals being likely workers or local residents.

It is important to note that the temporal criterion was chosen to meet the aim of the analyses with the best accuracy as possible. Hence preferring to have false negatives rather than false positives, in other words, to drop some true spectators, rather than to count false spectators. This step would however not be necessary for real-time analyses of spectators arrival, departure of the stadium.



**Figure 1: Small Geometry Bounding Box**

The last steps perform to clean the GPS trajectories and identify the unique spectators are summarized below. These were:

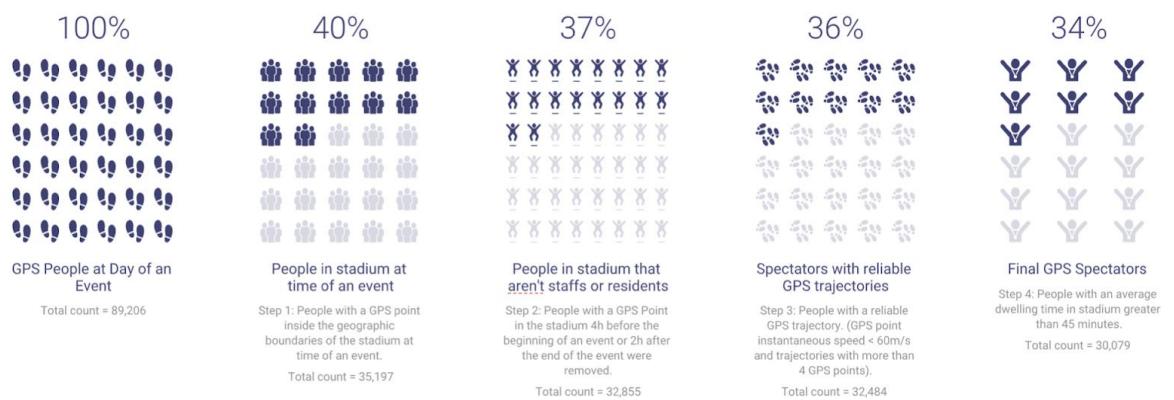
Discard GPS records:

- (1) If one characteristic (user\_id, timestamp, longitude and latitude) is missing.
- (2) If the timestamp of the previous point is identical.
- (3) If the instantaneous speed is higher than 60m/s.

Discard GPS users:

- (4) If their trajectories consist of fewer than 4 points.
- (5) If there are no points in their trajectory falling inside the stadium geometry bounding box at the time of the event.
- (6) If points of their GPS trajectories fall inside the geographic boundaries of the stadium more than 4 hours before the beginning and more than 2 hours after the end of the event.

After performing these steps, the dataset consists of 30,079 unique individuals (33,7%) compared to the initial number of 89,206 unique individuals.



**Figure 2:** Data Cleaning, Preprocessing Steps

## 4 Methodology

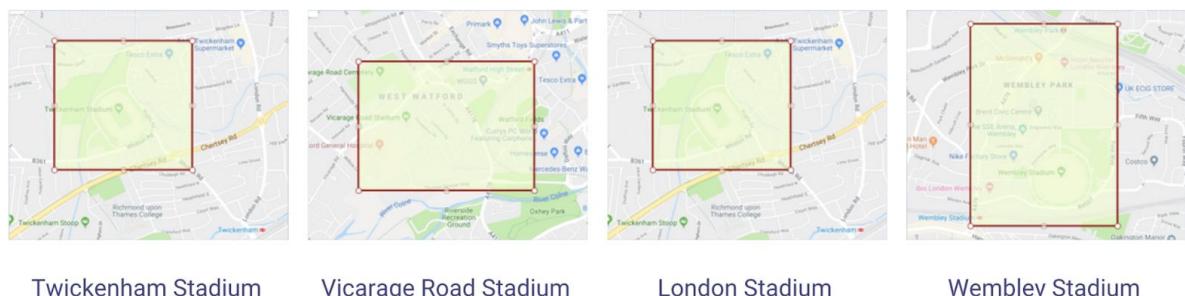
This chapter built on the GPS data pre-processing steps. It describes in more depth the procedures applied to characterize and identify spectators at the various events and stadia. The following processes are discussed:

- (1) Temporal Spectator Behaviour (Arrival, Departure and Dwell Time)
- (2) Spatial Spectator Behaviour
  - (a) Home Location
  - (b) Start Location
  - (c) Event Catchment Area
- (3) Spectators' Demographic Profile

### 4.1 Temporal Spectator Behaviour

Spectator behaviour can be characterized using various measures. Common metrics generally include their arrival and departure time as well as their time spent within the event area, defined as dwell time.

As mentioned earlier, stadia have seen a proliferation of facilities for pre-match entertainment. Consequently, sports spectators are not only expected to turn up for the game happening on the pitch but also to spend time around the event area before and after a game (Giulianotti, 2002). Thus, it is appropriate to use larger boundary boxes around the stadia so that arrival, departure and dwell time include these new behaviours. These geometries are illustrated in the figure below.



**Figure 3: Large Geometry Bounding Box**

Ouazzou (2018) discussed the challenges and strategies to measure the arrival, departure and dwell time of GPS users in a particular place. In line with her extensive discussion and thoughtful examination, this study follows her proposed methodology to compute these three factors.

#### 4.1.1 Arrival Time

The spectators' arrival time is understood as the first GPS points spectators' created within the event space. The steps undertaken to compute the arrival time are the following:

- (1) Count the number of spectators arriving inside the stadium for every 5 minutes interval.
- (2) Divide the count in each time interval by the total number of event attendees.
- (3) Plot the proportion of spectators arriving at the event at each time interval.  
(Graph describing the temporal profile of an event).
- (4) Add the proportion of spectators arriving in each time period to the previous one and plot the results. (Graph describing the cumulative arrival of spectators).

#### 4.1.2 Departure Time

The spectators' departure time can be understood in two different ways. On one hand, it can be viewed as the last step that spectators have made within the stadium area, on the other, it can be viewed as the first step the spectators have created outside the stadium area. Here, the second way was chosen. This decision was taken due to non-continuous GPS time-record, but also as a way to increase confidence regarding the complete departure of spectators from the stadium arena. The steps undertaken to compute the departure time are the following:

- (1) Add the next timestamp to the current GPS point.
- (2) Selection the last GPS point created by the spectators inside the stadium. (GPS points have now two timestamps, the real timestamp and the next GPS point timestamp).
- (3) Compute the number of spectators outside the stadium arena aggregated for 5 minutes intervals using the next point timestamp. (Thus, spectators have confidently left the stadium).
- (4) Perform the same steps (2,3,4) than for the arrival time.

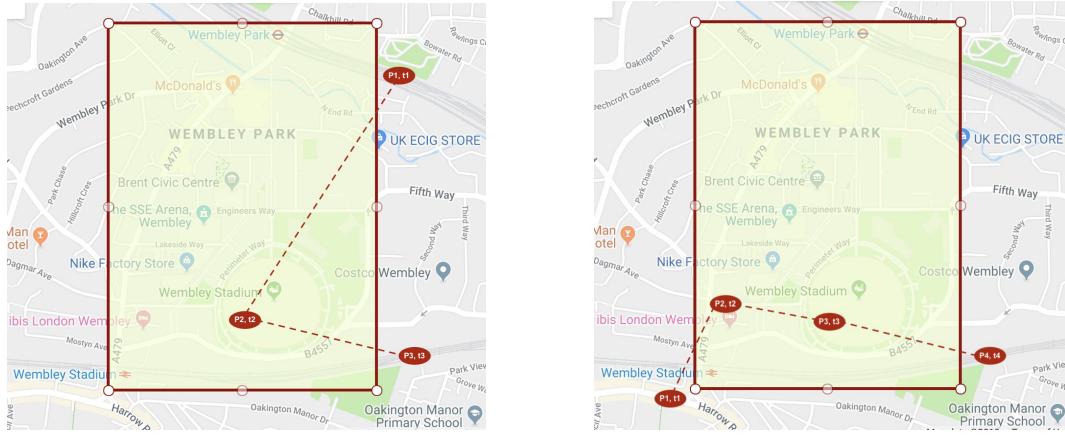
#### 4.1.3 Dwell Time

The spectators' dwell time is understood as the time spent by spectators in the stadium area. As each GPS module varies in how its records data, each spectator shows different GPS point patterns inside and outside the stadium area. The dwell time is therefore calculated using the minimum and maximum dwell time measures. The minimum dwell time is understood as the minimum time spent by a spectator at an event; in other words, it calculates the time lapse between the first point and last point made by a spectator inside the stadium area (being null for spectators that have only one point within the event venue). The maximum dwell time calculates the time lapse between the last point and first point release by a spectator before entering the stadium area. Finally, the average dwell time for each spectator is computed by dividing by two the sum of the minimum and maximum dwell time.

Looking at the spectators' GPS trajectories, the four possible scenarios can be observed:

- (1) A spectator triggers only one point in the geography bounding box of the stadium.
- (2) A spectator triggers multiple points in the geography bounding box.
- (3) A spectator trajectory starts inside the stadium bounding box. This can be the case when the spectator is a stadium worker and uses a work device.
- (4) A spectator trajectory ends inside the stadium bounding box. For instance, if the spectator GPS devices run out of battery.

In scenarios three and four, it is not possible to compute the spectators' average dwell time as the time-lapse between points within or outside the stadium area can not be defined. If a spectator shows one of these cases, the spectator was not considered further in the research. Moreover, spectators with an average dwell time of fewer than 45 minutes were deleted.



**Figure 4:** Average Dwell Time Scenarios (1), (2)

## 4.2 Spatial Spectator Behaviour

### 4.2.1 Home Location

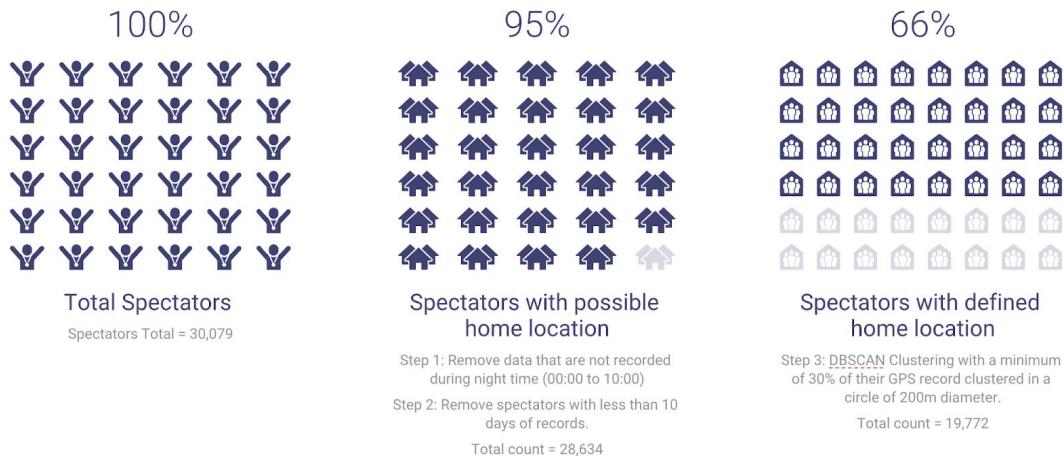
To identify spectators home, the second dataset is chosen. This dataset shows the advantage of having multiple users' GPS records over a 4-month window, increasing the accuracy of spectators' home identification. However, it has the peculiarity to give only the first daily user's GPS record and thus presents major limitations to how home location detection methods can be used.

First, the identification of the GPS users' home relies solely to the first daily point recorded by the users' GPS device. This location is therefore highly dependent on the users' behaviour. When do users first activate their device? Is it at home, when leaving home, when starting work? Secondly, how should we deal with the variation in the number of days recorded for each user? Is there a minimum threshold to set to guarantee that recurrent locations represent home? How many days should it be? This threshold is difficult to define accurately, as human's working habits may change significantly. Numerous people may indeed, spend half of the week in locations other than their home due to work travel or earlier commuting. Both factors result in the impossibility to employ traditional time duration or density-based trajectory algorithms methods. However, spatial clustering methods remains useful. As a result, the identification of spectators' home involved the following steps:

- (1) Only GPS points that are recorded during the night and early morning (from 00:00 to 10:00 AM) are considered.
- (2) Only users with more than 10 days of data over the 5 months are selected.

- (3) A DBSCAN is performed.
- (4) A cluster is considered if at least  $\frac{1}{3}$  of the points falls inside a 200m diameter.
- (5) The home location is defined as the cluster with the highest number of points.

Performing the previous steps, a home location was assigned to 19,772 spectators or 66% of all event attendees.



**Figure 5:** Data Cleaning, Preprocessing Steps - Home location

#### 4.2.1 Start Location

Another interesting measure to characterize spectators is to define their start location at an event day. Large sporting events draw visitors from overseas or other parts of the UK. As mentioned by Deloitte (2018), the largest economic impact for events at Wembley Stadium comes from non-local spectators, whose main expenditure is on accommodation. This measure is particularly relevant in tourism research. In contrast to the home location, it gives information on where spectators may have stayed during their visit. The tourists are defined as spectators travelling and staying away from their home to attend an event.

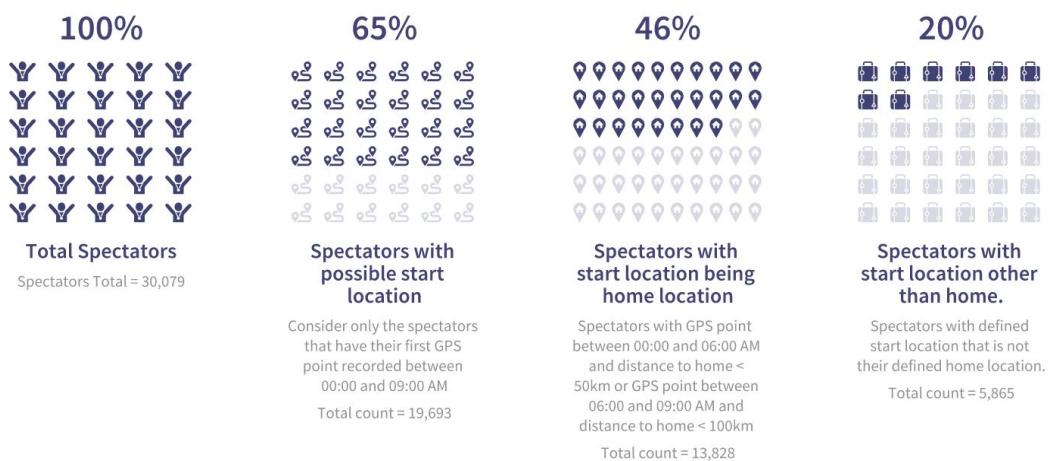
Considering the previous challenges and the procedures adopted while identifying spectators' home, additional questions needed to be addressed. How far away from home can GPS users be considered as tourists? What is the potential distance a GPS user is able to travel in two, three hours?

With regard to these questions, it was assumed that users create their first point between 00:00 and 09:00 AM; i.e they are most likely to be at home. Moreover, it was decided

to set a distance threshold regarding the time at which users create their first point. To clarify, it was assumed that GPS users being located more than 50km from home between 00:00 and 06:00 AM would have spent the night previous to the event to a location other than their home, thus being potential “tourists”. For GPS users having their first point recorded between 06:00 AM and 09:00 AM, a distance threshold of 100km was chosen. This decision results in the consideration that driving a car for one hour on motorways may transport a user up to 100 kilometres from home. Thus, a 50 kilometres distance threshold would not be sufficient. The identification of the spectators’ start location can be summarized as follows:

- (1) Consider only spectators with first GPS point recorded between 00:00 and 09:00 AM.
- (2) Compute distance between the home and the first GPS record, for spectators with a defined home location.
- (3) Consider spectator starting from home, if first point recorded lies between 00:00 and 06:00 AM and distance to home is less than 50 kilometres.
- (4) Consider spectator starting from home, if first point recorded lies between 06:00 and 09:00 AM and distance to home is less than 100 kilometres
- (5) Consider spectator starting from their GPS first point location, if point 3 and 4 is false.

By performing the previous steps, it was possible to assign a start location to 19,693 spectators (65%) of all participants. With 13,828 (70,2%) of spectators having their start location similar to their home.



**Figure 6:** Data Cleaning, Preprocessing Steps - Start location

#### 4.2.2 Travel Distance and Time Travel

As discussed in the literature review, the spectators distance and time of travel give an understanding of the attractiveness of a specific event. Having defined the spectators' home, their travel journey can be supposed.

To do so, the Google Distance Matrix API was used. The API service computes the distance and time of travel between an origin and a destination. Several parameters such as the mode of transport, the departure time at origin or the arrival time at destination can be defined. In this research, the following parameters were set:

- (1) Mode of transport: Driving
- (2) Arrival time at destination:
  - (a) Noon for midday games.
  - (b) 02:00 PM for afternoon games.
  - (c) 06:00 PM for evening games.

#### 4.2.3 Catchment Area

The visualization of the events' catchment area is particularly useful to represent the spatial extent of each event. To this aim, the spectators with a defined home were selected and joined to the geographic boundary of England Counties (174), Districts (380) and London Wards (633). The proportion of spectator for each boundary was then calculated and maps were created for each of the events.

##### 4.2.3.1 Spatial Autocorrelation

Spatial autocorrelation analyses the underlying structure of patterns and determines if observations across a spatial area are independent, thus showing a random pattern or either positively or negatively correlated Longley et al. (2013). Positive correlation corresponds to similarity in space which exists when similar values are close to one another. Negative correlation corresponds to dissimilarity in space which exists when dissimilar values are close to one another. Two perspectives can be taken to analyze spatial autocorrelation. First, globally, which involves the study of the entire map and aims to answer if the global pattern cluster or not. Second, locally, which explores smaller units of the map and aims to identify hot- or cold-spots that drive local clusters or would explain heterogeneities and the overall global pattern. Common tests for spatial autocorrelation are Moran's I, Geary's C and Getis

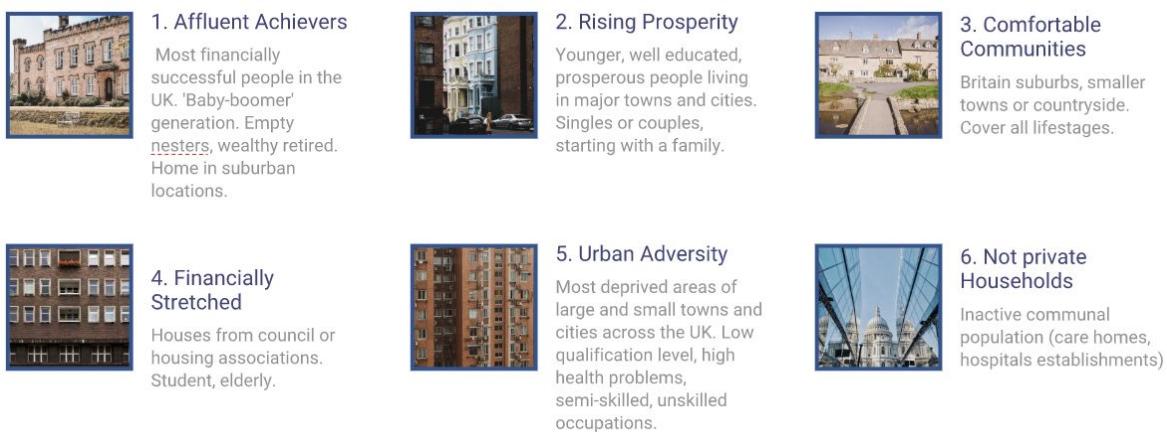
Ord's G for the global test and Local Moran for the local test. A more detailed overview of each test can be found in the Appendix.

## 4.3 Demographic Spectators Behaviour

### 4.3.1 ACORN Classification

One of the richest features to understand spectators behaviour is to define their demographic profile. This allows capturing spectators' lifestyle (expenditure and activities) as well as socioeconomic conditions (age, education, wealth and health status) (Birkin, 2019; CACI, 2018). This segmentation benefits government and businesses as it helps them to target people who are the most likely to benefit from their products and services, thus allowing better commercial and public service planning applications.

In the UK, many data sources are available in order to classify neighbourhood. For this research, ACORN geodemographic segmentation was chosen. It assumes that individuals within the same postcode (counting for around 30 households) present similar characteristics. This basic building block is used to segments each UK postcodes into 6 categories, 18 groups and 62 types.



**Figure 7:** ACORN Categories Segmentation

## 4.4 Stadium and Event Selection

Sporting events and stadia were selected similarly to Calabrese et al. (2010):

- (1) The event should be isolated in space and time. Thus, only one event per day and per stadium was selected.
- (2) The stadium should correspond to a well-defined area, its geography boundary should minimize the misinterpretation between event spectators and non-event spectators (e.g people visiting a shop or a restaurant nearby).
- (3) The event should attract a significant number of spectators.

The three largest stadia in London namely Wembley Stadium, Twickenham Stadium and London Stadium, as well as the smaller Vicarage Road Stadium, were therefore selected. These stadia hosted the popular NFL, UEFA, UCL and EPL games as well as the rugby Autumn Internationals. In the figure below, the location of the selected stadium can be viewed.



**Figure 8:** Selected London Stadium in Greater London Area

## 5 Results

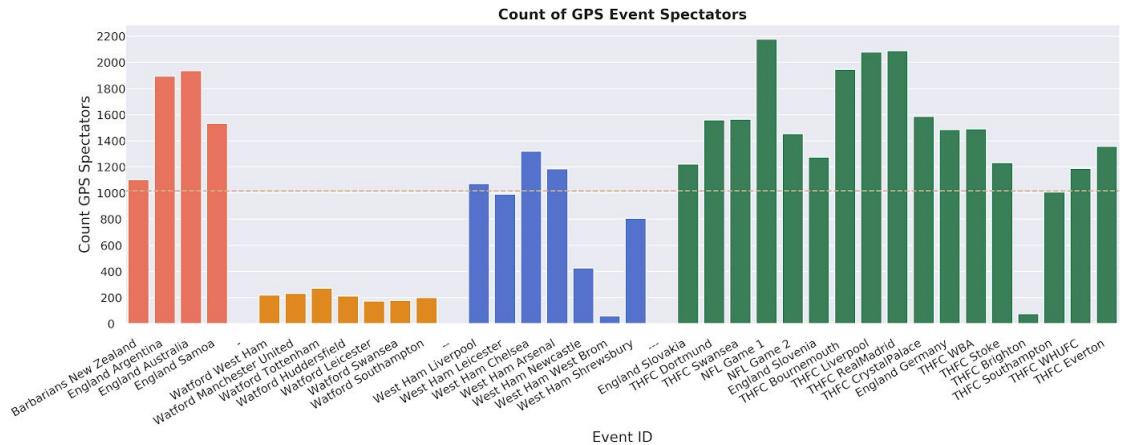
This chapter walks through the main findings of this research. The results are presented for the four parts of the analyses: the exploratory, temporal, spatial and demographic. The dataset consisted of 35 diverse sporting events, of which 7 categories could be identified according to the type of the event and its venue. For more clarity, it was therefore chosen to discuss these 7 categories rather than single sporting games. All results and analyses for the single sporting games can however be viewed in the Appendix. The 7 categories are:

- Premier League at Wembley (10 games)
- Premier League at London Stadium, Stratford (7 games)
- Premier League at Vicarage Road, Watford (7 games)
- Champions League at Wembley (2 games)
- International Football World Cup 18 Qualification, FWCQ at Wembley (3 games)
- NFL at Wembley (2 games)
- Rugby Autumn International at Twickenham (4 games)

### 5.1 Exploratory Data Analyses

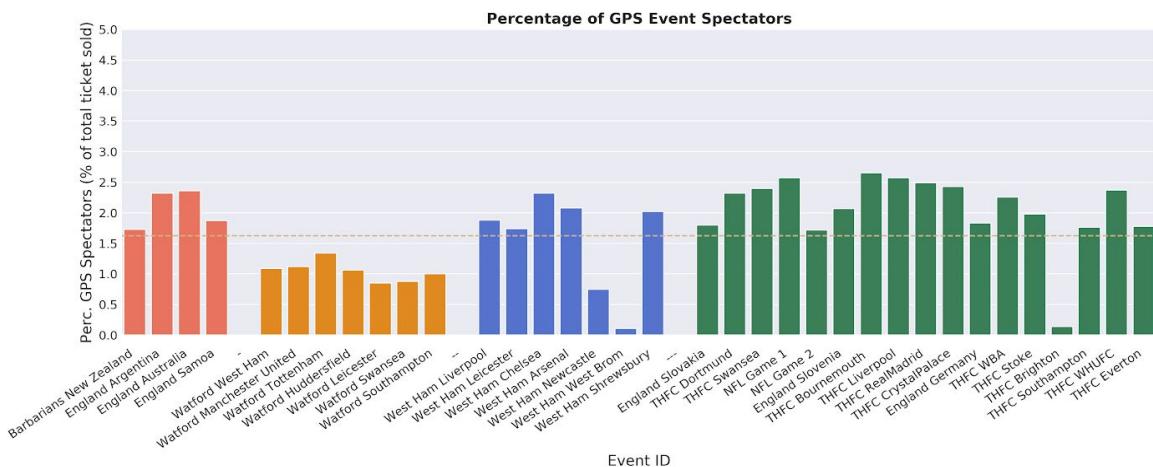
#### 5.1.1 Number of Spectators

The number of spectators identified via the GPS dataset for each sporting event happening in Twickenham Stadium (red in graphs), Vicarage Road Stadium (orange in graphs), Olympic London Stadium (blue in graphs) and Wembley Stadium (green in graphs) from September 2017 to January 2018 can be observed in the figures below. Graph 1 shows the count of GPS spectators, while Graph 2 shows the percentage of GPS spectators according to the attendance figures published by each club.



**Graph 1:** Count of spectators

Graph 2 shows that across all the events, the GPS dataset covers 1.6% of the event attendees. Watford Stadium indicates a slightly lower coverage, with results being constantly below the average, in contrast to EPL games at Wembley, whose event attendees coverage tends to be higher than the average.



**Graph 2:** Percentage of spectators

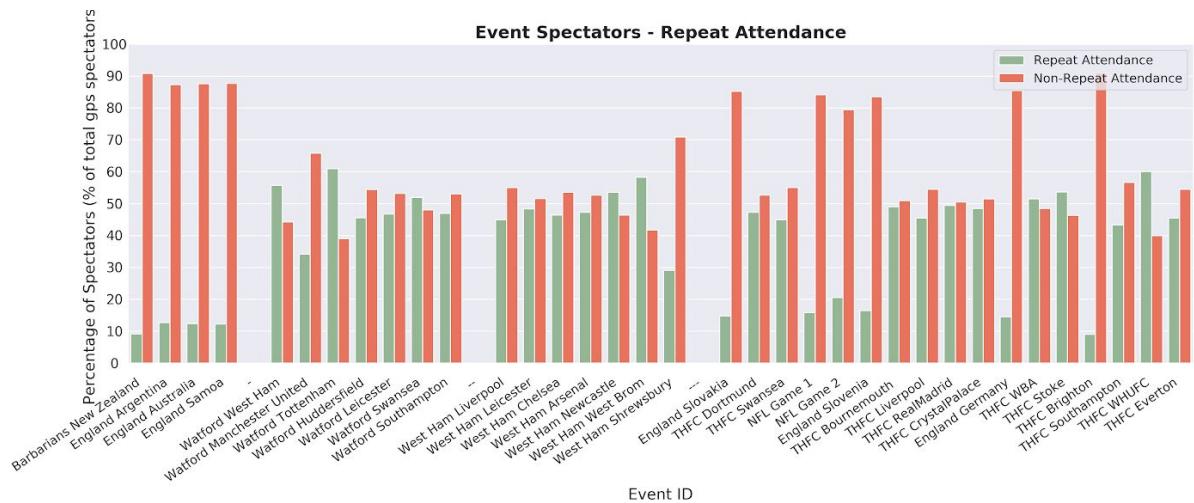
Both graphs above show particularly low percentage of spectators being identified for EPL games West Ham West Brom and THFC Brighton. According to an investigation from BBC Sport, the clubs' published attendance differ from 2 to 20% to councils and/or police figures. Interestingly, the research points out to both West Ham - West Brom and THFC - Brighton games:

*"For West Ham's against West Brom on Tuesday, 2 January 2018, the official attendance was 56,888 but the council said it was 39,365. For Tottenham's game with Brighton on the 3rd December 2017, the official attendance was 55,124 compared to the real of 46,438"* (Magowan, 2018).

Taking this into account, it is thus not surprising to get meagre results for both games. Excitingly, if the attendance released by the council is taken to compute the percentage of spectators covered by the GPS dataset, results would correspond to the computed average. (West Ham West Brom would equal to 1.5% and THFC Brighton would equal to 1.6%).

### 5.1.2 Spectators Attendance

Spectators attending more than one game in the period of this research are shown in green ("repeat attendance"), in contrast to spectators attending only one game (shown in red "non-repeat attendance"). Graph 3 below shows the regular and occasional spectators. A distinct pattern emerges from this analysis. While international games such as rugby, NFL and UEFA show a majority of occasional spectators, UCL and EPL games indicates a share percentage between regular and occasional spectators.

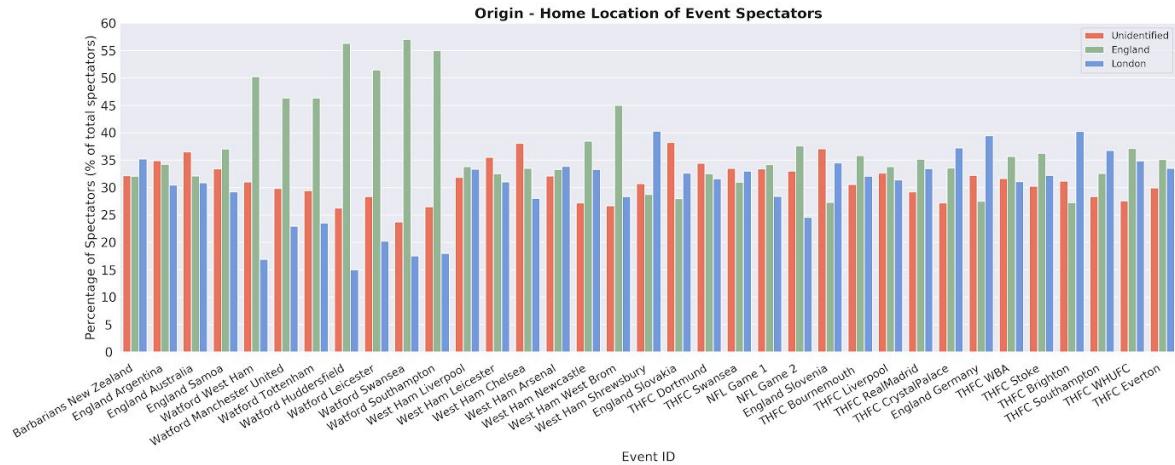


**Graph 3:** Percentage of spectators with repeat games attendance v. non-repeat attendance.

### 5.1.3 Spectators Home Location

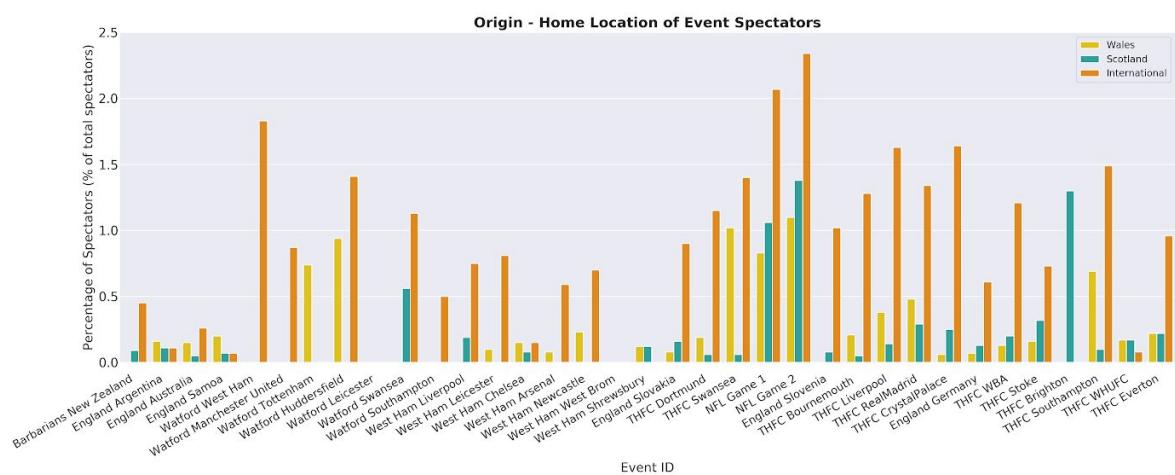
Graph 4 and 5 show the percentage of spectators, whose home location has been identified in England, London, Wales, Scotland, or overseas as well as for whose home location could not be identified, being described as "Unidentified". The results in graph 4 suggest that around one third of spectators across all events live in England, with a third living

specifically in London. Looking at Vicarage Road stadium, located outside Greater London, in Watford, a notable distinction is observed. Percentages of spectators from England rise to 50%, while percentages of spectators from London drop to around 20%.



**Graph 4:** Spectators' Home Location (Unidentified, England, London) - % in total of GPS spectators.

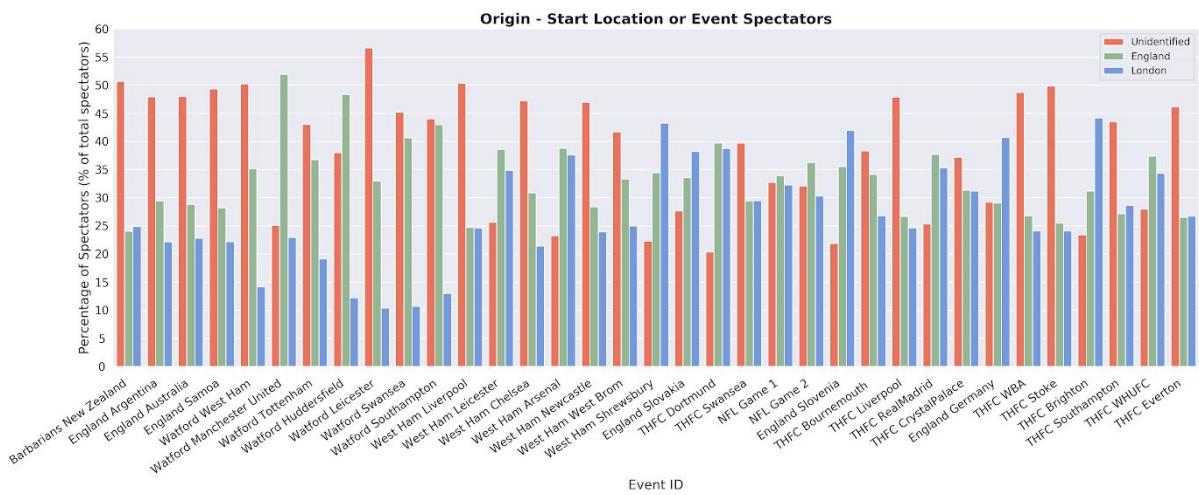
Graph 5 reveal that international spectators represent a small number of the event attendees. NFL games exhibit their “international” appeal, showing the highest percentages of spectators with home in Wales, Scotland or overseas. A striking pattern however emerges from this graph. Rugby International witness a low number of Welsh, Scottish and overseas, having less than 0.5 percent of spectators from these regions, whilst EPL games in Watford and Wembley denote to attract double the amount of overseas spectators.



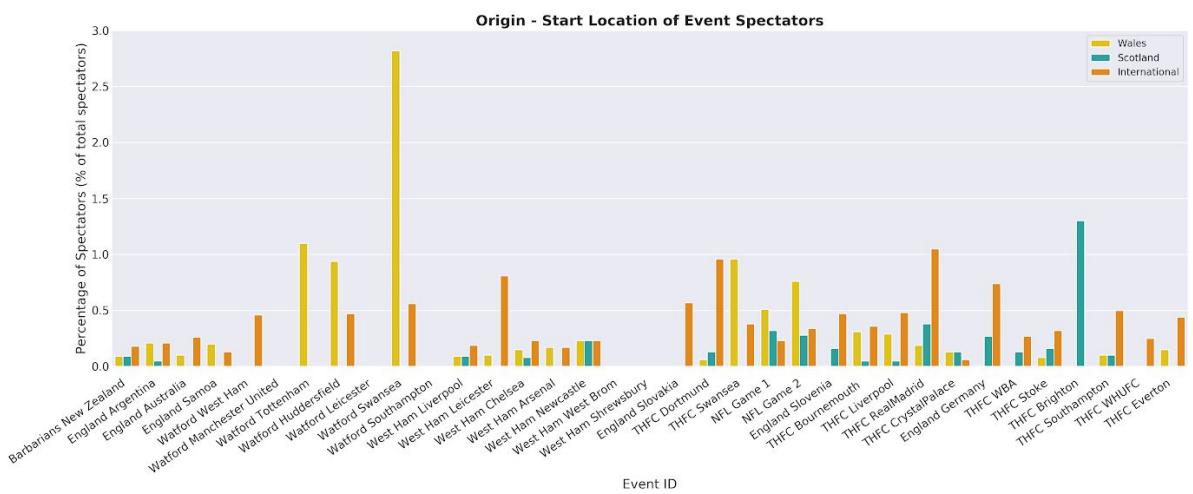
**Graph 5:** Home Location of Spectators (Wales, Scotland, International) - % in total of GPS spectators.

### 5.1.4 Spectators Start Location

Graphs 6 and 7 show the spectators' origins on the day of an event. Both graphs show similarities compared to graphs 4 and 5. Graph 7 outlines the decrease of spectators, whose origins correspond to overseas compared to graph 5. A marked difference can be viewed for NFL games. While 2% of all spectators have their home overseas, only 0.5% of the spectators have their start location outside the UK.



**Graph 6:** Start Location of Spectators (Unidentified, England, London) - % in total of GPS spectators.



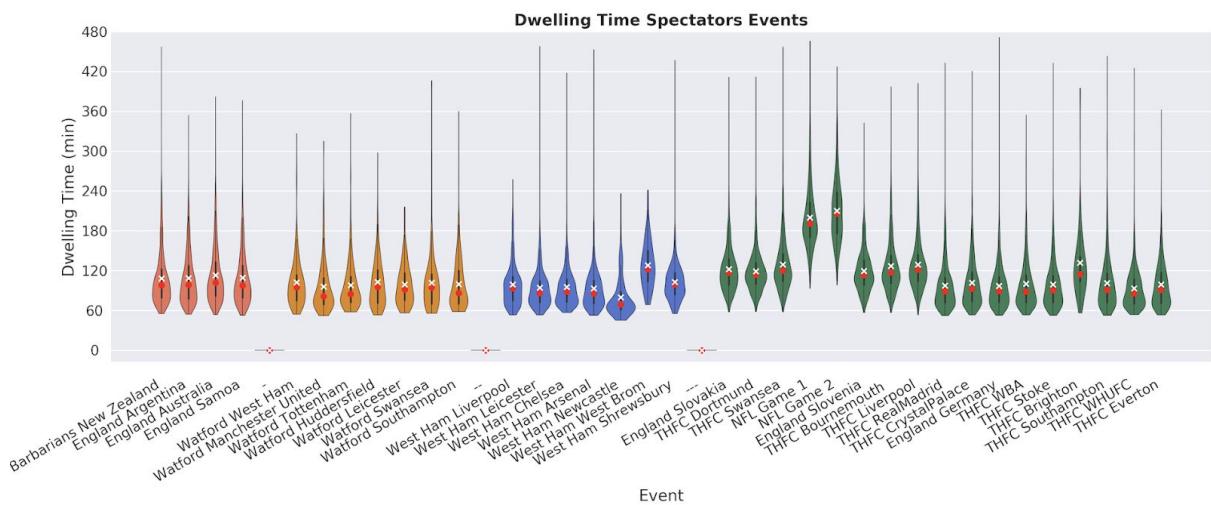
**Graph 7:** Start Location of spectators (Wales, Scotland, International) - % in total of GPS spectators.

## 5.2 Temporal Data Analyses

### 5.2.1 Dwell Time

Graph 8 visualises the time spent by spectators within the event arena. The red dots inside each violin plot denote the median dwell time and the white crosses denote the mean dwell time of spectators for each specific event.

A clear difference in dwell time for NFL games can be observed. Both games manifest the longer stay of spectators within the stadium arena (205 minutes). This contrasts with the other games, which show spectators' dwell time lying between 90 and 120 minutes. Interestingly, three games show less variance in time spent by the spectators around the stadium. These are Watford v. Leicester, West Ham v. Newcastle and West Ham v. West Brom EPL games. This may due to the date at which these games were played, being on December 26th, December 23rd and January 2nd respectively.

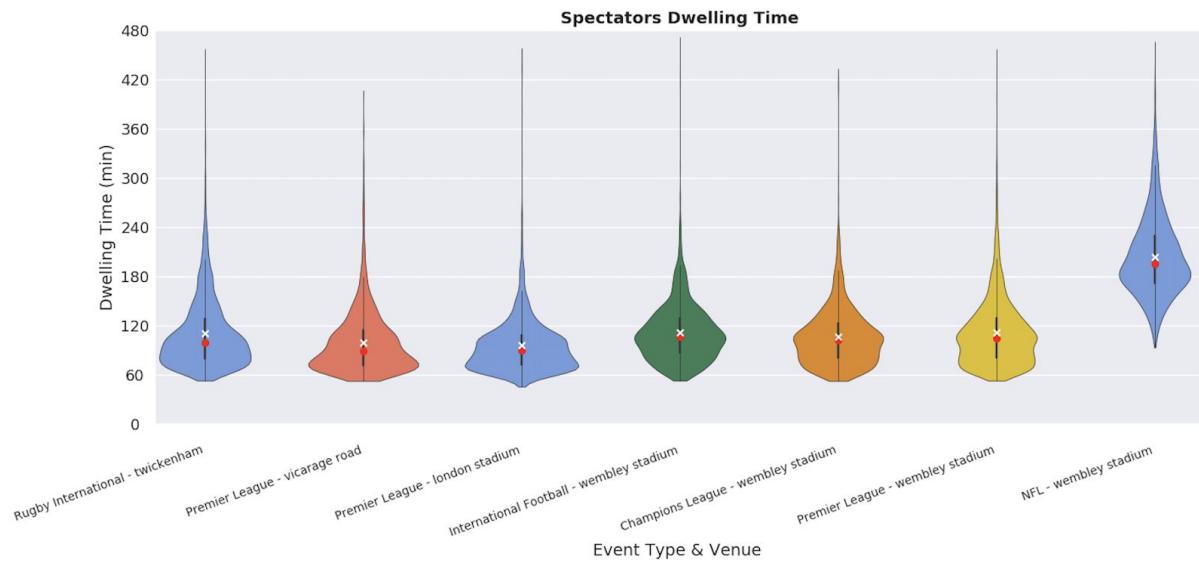


**Graph 8:** Spectators Dwell Time

Graph 9 shows the spectators' dwell time for the 7 categories. To assess if there were significant differences between the means categories dwell time, a one-way ANOVA statistic test was computed followed by independent t-tests, for which the significance level was set to 99.3% (p-value of 0.007) confidence according to Bonferroni correction principles. These tests confirm the apparent longer dwell time for NFL games compared to each of the other event. Additionally, they indicate that the dwell time for rugby games (mean of 110 minutes) is only significant compared to EPL games being played at Vicarage Road (mean of 99 minutes) and

London Stadium (mean of 95 minutes). Thus, it is possible to hypothesise that games at Wembley provide similar stimuli to rugby International, thus spectators in these stadia are likely to stay around the same amount of time in the event area.

Comparing the spectators' dwell time for the football games, only EPL games show significant differences. The football events at Wembley do not show statistical differences (UEFA: 112 minutes, UCL 107 minutes, EPL 111 minutes). It is thus possible to conclude that spectators at the diverse stadia show different temporal behaviour.



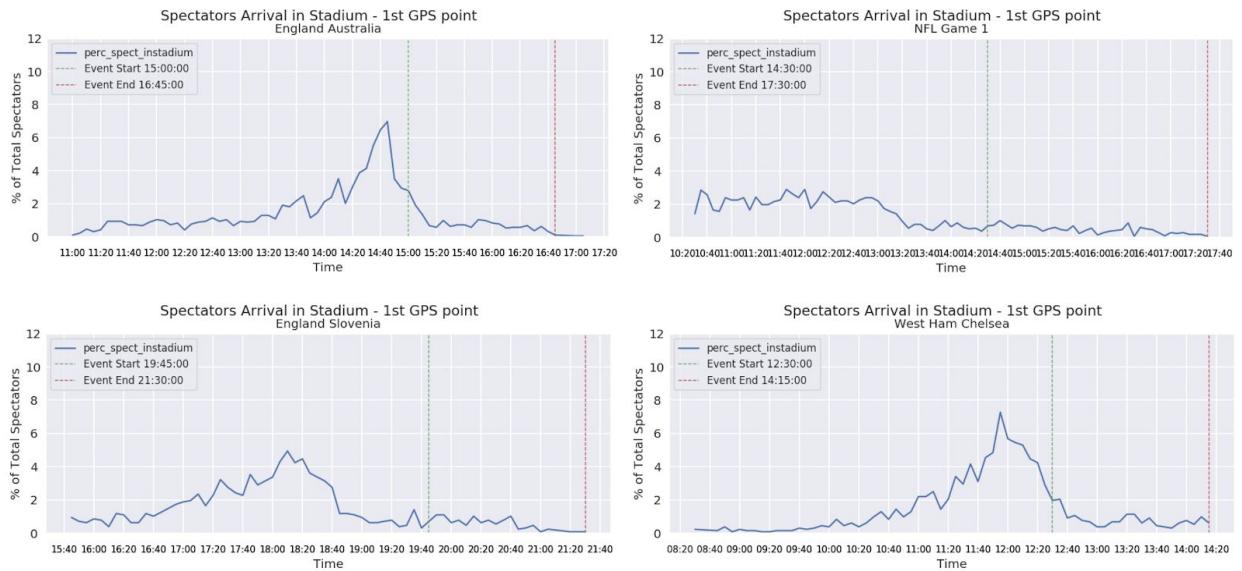
**Graph 9:** Spectators Dwell Time for the 7 categories.

### 5.2.2 Arrival and Departure Time

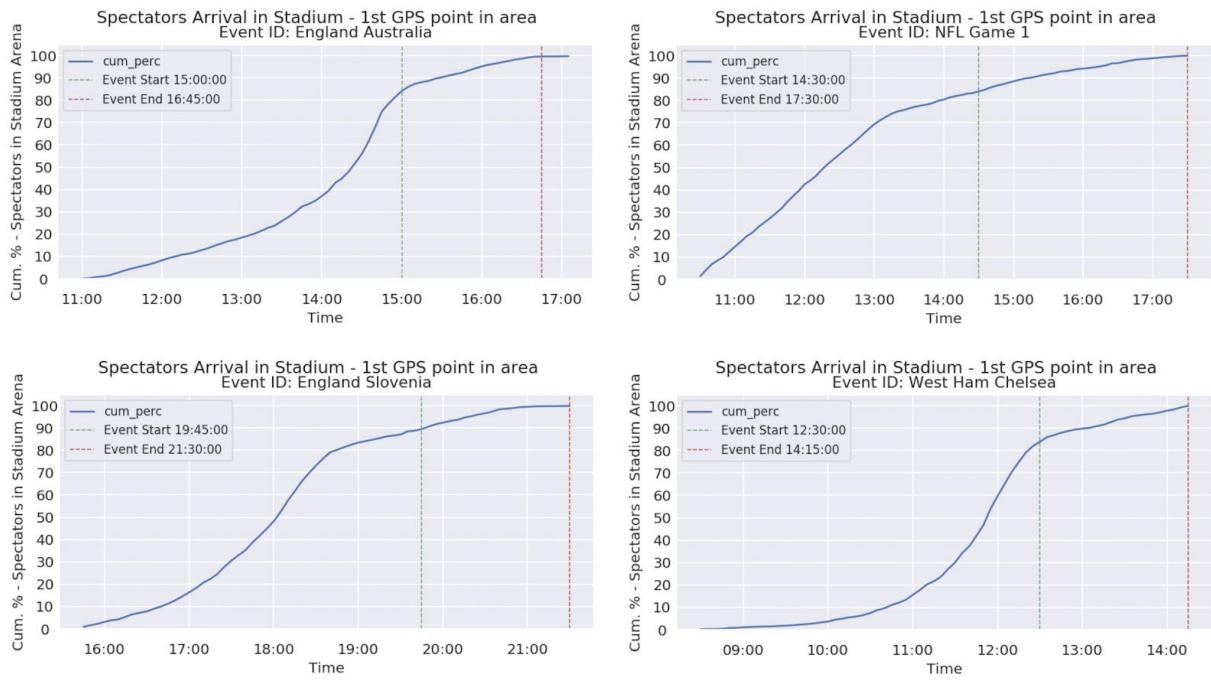
The figures below illustrate the arrival and departure of spectators for four different event types, namely a rugby game at Twickenham, an NFL game at Wembley, a UEFA game at Wembley, and an EPL game at London Stadium. These events were chosen due to their highest number of spectators that could be identified with the GPS data. The temporal changes for all other events can be viewed in the Appendix. These figures show some characteristics related to the event place and type. These can be summarized as:

- (1) UEFA and NFL games attract a considerable number of spectators within the stadium area before the beginning of the event. In the examples below, half the spectators for the UEFA game arrive with an advance greater than 1 hour and a half, compared to around 3 hours for half NFL spectators.

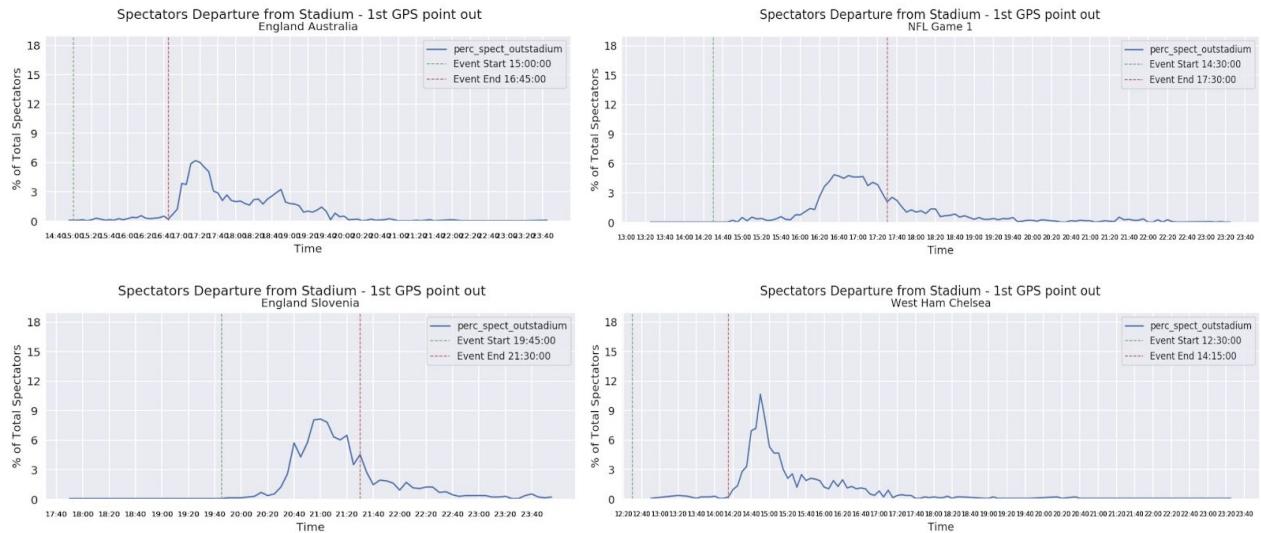
- (2) EPL games show a clearly different temporal pattern. While the game in the example happened on a weekend day (similarly to the NFL game) half of the spectators made their way to the stadium area only half an hour before the start.
- (3) Extensive commercial stadium facilities seem to influence the early arrival of spectators at large events. Comparing rugby international and NFL games at Twickenham respectively Wembley, it is apparent that most of the spectators at Wembley arrive far earlier than spectators at Twickenham.
- (4) Games at smaller venues (Watford, London Stadium) retain spectators until the end compared to games at larger venues (Wembley, Twickenham). For large venues, spectators tend to leave earlier thus avoiding large queues at train stations or parking exits.



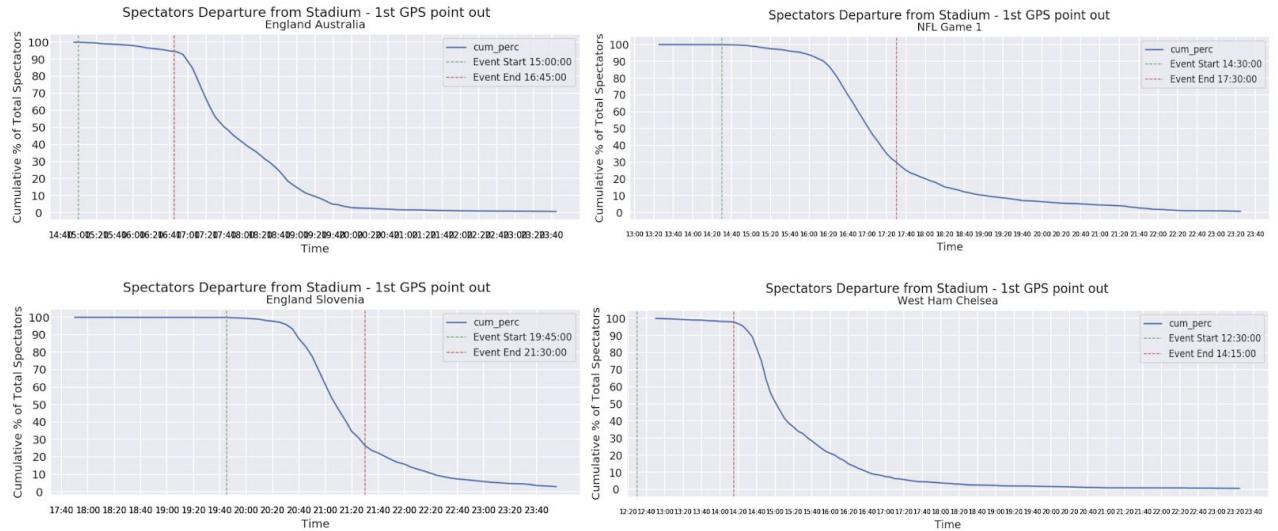
**Graph 10:** Spectators Arrival - Temporal Profile



**Graph 11:** Spectators Arrival - Temporal Change - Cumulative Percentage



**Graph 12:** Spectators Departure - Temporal Profile



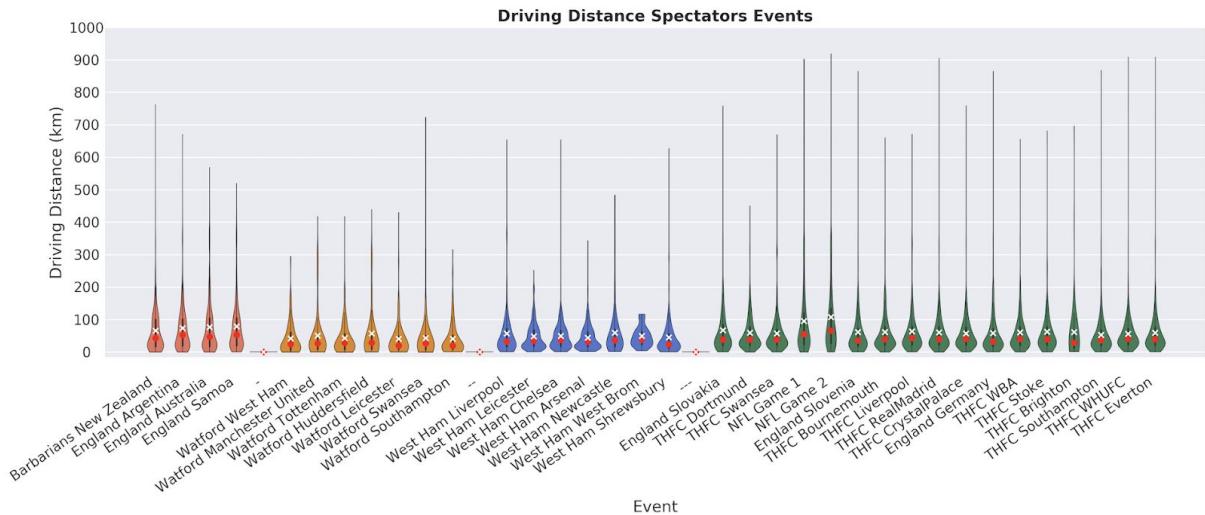
**Graph 13:** Spectators Departure - Temporal Change - Cumulative Percentage

### 5.3 Spatial Analyses

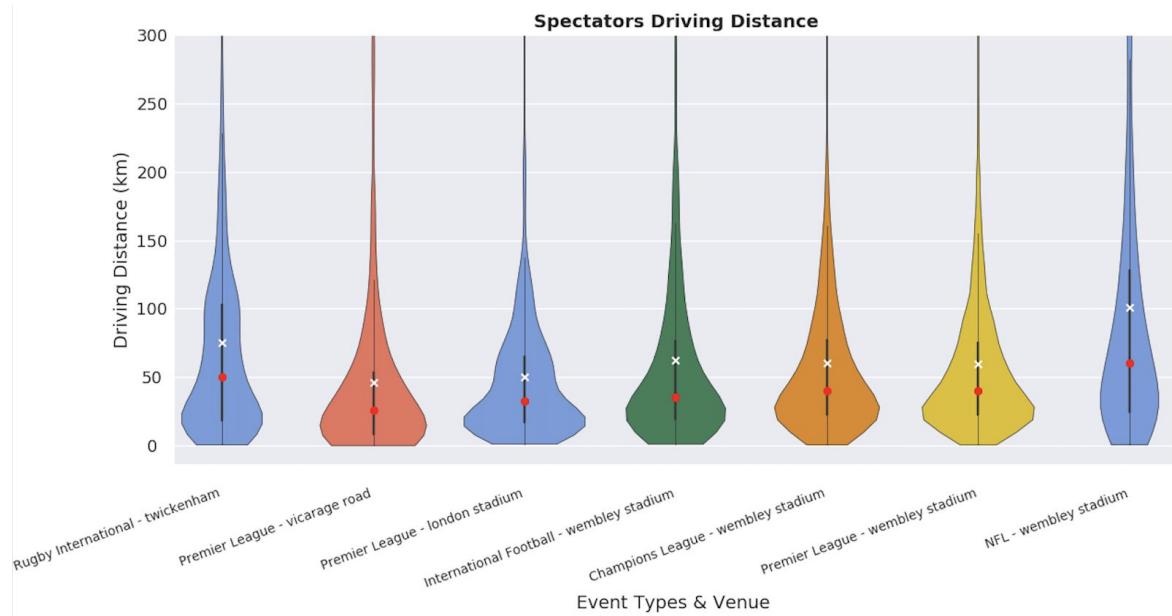
This section is divided into two subsections and focuses on the spatial differences of events and venues. First, the results for the potential driving distance travelled by the spectators are described. Second, the catchment areas for the 7 predefined categories are visualized. Finally, the results of the spatial autocorrelation tests are considered.

#### 5.3.1 Spectators Travelling Distance

Graphs 14 and 15 show the distance travelled by spectators for each event, each predefined category. NFL games with mean of 100km and rugby games with mean of 75km strongly suggest that those games attract spectators from further away. To test whether the different categories show significant difference in mean driving distance, an ANOVA statistic test was computed followed by independent t-tests. Significance level was set to 99.3% confidence (p-value of 0.007) according to Bonferroni correction principles. These tests indicate that in exception of UCL (mean of  $60.3\text{km} \pm 65.2\text{km}$ ) when compared to EPL games at Wembley (mean of  $59.8\text{km} \pm 65.2\text{km}$ ) and rugby games at Twickenham (mean of  $75.1\text{km} \pm 82.4\text{km}$ ), all other categories have significant differences in mean distance of travel when compared between each other.



**Graph 14:** Spectators Driving Distance, from spectators' home to event stadium.



**Graph 15:** Spectators Driving Distance for the 7 categories.

### 5.3.2 Spectators Catchment Area

The following observations can be drawn out of figures 9, 10 and 12, which visualize the catchment areas of the 7 categories:

- (1) EPL games show a smaller spatial sprawl compared to rugby, NFL, UEFA and UCL games.

- (a) At England counties level, rugby, NFL, UEFA and UCL attract no more than 10% of spectators from the same county. This contrasts sharply with EPL games. Whilst both West Ham and THFC teams attract more than 12% of the spectators from the same county (Hertford respectively Essex), the most apparent result is viewed for Watford team, which shows 40% of its spectators having origin in Hertford county.
  - (b) At England districts and London wards level, the previous observation is supported. EPL games attract a higher proportion of spectators from nearby districts. More than 12% of spectators for games at Watford come from Havering, while more than 8% of spectators attending games at London Stadium come from Enfield. Interestingly, rugby games at Twickenham show to have a cluster pattern around the four districts of Twickenham, Richmond, Wandsworth and Battersea, which account for more than one-third of all rugby spectators.
- (2) For all events, the London regions witness the highest percentage of spectators. Between 2 to 3% of all spectators have their home in one of the London districts, compared to 0 to 2% of spectators with home outside London districts.
- (3) A North-South, West-East division can be viewed for each category. Rugby, NFL and UEFA games draw spectators mostly from the south of London (Surrey and Kent counties). EPL and UCL games attract spectators either from the north-east or north-west London according to the geographic location of each venue.

The results of the global and local spatial autocorrelation tests support the aforementioned observations. In tables 1 and 2, the values for the global Moran's I, Getis Ord's G and Geary's C are shown, while in figures 11 and 13 the local Moran's are visualized. Regions with significant high number of spectators, so-called hotspots are indicated in red, whereas regions with considerably low number of spectators, coldspots, are indicated in blue. The results from these analyses can be summarized as follows:

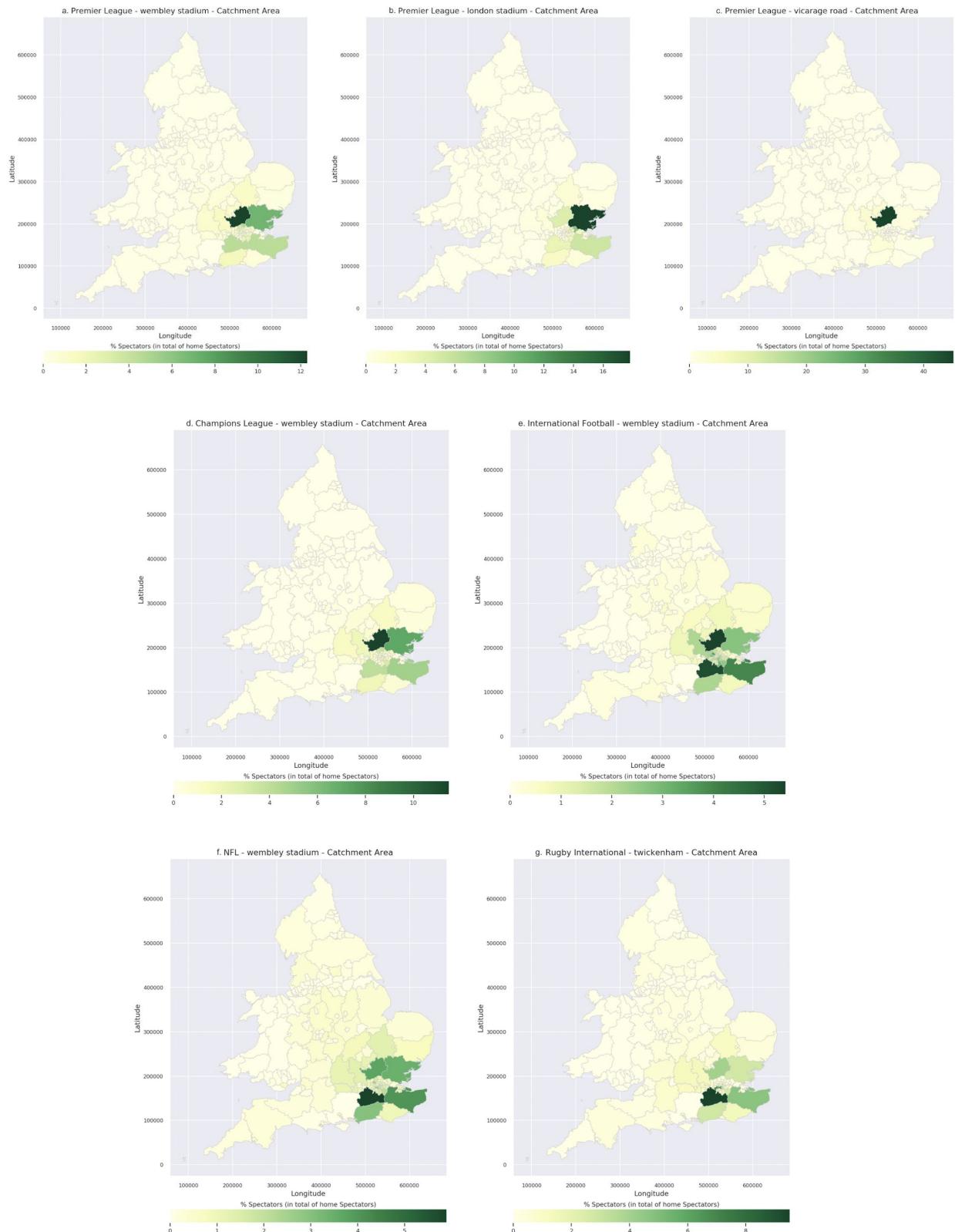
- (1) At England districts level, spatial autocorrelation is observed. Global Moran's I is positive ( $>0.5$  with p-values  $<0.05$ ), Geary's C is positive ( $<1$  with p-values  $<0.05$ ) and Getis Ord's G<sub>observed</sub> is positive and greater than Getis Ord's G<sub>expected</sub>. In other words, if a district attracts a considerable number of spectators, it is likely that a neighbouring district will also attract spectators.
  - (a) NFL games show the less clear clusters (lowest Getis Ord's G<sub>observed</sub>).
  - (b) EPL games at Watford show the most clear clusters (highest Getis Ord's G<sub>observed</sub>).
- (2) At London wards level, spatial autocorrelation is also observed but less significantly than at England districts level. Watford being situated outside London, EPL games at Watford show the poorest autocorrelation: Global Moran's I close to 0 (0.119) and Geary's C close to 1 (0.892). These less significant autocorrelation results are also observed for the international events such as NFL, UEFA and UCL.
- (3) In exception to NFL games, all categories show hotspots in proximity of the event stadium. Regarding UCL and EPL games at Wembley, the largest hotspots are found in the north and south-east of London. (It is worse noting that the original THFC home stadium is located in Enfield Borough, in north of London but as the stadium was renovated in 2017/18, THFC played the season in Wembley).
- (4) In exception to EPL games at Watford, all categories show coldspots occurring in the same London wards. These regions are part of Croydon, Bexley, Redbridge, Tower Hamlets and Southwark boroughs.

	Moran's I	Moran's I p-value	Geary's C	Geary's C p-value	Geti Ord's G observed	Geti Ord's G expected
Premier League (Wembley)	0.575	0.00E+00	0.468	2.94E-16	0.074	0.038
Premier League (London Stadium)	0.574	0.00E+00	0.484	2.30E-15	0.090	0.038
Premier League (Watford)	0.574	0.00E+00	0.362	1.44E-22	0.196	0.038
Champions League (Wembley)	0.595	0.00E+00	0.441	9.62E-18	0.072	0.038
Football World Cup Qualification (Wembley)	0.673	0.00E+00	0.352	3.55E-23	0.073	0.038
NFL (Wembley)	0.534	0.00E+00	0.483	1.95E-15	0.059	0.038
Rugby World Cup (Twickenham)	0.491	2.22E-16	0.443	1.23E-17	0.081	0.038

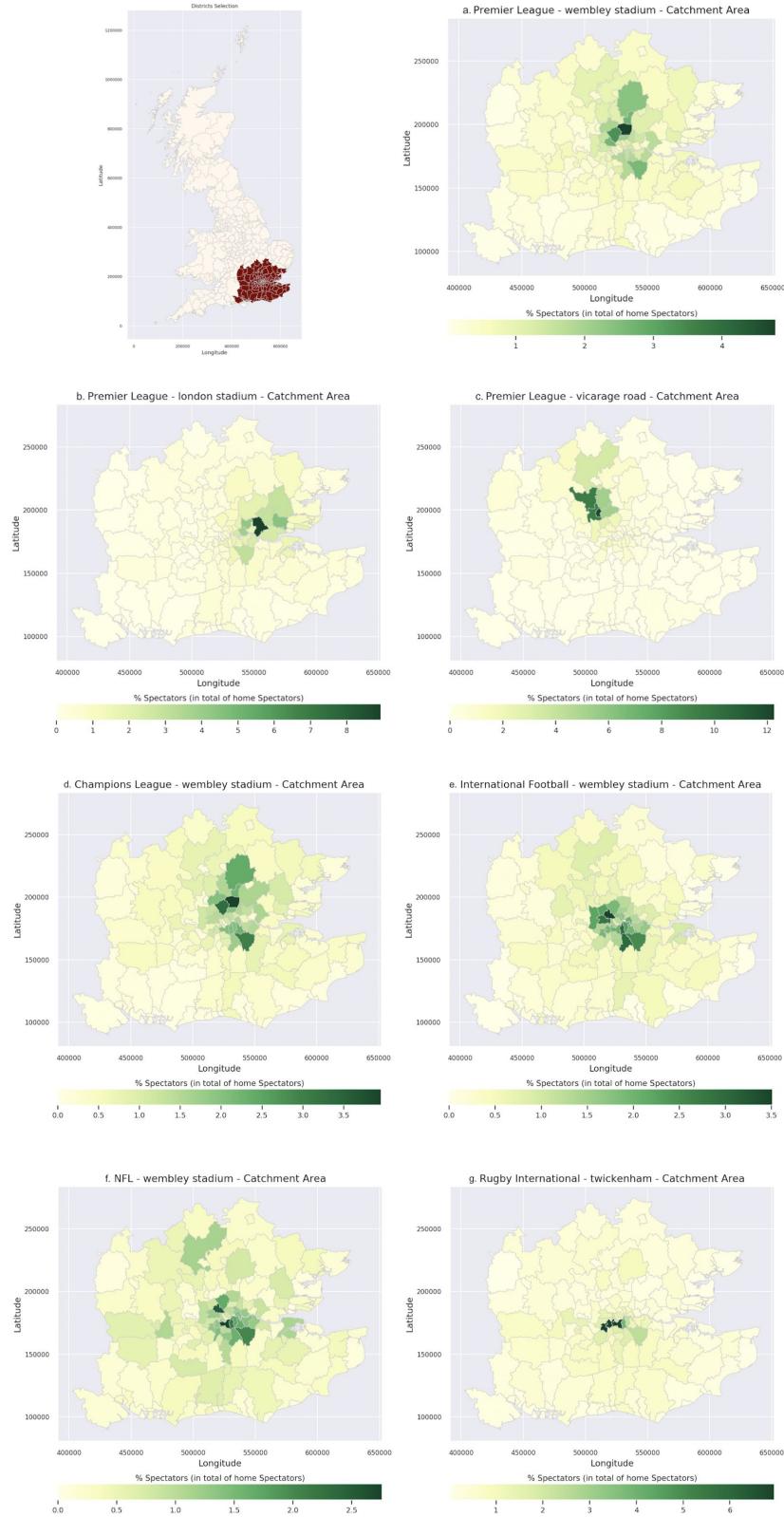
**Table 1:** England District Selection - Global Spatial Autocorrelation

	Moran's I	Moran's I p-value	Geary's C	Geary's C p-value	Geti Ord's G observed	Geti Ord's G expected
Premier League (Wembley)	0.514	0.00E+00	0.476	8.86E-101	0.016	0.009
Premier League (London Stadium)	0.545	0.00E+00	0.498	2.04E-92	0.030	0.009
Premier League (Watford)	0.119	3.06E-07	0.892	6.06E-06	0.016	0.009
Champions League (Wembley)	0.412	0.00E+00	0.598	3.42E-60	0.016	0.009
Football World Cup Qualification (Wembley)	0.312	0.00E+00	0.749	9.72E-25	0.014	0.009
NFL (Wembley)	0.208	0.00E+00	0.812	1.07E-14	0.014	0.009
Rugby World Cup (Twickenham)	0.656	0.00E+00	0.379	9.46E-141	0.030	0.009

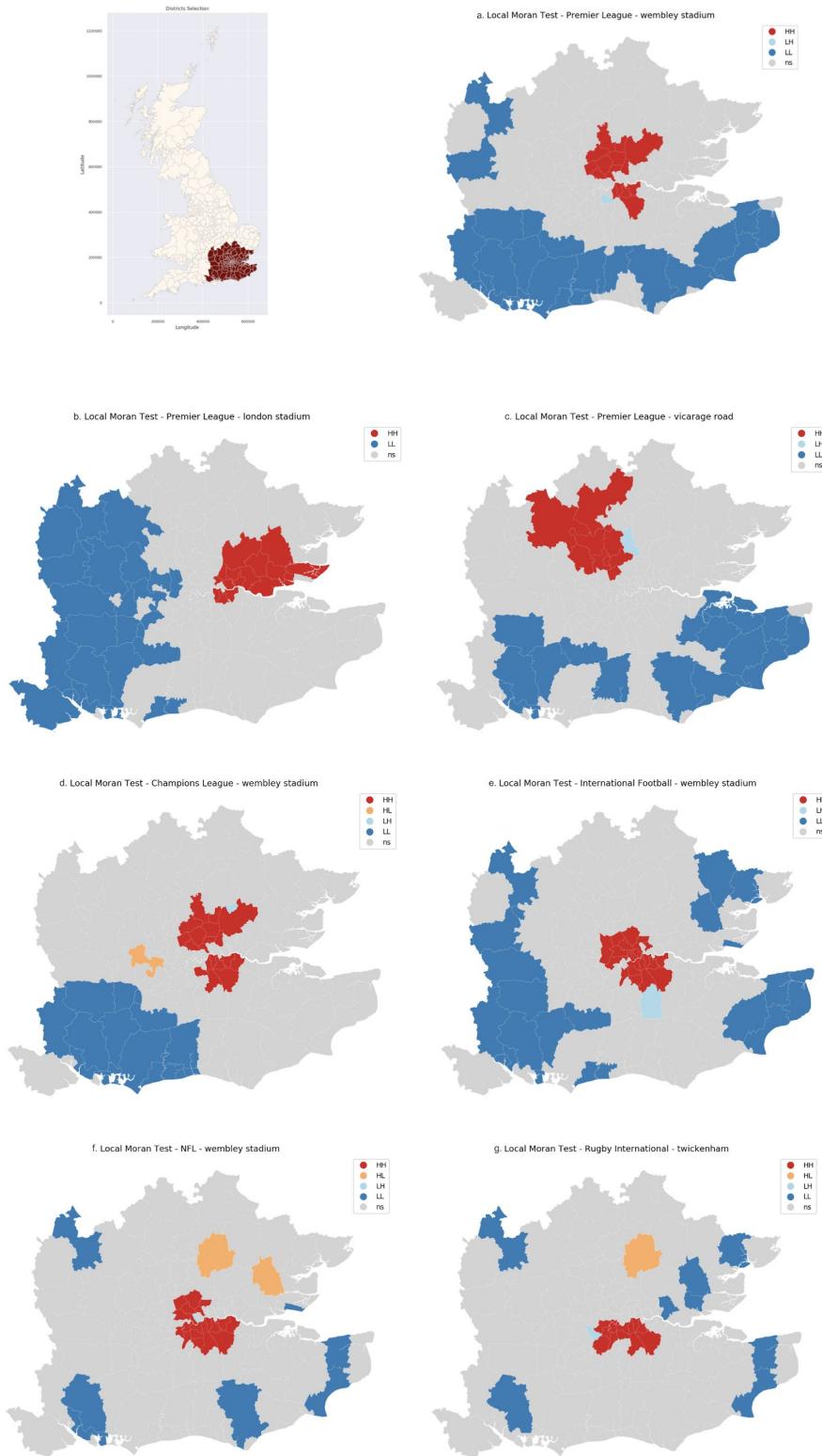
**Table 2:** London Wards - Global Spatial Autocorrelation



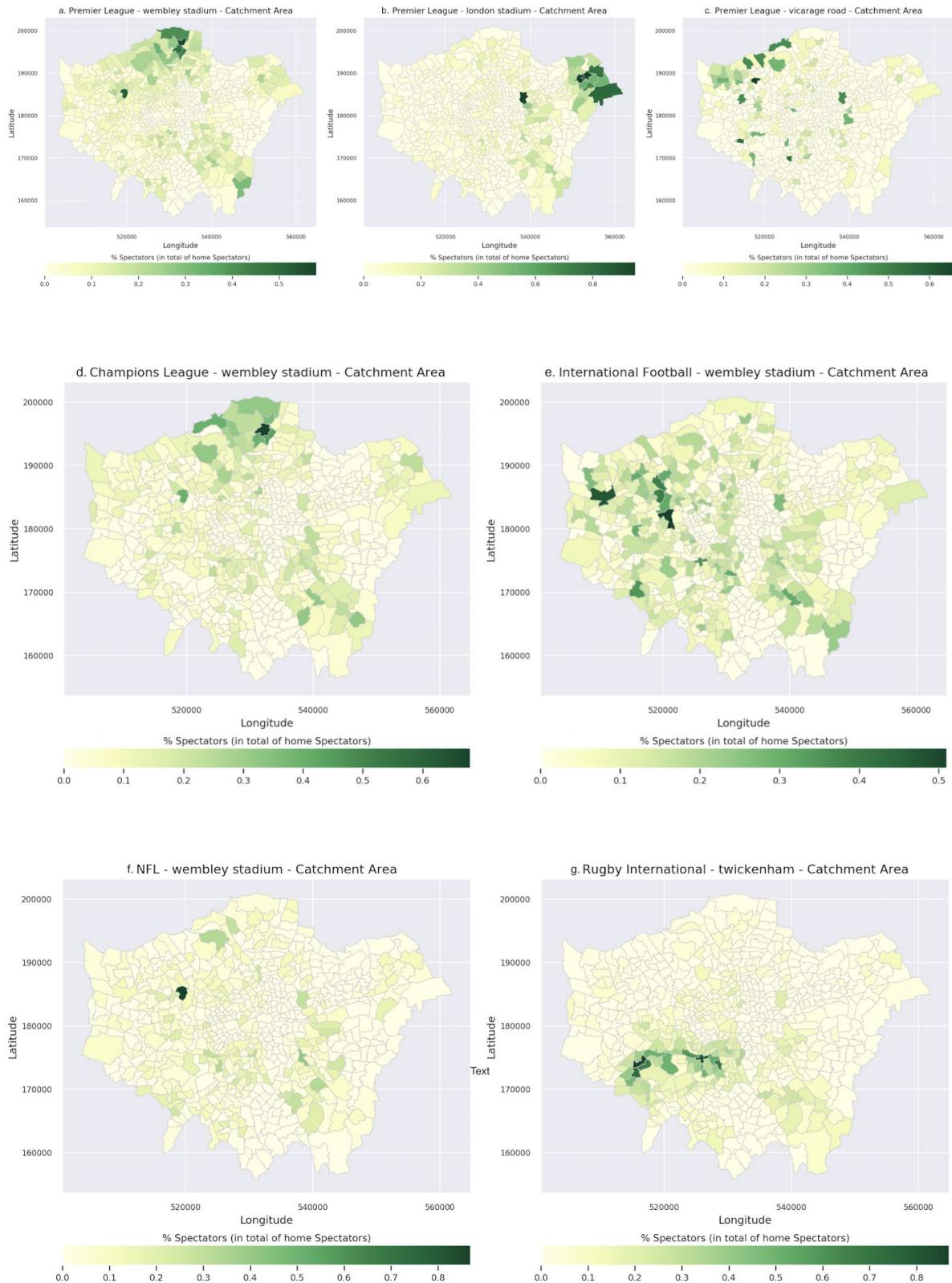
**Figure 9:** Events Catchment Areas - England Counties (a, b, c, EPL at Wembley, London stadium and Watford, d, e, f, UCL, UEFA, NFL at Wembley, g, rugby at Twickenham)



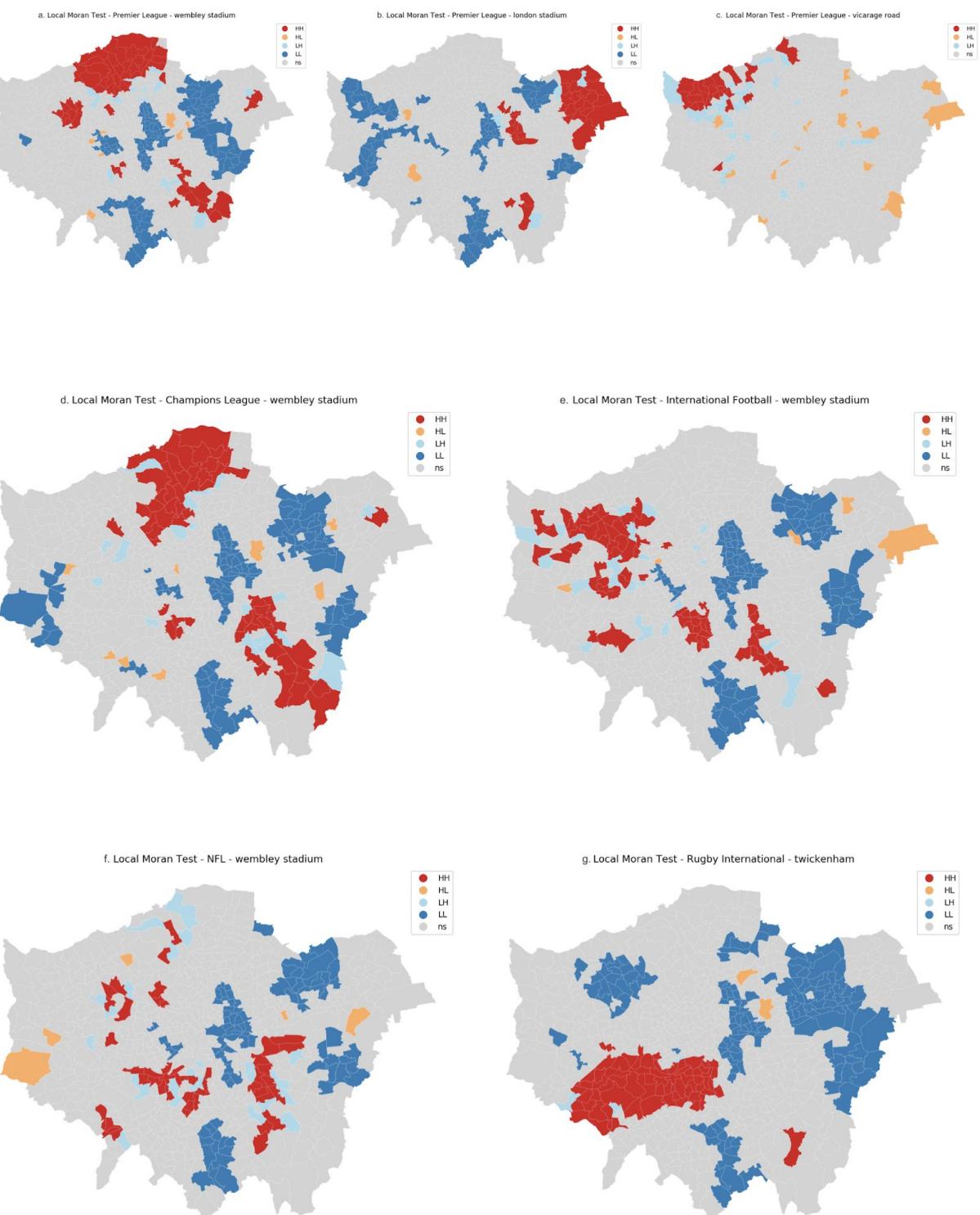
**Figure 10:** Events Catchment Areas - Selected England Districts (a, b, c, EPL at Wembley, London stadium and Watford, d, e, f, UCL, UEFA, NFL at Wembley, g, rugby at Twickenham)



**Figure 11:** Spatial Autocorrelation Local Moran - Events Catchment Areas - Selected England Districts (a, b, c, EPL at Wembley, London stadium and Watford, d, e, f, UCL, UEFA, NFL at Wembley, g, rugby at Twickenham)



**Figure 12:** Events Catchment Areas - London Wards (a, b, c, EPL at Wembley, London stadium and Watford, d, e, f, UCL, UEFA, NFL at Wembley, g, rugby at Twickenham)



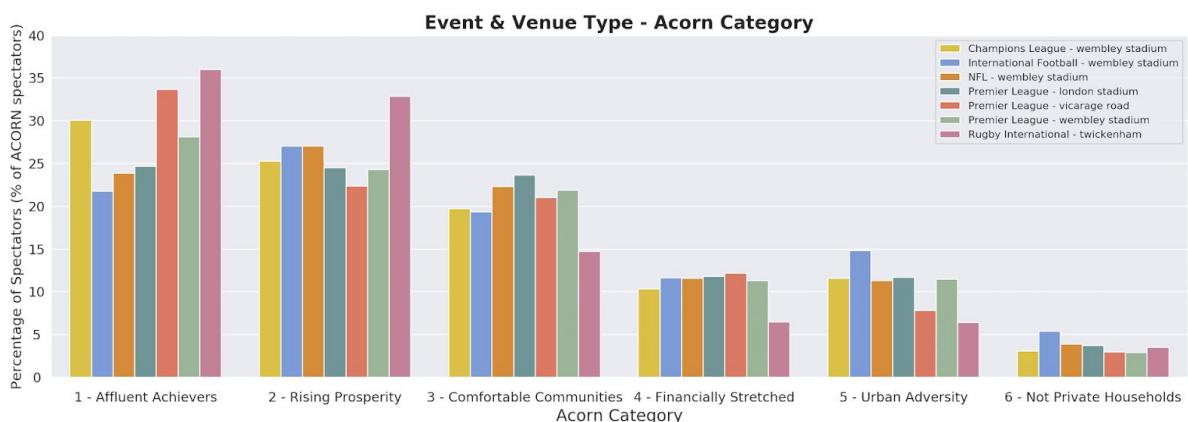
**Figure 13:** Spatial Autocorrelation Local Moran - London Wards (a, b, c, EPL at Wembley, London stadium and Watford, d, e, f, UCL, UEFA, NFL at Wembley, g, rugby at Twickenham)

## 5.4 ACORN Classification

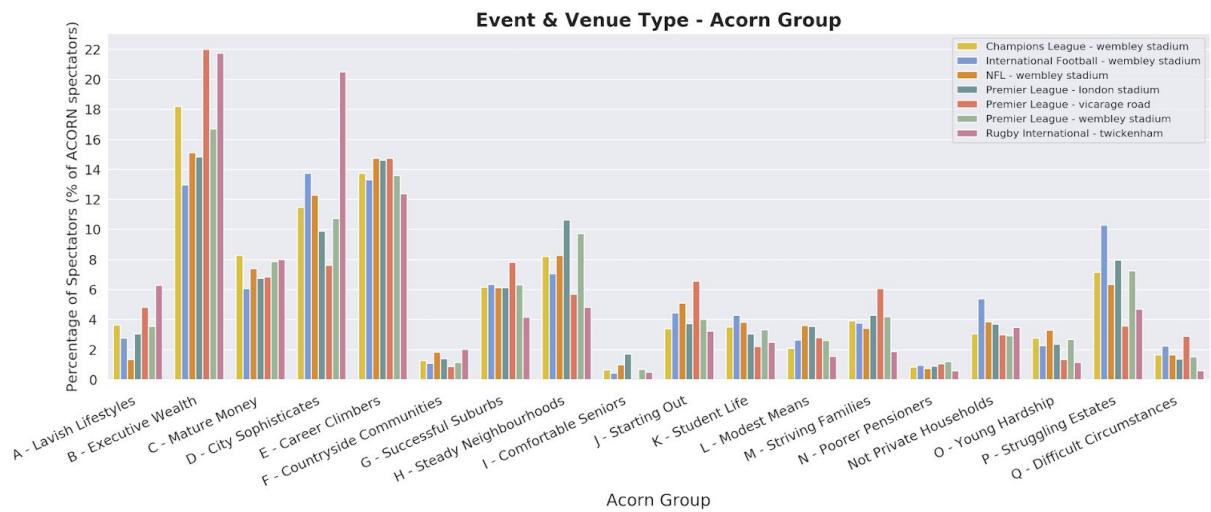
Graphs 17 and 18 show the demographic profile of spectators according to ACORN category and group classification. These findings allow to learn about the lifestyle, behaviour and attitudes of event attendees.

The results demonstrate that high percentages of spectators belong to relatively wealthy classes, being classified as “affluent achievers” or “rising prosperity”. This can be especially viewed for rugby games, whose 22% belong to “executive wealth”, respectively 20% to “city sophisticates”. Observing the other events and venues, a clear trend is more difficult to spot. The results suggest that EPL games in Watford attract a slightly different population compared to EPL games in Stratford or Wembley. Games in Watford show to have higher percentages of spectators categorized as “executive wealth” (22% v. 14% and 16%) or “starting out” (6% v. 4% and 4%) and lower percentages of spectators belonging to “city sophisticates” (8% v. 10% and 10%) or “struggling estates” (4% v. 8% and 7%) categories.

A further observation is the considerably low percentages of spectators (fewer than 2%) belonging to seniors groups such as “comfortable seniors” or “poorer pensioners”.



**Graph 16:** Acorn Category Classification for the 7 categories.



**Graph 17:** Acorn Category Classification for the 7 categories.

## 6 Discussion

Stadiums have external forms and internal elements. Their external forms are composed of their architectural design and their built environment. Their internal elements are individuals characteristics and express the variety, richness of their activities. Both forms and elements are required to create the experience and regarding only one of this entity would not allow to discover their true importance and distinguishes them from other stadiums. Accordingly, in analyzing different stadia and events, not only was it necessary to integrate the spectators, but also the game and its event location. (Inspired from "*On Art and Life*" by John Ruskin)

### 6.1 Key Findings

#### 6.1.1 Twickenham

Spectators for rugby games are more likely to be one-off spectators, such that their attendance to the games step out of their usual habits. As a consequence, spectators spend more time (close to 2 hours) in the stadium area and are coming from further away (driving around 75km). These games show to attract a majority of south-east Londoners, who are financially secure, having considerable incomes and being well-educated. However, these spectators arrive to the stadium close to the beginning of a game, thus not dwelling considerably long in the event arena.

#### 6.1.2 Vicarage Road, Watford

Spectators for EPL games in Watford were the least represented by the GPS dataset. However, the analyses demonstrated that those games are of great importance for the local residents, with 40% of spectators having their home in the stadium county, and even 12% in Watford district. These games are very likely attended by a large number of season ticket holders. Regarding ACORN segmentation, most of them have families, those being from various social-classes (from financially secured to fragile and tight income). This specificity may be interesting for Watford Football club to explore in order to further engage with the local community. Community activities similar to those proposed by THFC Football Club foundation could be delivered. Those would foster employment, education, health and fitness as well as social cohesion and may increase supporters participations. As indicated by (Magowan, 2018), around 15% of the ticket holders for Watford games do not turn at the venue.

#### 6.1.4 London Stadium, Stratford

Spectators for EPL games at London Stadium have a similar profile to those at Vicarage Road.

#### 6.1.5 Wembley

Wembley Stadium attract spectators from a mixed background and broad geographic area. While NFL games indicate to be particular one-off occasion, attracting a significant number of visitors from outside England, welcoming spectators earlier in the stadium arena (~3h before the start of the game) and hosting them for the longest period of time (~4h), football games like UEFA, UCL and EPL show similarity in spectators behaviours compared to the other football events of this study.

## 6.2 Limitations

The study showed to be a reliable instrument for measuring sporting event attendees behaviours. However, it is necessary to mention that the results are subjected to limitations and may suffer from random as well as systematic errors, so-called bias.

The most obvious limitation corresponds to the nature of the dataset. As mentioned by (Longley et al., 2018), the use of crowd sourced data contrast highly with principles of scientific sampling, which goal is to ensure a complete coverage of the studied population. The study dataset, however, consists only of the spectators that have downloaded a specific application and agreed to share their location. Thus, people not having the application on their smartphone, not sharing their location or not owning a mobile device have been completely ignored.

Another limitation regards the apparent false reported percentages of international spectators for large international events such as rugby international and NFL. The findings indicate that less than 2% of spectators have their home outside the UK, thus contrasting sharply with previously published surveys. Deloitte (2018) indicated that 18% of spectators attending NFL games came from outside England, EY (2016) indicated that 25% of the tickets games for Rugby World Cup at Twickenham were purchased by internationals. This number, while probably lower for rugby Autumn games, indicate however that a certain number of overseas may have attended the games.

These discrepancies could be attributed on one hand to the bias of the dataset, which constitute mostly of Englanders, on the other, to the impossibility to identify the home for a third of the spectators due to their insufficient number of records. It is very likely that there is a considerable number of overseas spectators inside this group. This can be assumed as international spectators are the most likely to have downloaded a local application on their smartphone only for the period of their travel and thus not having enough datapoint in order to be assigned to a home location.

Furthermore, the tendency of GPS data to include random errors such as missing data or wrongly recorded location and timestamp by the GPS modules. This leads to limitations in the number of available data and causes difficulty to retrieve information about the spectators. While thorough steps were undertaken to accurately define stadium visitors, their dwell time, home and start locations, uncertainty remains. First, it was not possible to identify the home location for all spectators, as these had not enough records. Secondly, there were high variations in GPS points record for each individual ranging from points record every 30 seconds to every 2 hours. Thus results for the arrival, departure and average dwell time show some considerable variation.

### 6.3 Further Research

Regarding the numerous publications on GPS data analyses, Sport Spectators as well as Customer Segmentation, a variety of scholars could be interested to work further with this dataset. Extended research could engage with diverse approaches, and benefit the following actors:

- (1) Traffic Planners and City Tourism Officers would benefit from a further study looking at the movement of spectators at the day of an event. Identifying spectators' activities at an event day, would allow them to better predict the route, type of transport, and interests of the event attendees. A further study could, therefore, look into the spectators' GPS trajectories and identify their stop locations. Linking these locations with google "Point of Interest" (such as schools, museums, businesses, ...) would allow answering questions such as: where do the spectators come from? Is it straight from their home, is it from their workplace, or from another cultural venue?

- (2) Event Organizers and Stadium Managers may be interested in gaining knowledge in the various needs of their visitors, thus being able to improve their offer and content their visitors. A future research could link the current dataset with other sources such as spending data or social media data. While the first source would allow to learn more about the specific needs of the spectators (Which goods are purchased by whom?), the second source would give event organizers rich information on the attitudes, opinions and perspectives of the spectators (What was the overall sentiment of spectators?).
- (3) Event Promoters may be willing to increase the efficiency of their advertising campaigns. Thus, they might want to learn about their potential next customers. A natural progression of this work would concern in the building of a predictive model or recommender system allowing to define the likelihood of someone to attend a rugby, NFL, UEFA, UCL or EPL game. Using the present dataset, and selecting the spectators' ACORN class, their postcode location, as well as the event time as features, it might be possible to predict the event a new person may want to attend.

## 7 Conclusion

The study gained valuable insights into the spectators' behaviour for sporting events across stadia in London. The findings specifically enhanced the understanding of arrival, departure, dwell time and travel distance of spectators, as well as event catchment area and spectators' demographic profiles. Compared to previous GPS or geodemographic research, this study has key strengths in the number of its subjects as well as events and venue types. This research may benefit transport planners, tourism officers and event managers in order to better manage spectators flows or target new spectators. Significant differences in the dwell time, spectator's origin and spectators' demographic profile could be identified for the observed sporting events (NFL, rugby and football games). Future research should, therefore, explore how these variables could be used to predict potential spectators for diverse sporting events. The integration of other data sources would moreover allow researcher to interpret in greater depth the spectators' attitudes.

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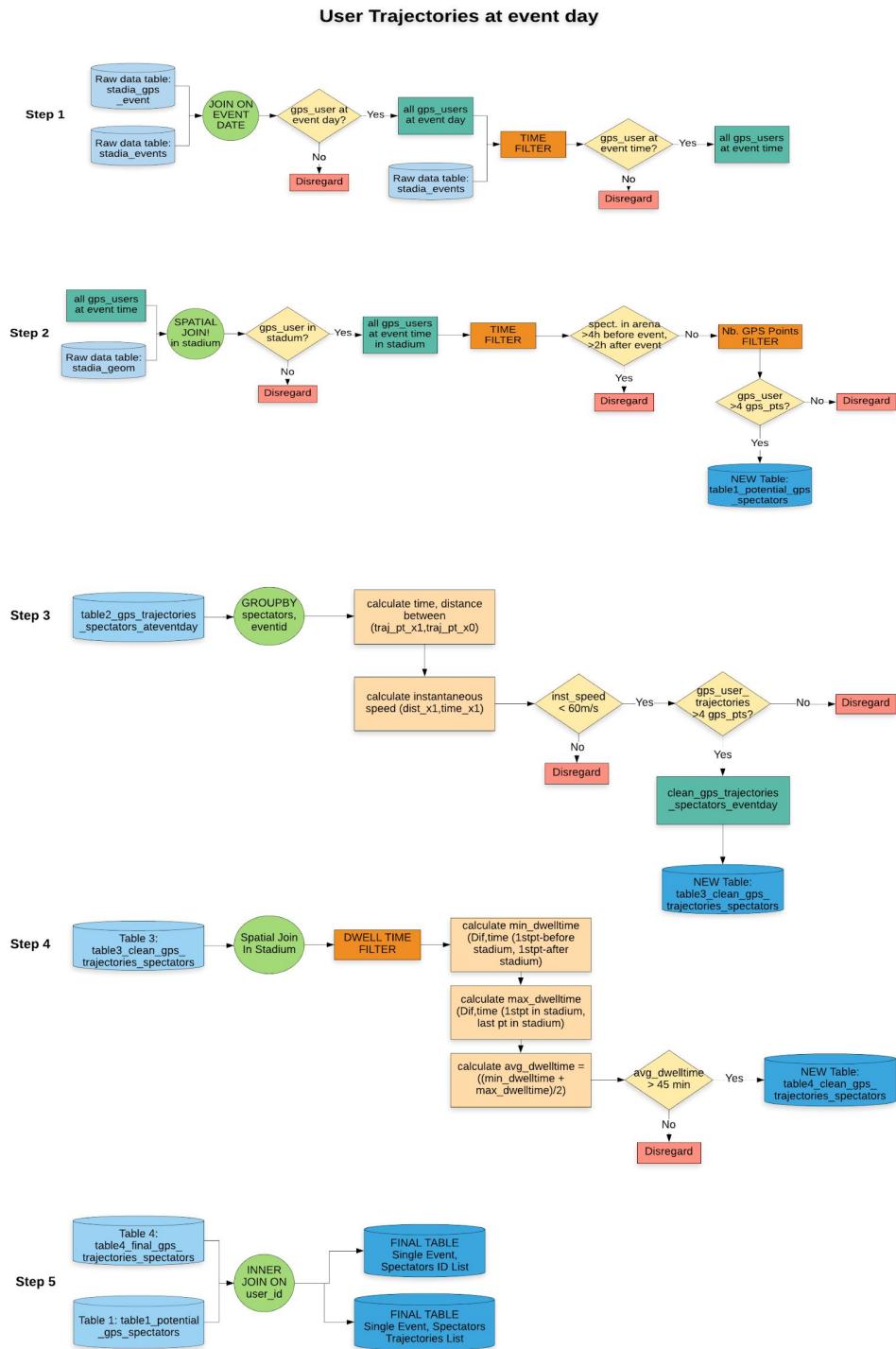
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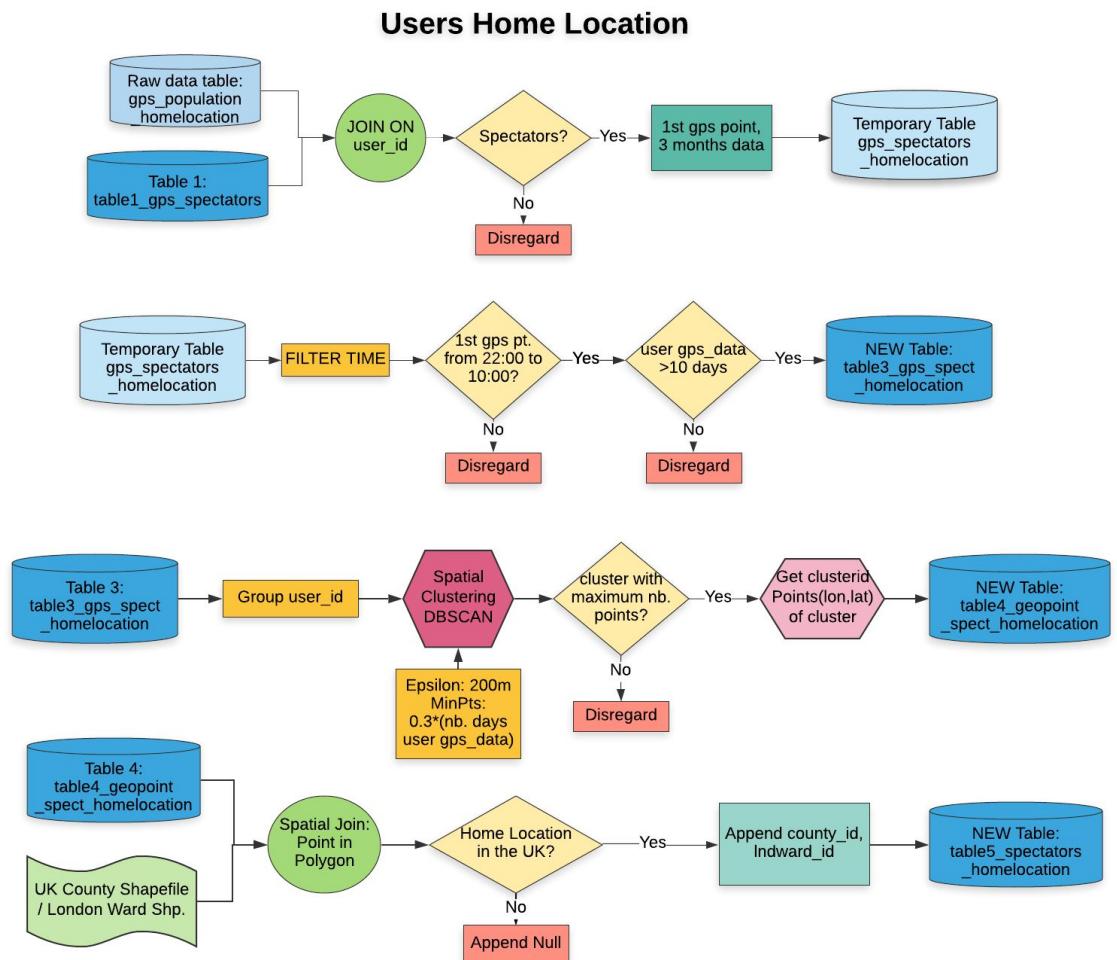
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# Appendix A: Flow Diagrams

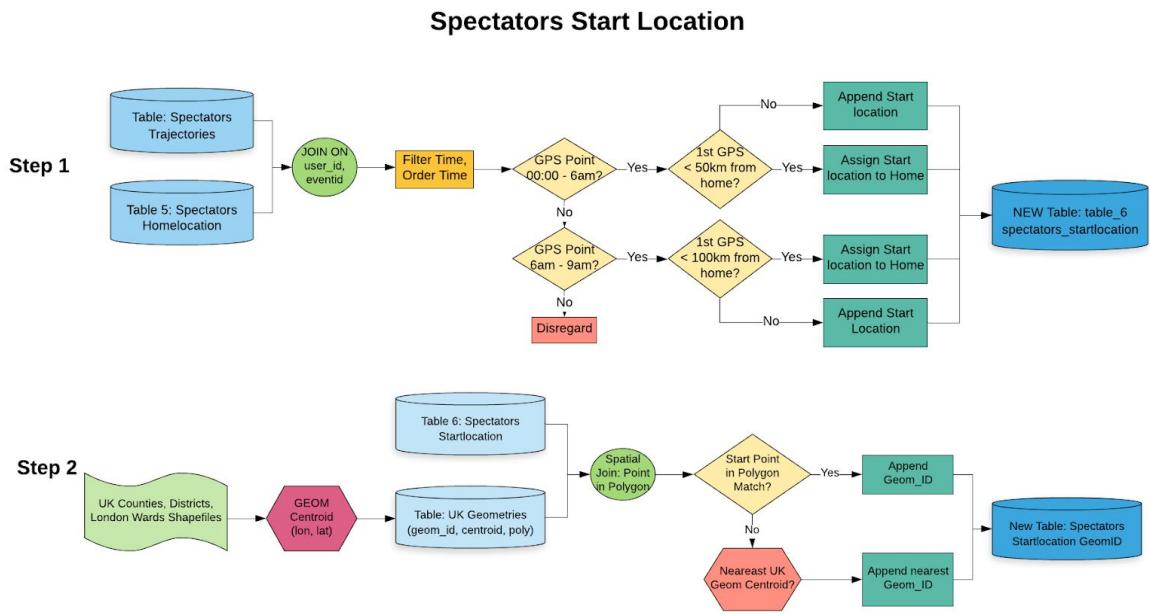
## 1. Data Cleaning GPS Trajectories



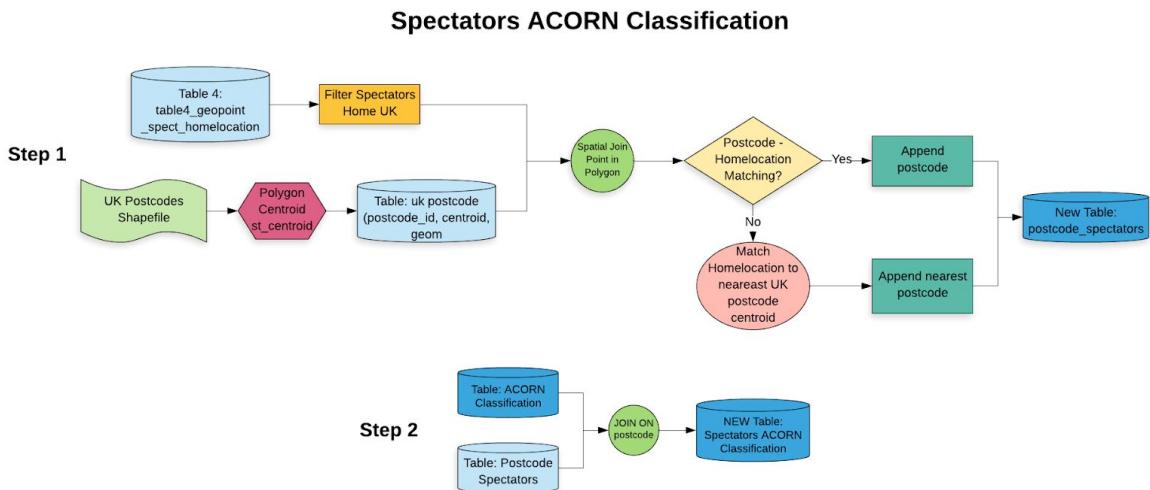
## 2 Identification Spectators Home Location



### 3 Identification Spectators Start Location



### 4 Identification Spectators ACORN Classification



## Appendix B: List of Events

index	venueid	event	venue	date_dt	start_time	end_time	attendance
0	1	Barbarians New Zealand	twickenham	04/11/2017	15:00:00	16:45:00	63511
1	1	England Argentina	twickenham	11/11/2017	15:00:00	16:45:00	81683
2	1	England Australia	twickenham	18/11/2017	15:00:00	16:45:00	81909
3	1	England Samoa	twickenham	25/11/2017	15:00:00	16:45:00	81911
4	2	Watford Tottenham	vicarage road	02/12/2017	15:00:00	16:45:00	20278
5	2	Watford Huddersfield	vicarage road	16/12/2017	15:00:00	16:45:00	20026
6	2	Watford Leicester	vicarage road	26/12/2017	15:00:00	16:45:00	20308
7	2	Watford Swansea	vicarage road	30/12/2017	15:00:00	16:45:00	20002
8	2	Watford Southampton	vicarage road	13/01/2018	15:00:00	16:45:00	20018
9	2	Watford West Ham	vicarage road	19/11/2017	16:00:00	17:45:00	20018
10	2	Watford Manchester United	vicarage road	28/11/2017	20:00:00	21:45:00	20552
11	3	West Ham Chelsea	london stadium	09/12/2017	12:30:00	14:15:00	56953
12	3	West Ham Liverpool	london stadium	04/11/2017	17:30:00	19:15:00	56961
13	3	West Ham West Brom	london stadium	02/01/2018	19:45:00	21:30:00	56888
14	3	West Ham Shrewsbury	london stadium	16/01/2018	19:45:00	21:30:00	39867
15	3	West Ham Newcastle	london stadium	23/12/2017	15:00:00	15:45:00	56955
16	3	West Ham Leicester	london stadium	24/11/2017	20:00:00	21:45:00	56897
17	3	West Ham Arsenal	london stadium	13/12/2017	20:00:00	21:45:00	56921
18	4	MTV EMAs	wembley arena	12/11/2017	17:00:00	22:00:00	12500
19	4	THFC Southampton	wembley stadium	26/12/2017	12:30:00	14:15:00	57297
20	4	THFC Swansea	wembley stadium	16/09/2017	17:30:00	19:15:00	65366
21	4	THFC Everton	wembley stadium	13/01/2018	17:30:00	19:15:00	76251
22	4	NFL Game 1	wembley stadium	24/09/2017	14:30:00	17:30:00	84592
23	4	NFL Game 2	wembley stadium	01/10/2017	15:30:00	18:30:00	84423
24	4	England Slovakia	wembley stadium	04/09/2017	19:45:00	21:30:00	67823
25	4	THFC Dortmund	wembley stadium	13/09/2017	19:45:00	21:30:00	67343
26	4	England Slovenia	wembley stadium	05/10/2017	19:45:00	21:30:00	61598
27	4	THFC RealMadrid	wembley stadium	01/11/2017	19:45:00	21:30:00	83827
28	4	THFC Crystal Palace	wembley stadium	05/11/2017	12:00:00	13:45:00	65270
29	4	THFC Bournemouth	wembley stadium	14/10/2017	15:00:00	16:45:00	73502
30	4	THFC WBA	wembley stadium	25/11/2017	15:00:00	16:45:00	65905
31	4	THFC Stoke	wembley stadium	09/12/2017	15:00:00	16:45:00	62202
32	4	THFC Liverpool	wembley stadium	22/10/2017	16:00:00	17:45:00	80827
33	4	England Germany	wembley stadium	10/11/2017	20:00:00	21:45:00	81382
34	4	THFC Brighton	wembley stadium	14/12/2017	20:00:00	21:45:00	55124
35	4	THFC WHUFC	wembley stadium	04/01/2018	20:00:00	21:45:00	50034

Table 3: List of Events (teams, stadium, date, start and end time, attendance)

## Appendix C: Statistical Methods

### 1 Independent T-test (Two Samples T-test)

Test if there is a significant difference between the mean of two independent groups.

Null Hypothesis ( $H_0$ ) :  $u_1 = u_2$ , mean of event 1 = mean of event 2

Alternative Hypothesis ( $H_1$ ) :  $u_1 \neq u_2$ , mean of event 1 is not equal to mean of event 2

Test Assumptions:

- Independent samples and randomly drawn. (Yes, spectators at the event and venue type are independent and randomly drawn, the dataset has 7 independent samples).
- Variances between the two groups are equal. (Test with Levene Test)
- Distribution of the residuals follow a normal distribution.

### 2 ANOVA One-Way

Extension of the t-test. Test if there is a significant difference between the mean of two groups or more. Here, the test is used to test whether the mean of driving distance and average dwell time differ significantly between the seven events and venue types. While Anova may give significant results (p-value << 0.05 and F-statistic >> 0), the test will not indicate if the difference is between only one group, two groups or all groups. Thus, it is necessary to perform a post-hoc t-test.

Null Hypothesis ( $H_0$ ) : No difference between means,  $u_1 = u_2 = \dots = u_i$

Alternative Hypothesis ( $H_1$ ) : Difference b. means (somewhere),  $u_1 \neq (\dots) u_2 \neq (\dots) u_i$

Test Assumptions:

- Independent observations
- Homogeneity of variance
- Normality

### 3 Bonferroni Correction

Use to counteract the problem of multiple comparisons. When testing multiple hypotheses, the chance of a rare event increases, and therefore, the likelihood of incorrectly rejecting the null hypothesis (Type I error) increases. The Bonferroni correction compensates for that

increase by testing each individual hypothesis at a significance level of  $\alpha/m$  (with  $\alpha$  as the desired alpha level and  $m$  as the number of hypotheses).

Here, 7 categories are tested ( $m=7$ ) with a desired confidence level of 95% ( $\alpha=0.05$ ).

Bonferroni Correction:  $\alpha/m = 0.05/7 = 0.0071$

#### 4 Chi-Square Goodness of Fit

Test whether the observed proportions for a categorical variable differ from hypothesized proportions. Here, the chi-square test if the proportion of spectators for the different ACORN group are significantly different or not? Is there an ACORN group that show a significant difference regarding the expected hypothesized proportion? Or in other words, is there an ACORN group that show significantly higher or lower proportion of spectators attending a specific event?

### 5 Spatial Autocorrelation

#### 5.1 Moran's I

Morans' I (Moran 1950) tests whether clusters exist across the global map. It measures the similarity between nearby features. Values fall in the range -1 to 1, whereas negative values indicate negative spatial autocorrelation and positive values indicate positive spatial autocorrelation.

#### 5.2. Geary's C

Geary's C (Geary 1954) is based on the deviations in adjacent observations with one another. Values range from 0 to unspecified values greater than 1, where values significantly lower than 1 demonstrate positive spatial autocorrelation.

#### 5.3. Getis Ord's General G

Getis Ord's General G tests the presence of hotspot or cold spot. It indicates whether high or low values are concentrated over the study area. If the Getis Ord's G value is greater than the expected one, it suggests the presence of hotspots (high values cluster together), whereas if the Getis Ord's G value is lower than the expected one, the presence of cold spots (low values cluster together) is expected.

#### 5.4. Local Moran

The Local Moran (Anselin 1995) allows the identification of local clusters and local spatial outliers. The result gives a pseudo-p-value for each location, which can be used to assess the significance of high-high and low-low spatial clusters as well as high-low and low-high spatial outliers.

## Appendix D: Statistical Tests Results

### 1 Driving Distance (km)

#### 1.1 Shapiro Test - Normal Distribution

	Event Category	Shapiro test	p-value
	Rugby International - twickenham	0.981400	6.739313e-23
	Premier League - vicarage road	0.984801	6.434790e-09
	Premier League - london stadium	0.992426	2.231752e-13
	International Football - wembley stadium	0.996761	3.632619e-05
	Champions League - wembley stadium	0.990108	7.384706e-12
	Premier League - wembley stadium	0.988829	3.467346e-26
	NFL - wembley stadium	0.988488	1.210463e-12

Table 4: Shapiro Test - Event Category - Driving Distance (km)

#### 1.2 Independent t-test

	Event Category 1	Event Category 2	Independent t-test	p-value	Degree of Freedom
0	Rugby International - twickenham	NFL - Wembley	-9.9072	0.000000	4915.3573
1	Rugby International - twickenham	Champions League - wembley	1.5633	0.118028	6110.3424
2	Rugby International - twickenham	International Football WCQ - wembley	4.6233	0.000004	5815.9603
3	Rugby International - twickenham	Premier League - watford	15.1924	0.000000	1448.6942
4	Rugby International - twickenham	Premier League - wembley	2.9659	0.003029	6550.5344
5	Rugby International - twickenham	Premier League - london stadium	12.3059	0.000000	7906.6845
6	Premier League - vicarage road	NFL - Wembley	-20.5709	0.000000	1706.5127
7	Premier League - vicarage road	Champions League - wembley	-14.3182	0.000000	1438.3007
8	Premier League - vicarage road	International Football WCQ - wembley	-12.1794	0.000000	1548.6699
9	Premier League - vicarage road	Premier League - wembley	-14.7196	0.000000	1147.7982
10	Premier League - vicarage road	Premier League - london stadium	-8.8195	0.000000	1353.8234
11	Premier League - london stadium	NFL - Wembley	-20.8608	0.000000	4388.8900
12	Premier League - london stadium	Champions League - wembley	-10.6609	0.000000	5543.0015
13	Premier League - london stadium	International Football WCQ - wembley	-6.6254	0.000000	5233.4022
14	Premier League - london stadium	Premier League - wembley	-12.6805	0.000000	6717.8392
15	International Football - wembley stadium	NFL - Wembley	-13.5228	0.000000	4649.4685
16	International Football - wembley stadium	Champions League - wembley	-3.1569	0.001605	4864.7324
17	International Football - wembley stadium	Premier League - wembley	-2.8954	0.003809	3681.7727
18	Champions League - wembley stadium	NFL - Wembley	-11.2698	0.000000	4387.2928
19	Champions League - wembley stadium	Premier League - wembley	1.0155	0.309909	3893.2705
20	Premier League - wembley stadium	NFL - Wembley	-14.0113	0.000000	3121.8834

Table 4: Independent T-test - Event Category - Driving Distance (km)

## 2 Average Dwell Time (min)

### 2.1 Shapiro Test - Normal Distribution

Event Category	Shapiro test	p-value
Rugby International - twickenham	0.969611	6.916771e-35
Premier League - vicarage road	0.945768	6.301499e-23
Premier League - london stadium	0.962111	1.317307e-36
International Football - wembley stadium	0.989553	1.429507e-16
Champions League - wembley stadium	0.984110	7.825602e-20
Premier League - wembley stadium	0.982171	8.051567e-38
NFL - wembley stadium	0.996059	3.272752e-08

Table 5: Shapiro Test - Event Category - Avg. Dwell Time (min)

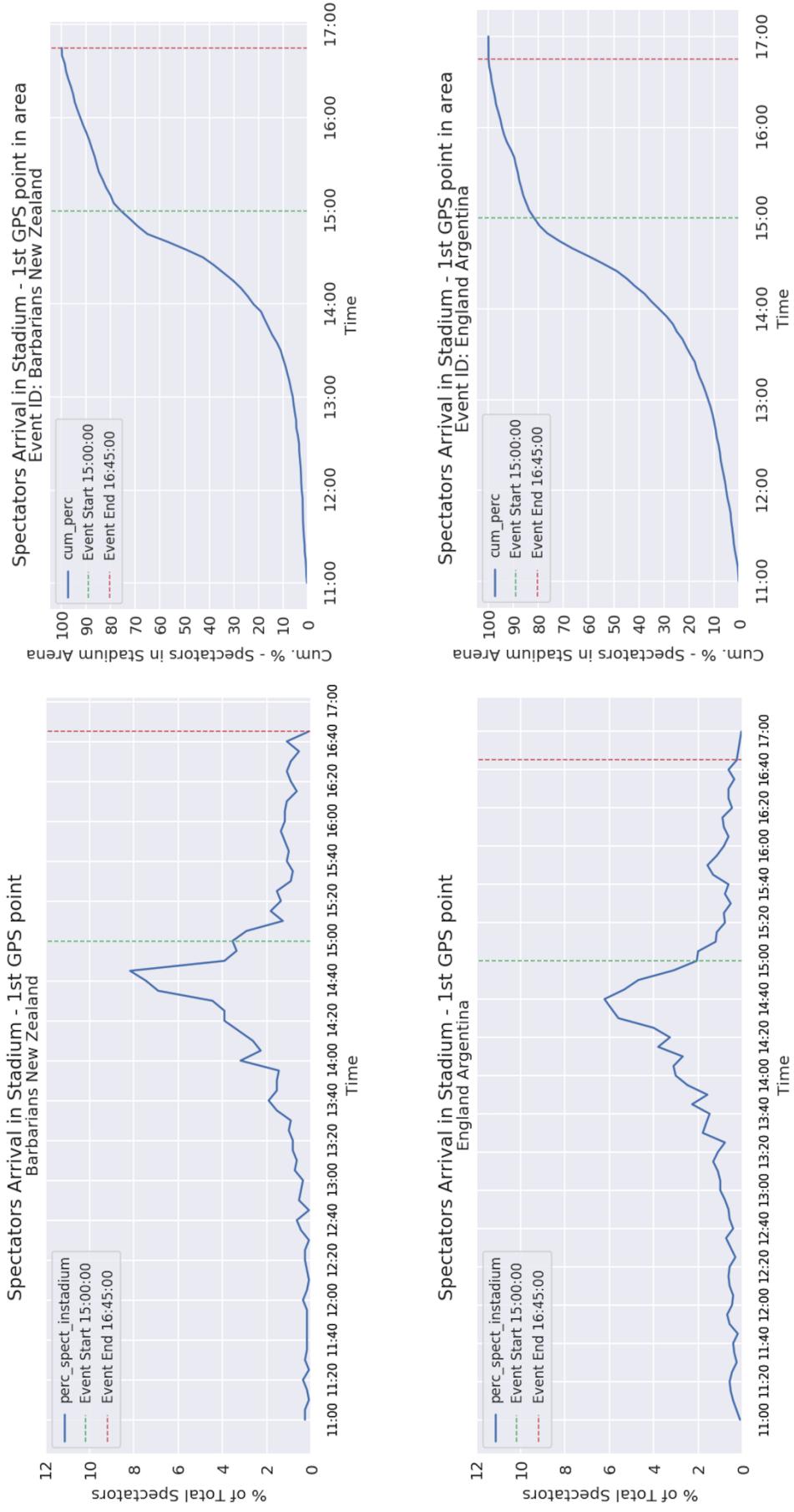
### 2.2 Independent t-test

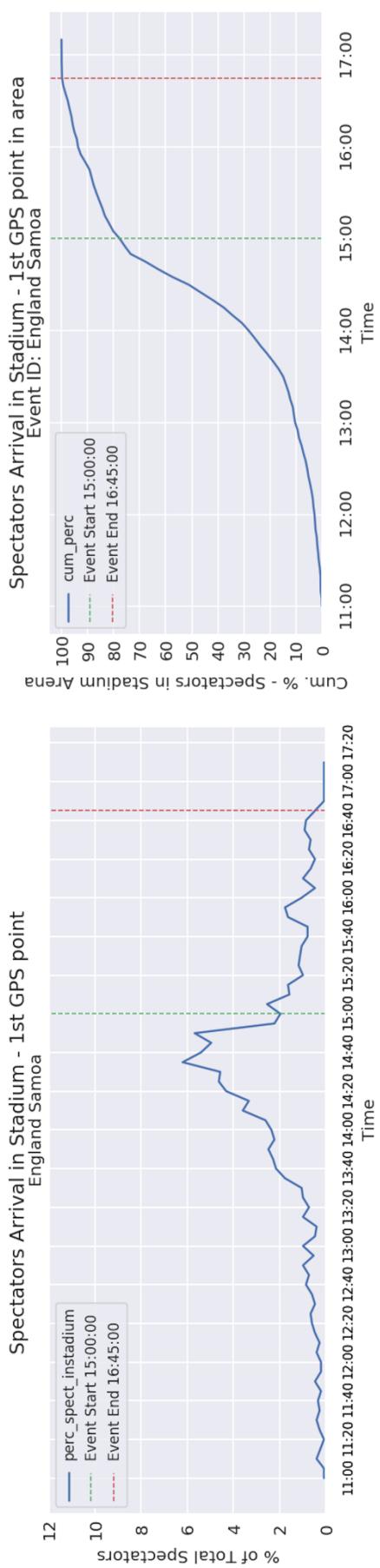
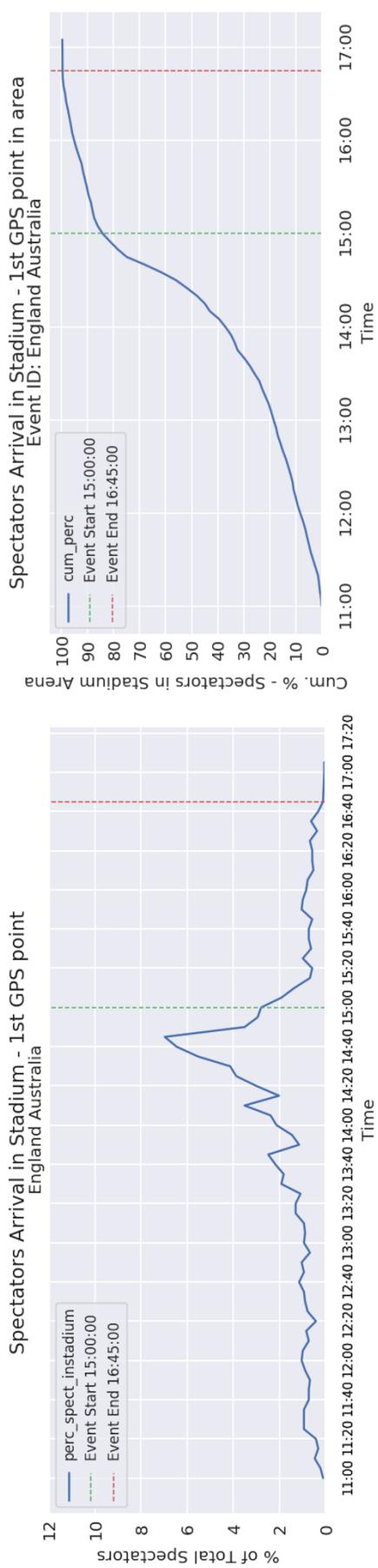
	Event Category 1	Event Category 2	Independent t-test	p-value	Degree of Freedom
0	Rugby International - twickenham	NFL - Wembley	-113.7312	0.000000e+00	9737.9255
1	Rugby International - twickenham	Champions League - wembley	2.9714	2.973150e-03	8173.0838
2	Rugby International - twickenham	International Football WCQ - wembley	-5.0010	5.800000e-07	9181.0566
3	Rugby International - twickenham	Premier League - watford	10.0404	0.000000e+00	2275.3857
4	Rugby International - twickenham	Premier League - wembley	-2.8506	4.371270e-03	12648.3969
5	Rugby International - twickenham	Premier League - london stadium	22.0100	0.000000e+00	12308.7025
6	Premier League - vicarage road	NFL - Wembley	-79.8445	0.000000e+00	2109.1868
7	Premier League - vicarage road	Champions League - wembley	-7.6163	0.000000e+00	2614.1585
8	Premier League - vicarage road	International Football WCQ - wembley	-13.0475	0.000000e+00	2478.5310
9	Premier League - vicarage road	Premier League - wembley	-12.2416	0.000000e+00	1845.6040
10	Premier League - vicarage road	Premier League - london stadium	3.3527	8.142500e-04	2148.4758
11	Premier League - london stadium	NFL - Wembley	-141.8773	0.000000e+00	9034.1995
12	Premier League - london stadium	Champions League - wembley	-16.6060	0.000000e+00	7528.9897
13	Premier League - london stadium	International Football WCQ - wembley	-25.6851	0.000000e+00	8485.4358
14	Premier League - london stadium	Premier League - wembley	-29.0489	0.000000e+00	12487.1845
15	International Football - wembley stadium	NFL - Wembley	-100.6577	0.000000e+00	7386.3311
16	International Football - wembley stadium	Champions League - wembley	7.3726	0.000000e+00	7534.9616
17	International Football - wembley stadium	Premier League - wembley	3.0934	1.986310e-03	7167.7014
18	Champions League - wembley stadium	NFL - Wembley	-104.5586	0.000000e+00	6743.1522
19	Champions League - wembley stadium	Premier League - wembley	-5.8365	1.000000e-08	6196.0522
20	Premier League - wembley stadium	NFL - Wembley	-131.9885	0.000000e+00	8263.0303

Table 6: Independent T-test - Event Category - Avg. Dwell Time (min)

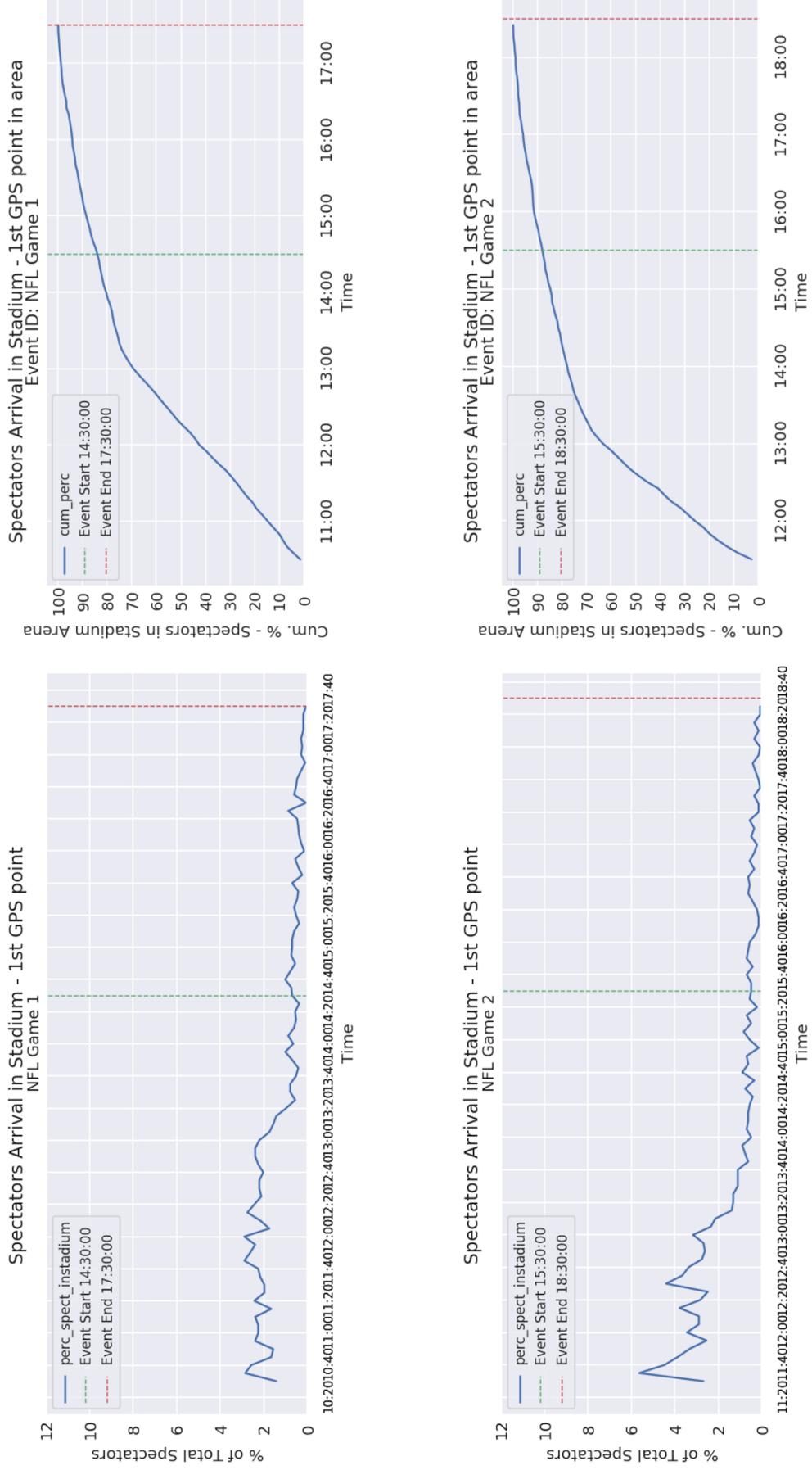
## Appendix E: Events Graphs and Maps

## 1. Rugby World Cup – Twickenham Stadium

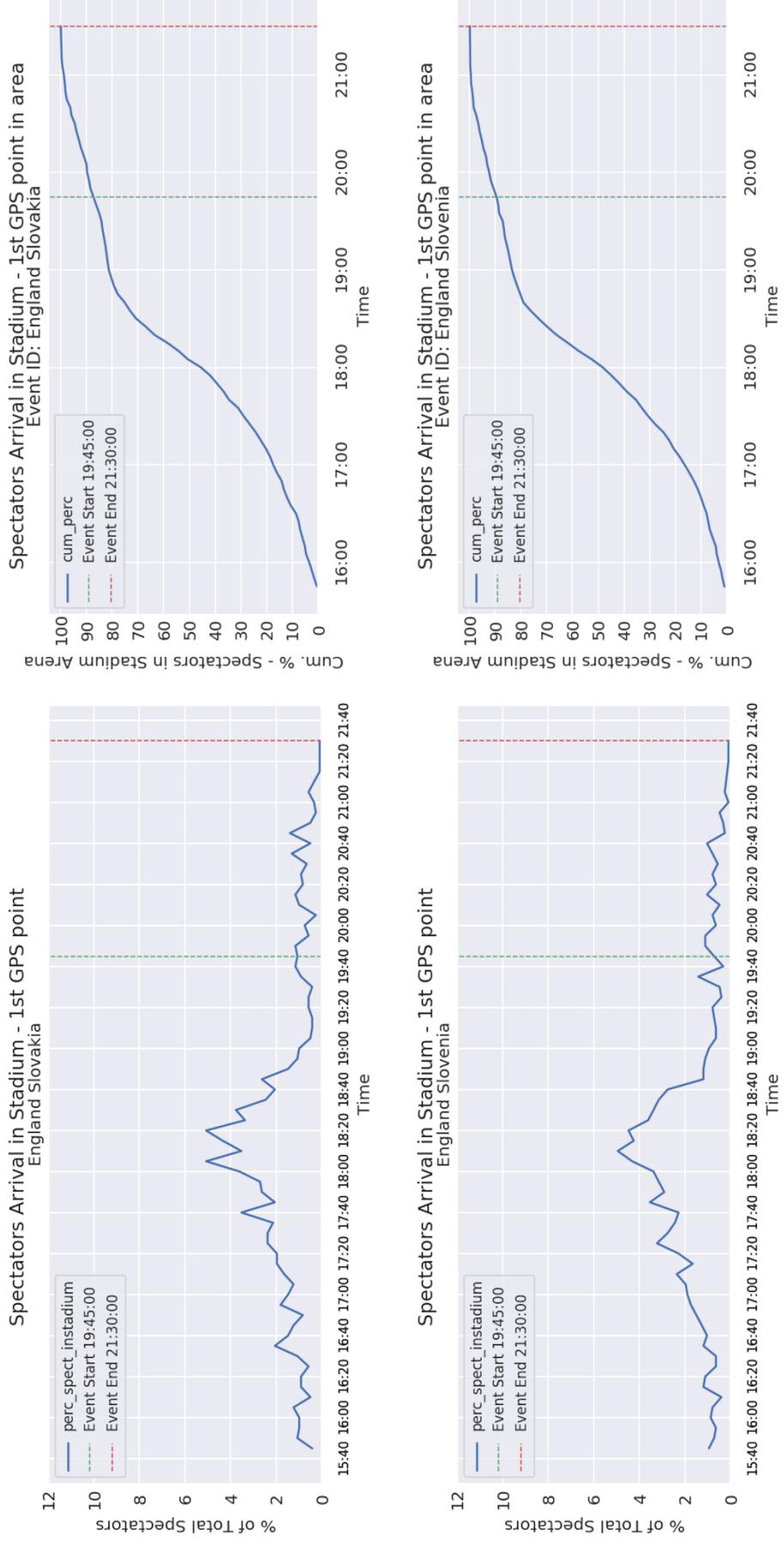


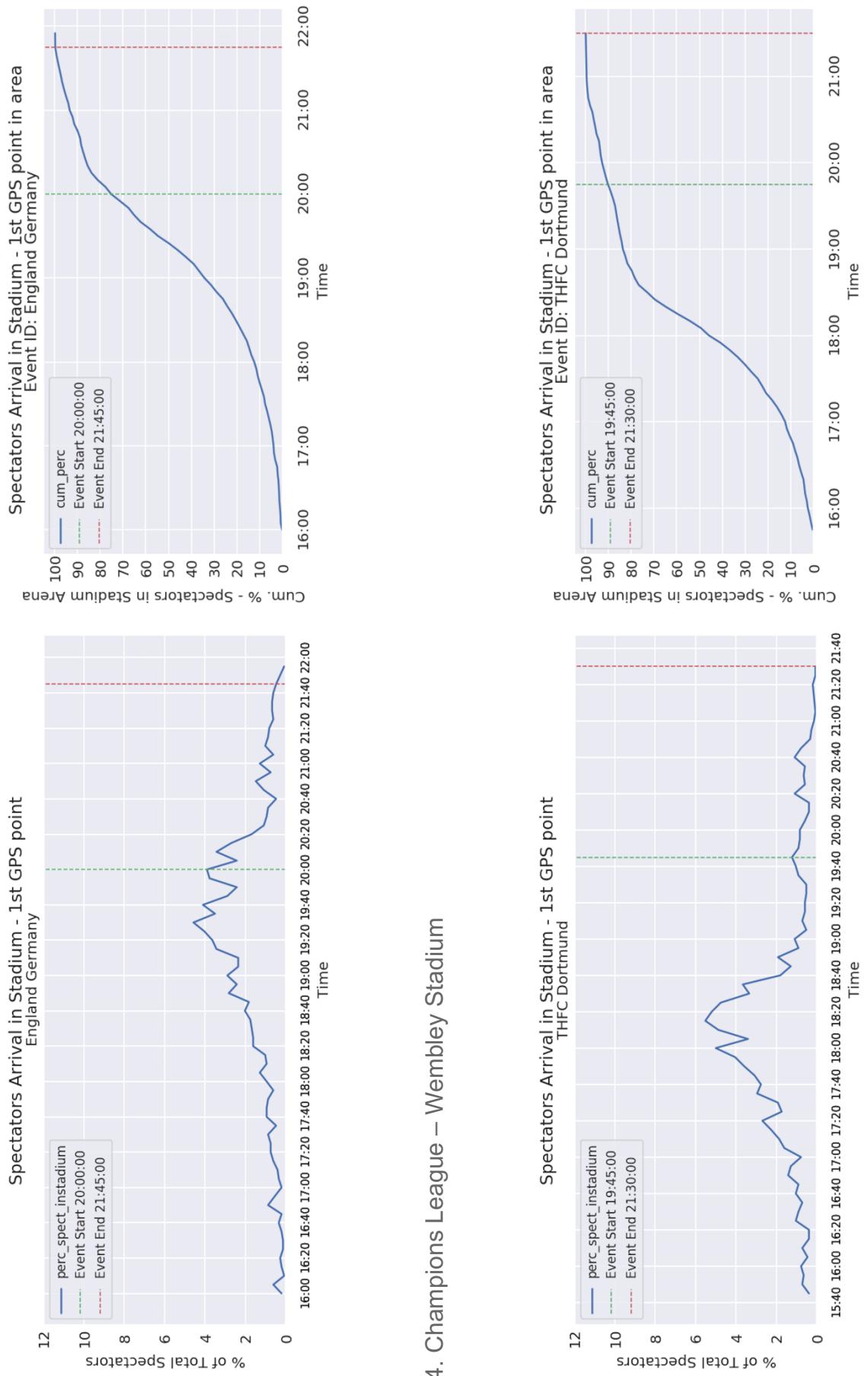


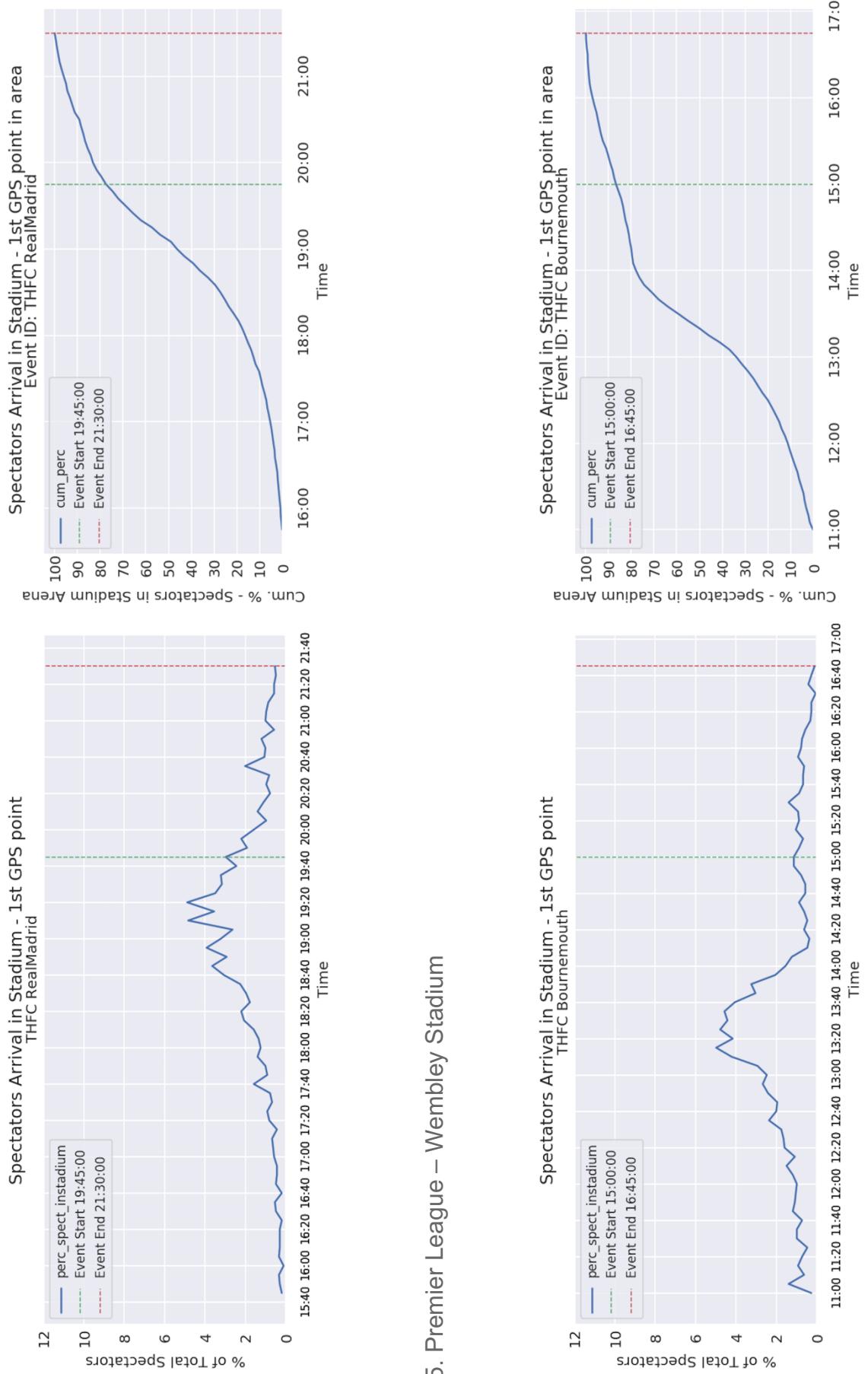
## 2. NFL – Wembley Stadium



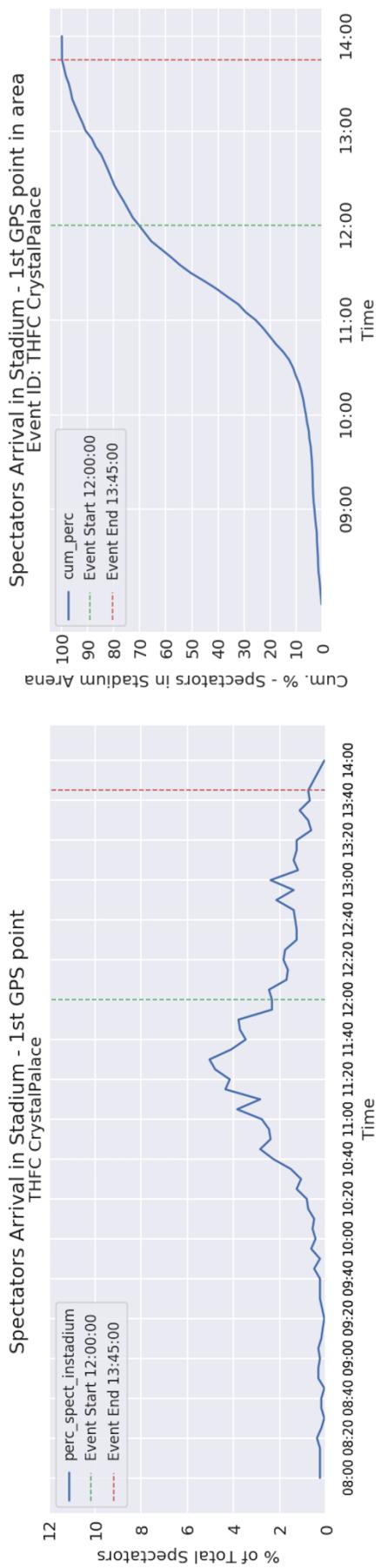
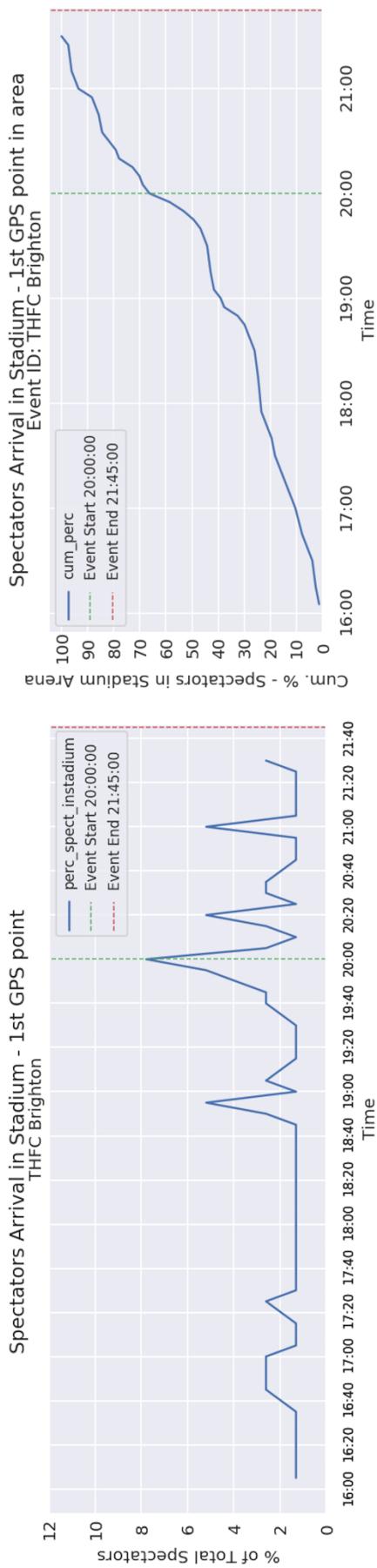
### 3. International Football World Cup Qualification 18 – Wembley Stadium

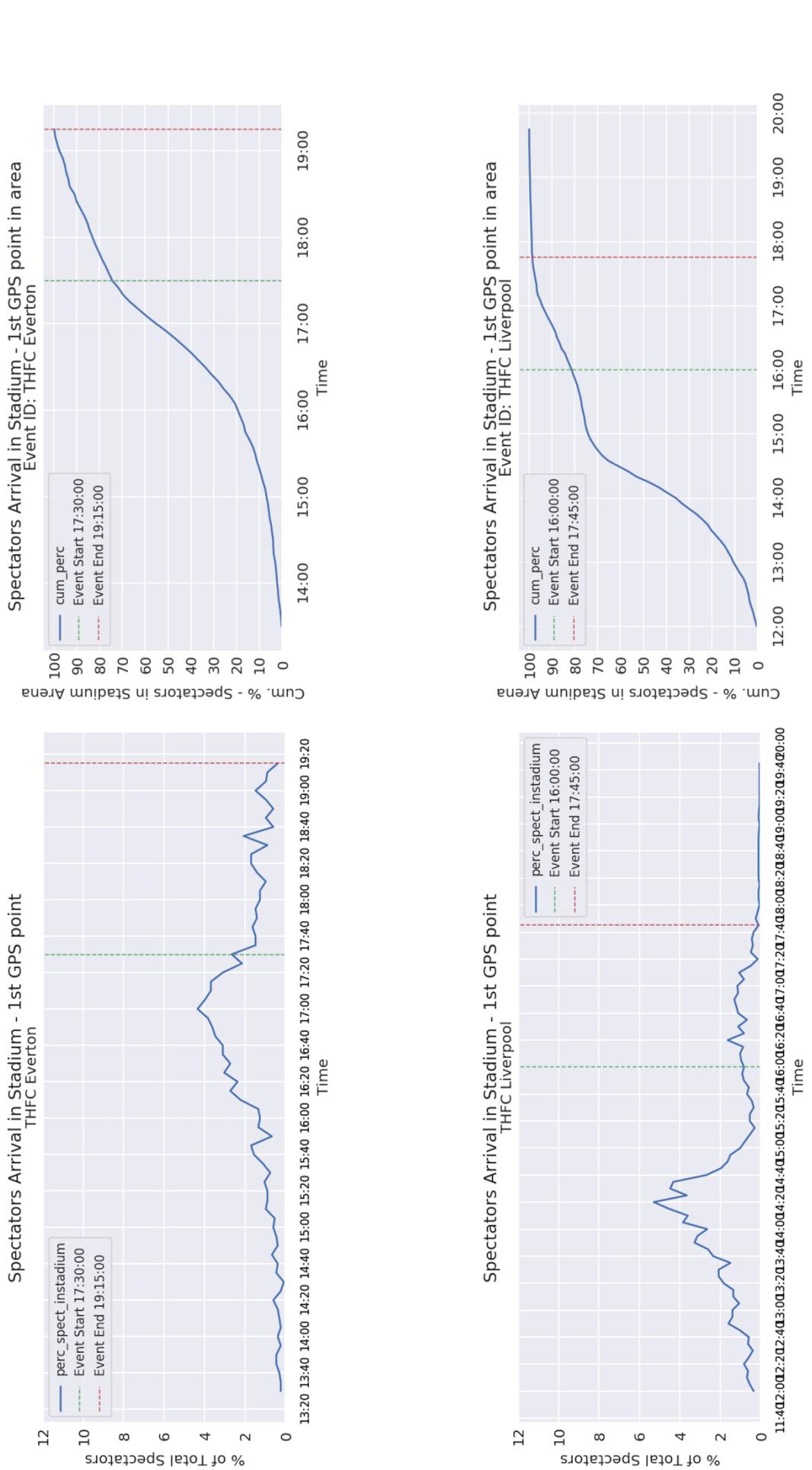


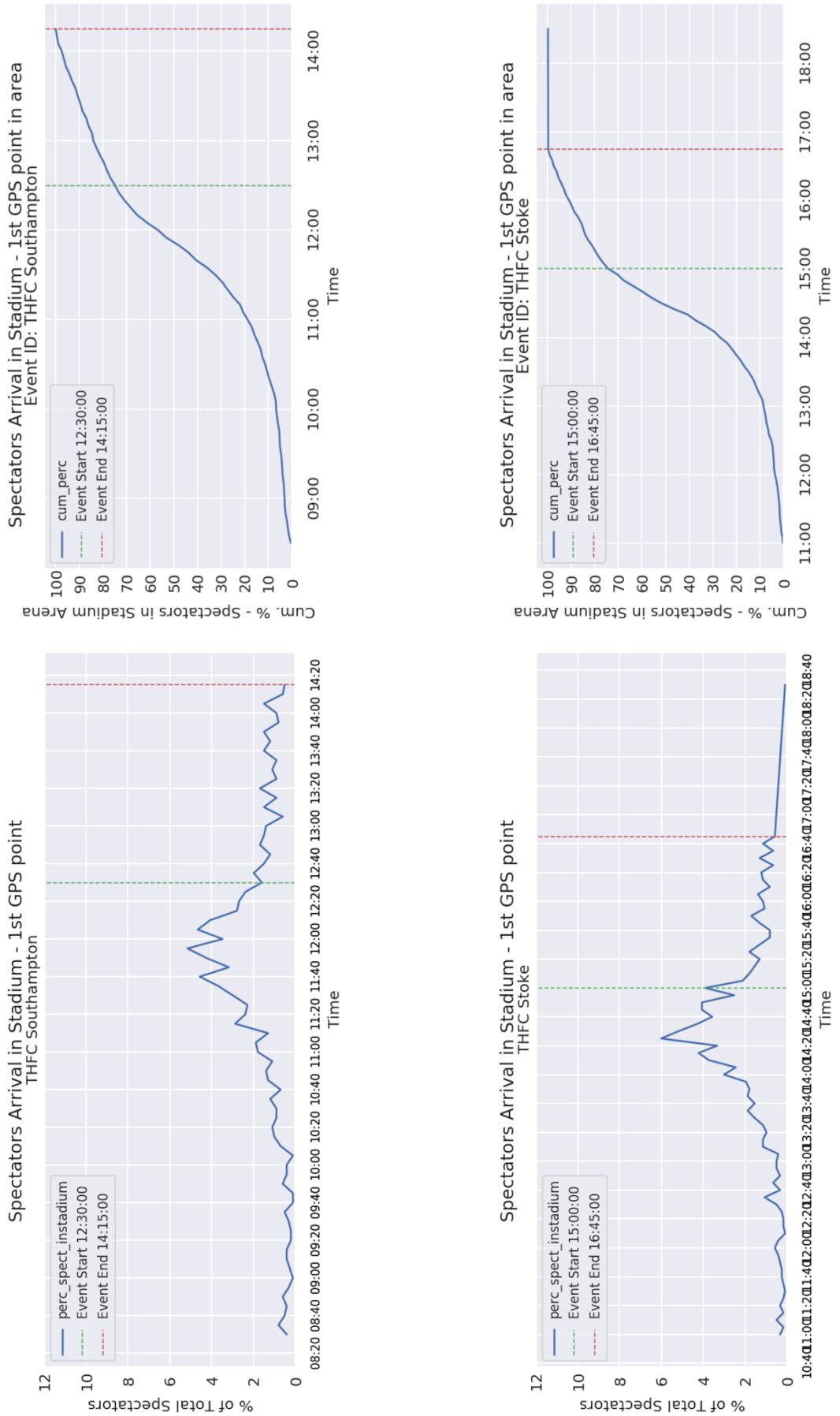


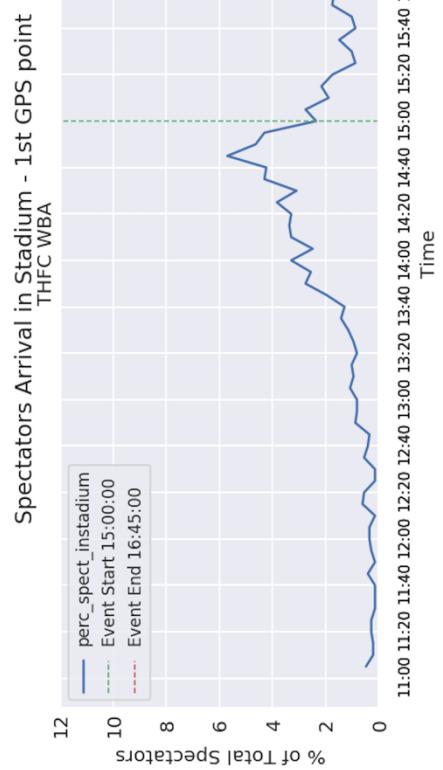
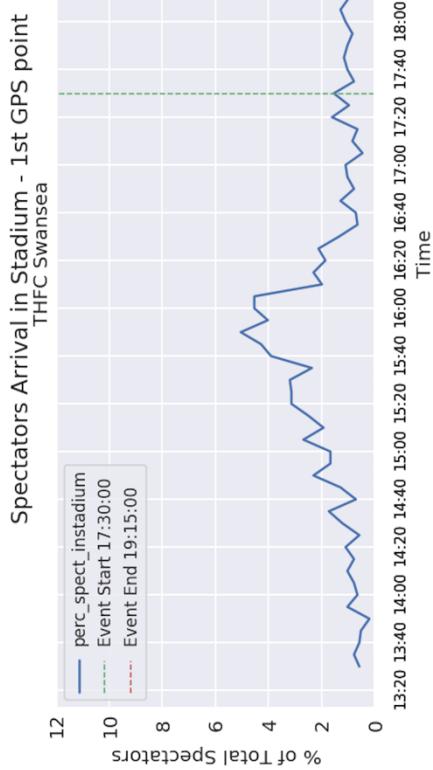
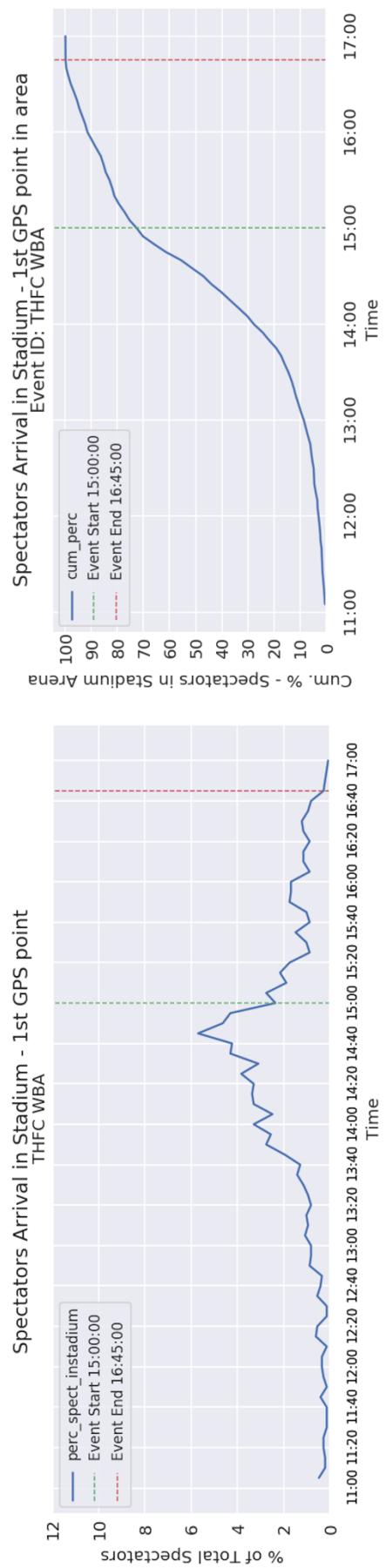


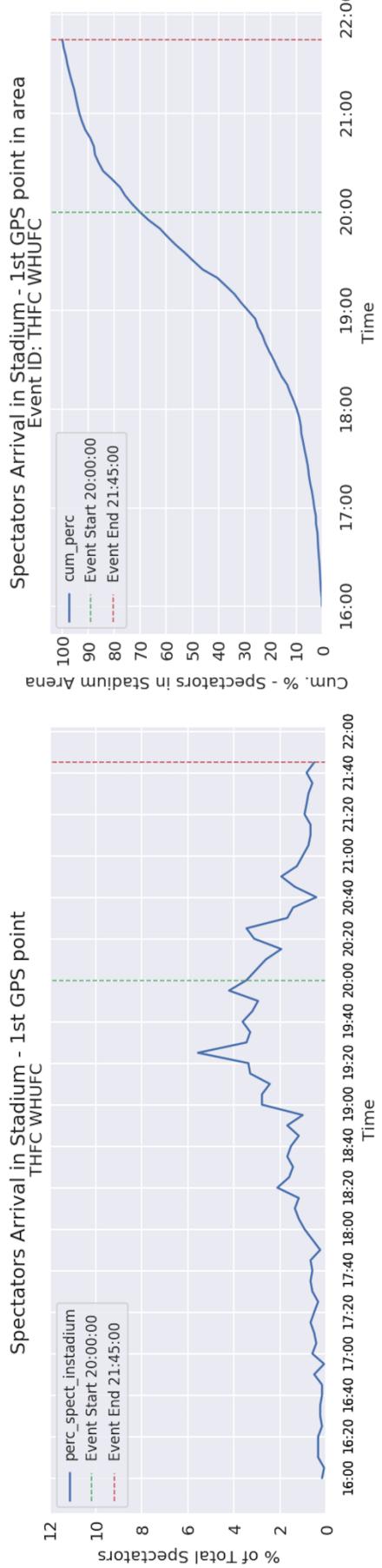
## 5. Premier League – Wembley Stadium



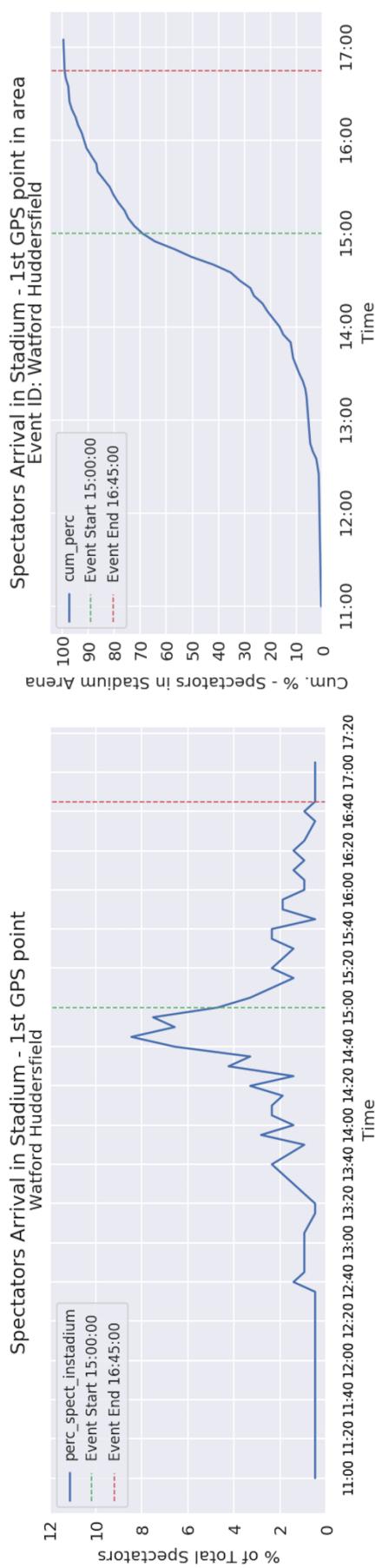


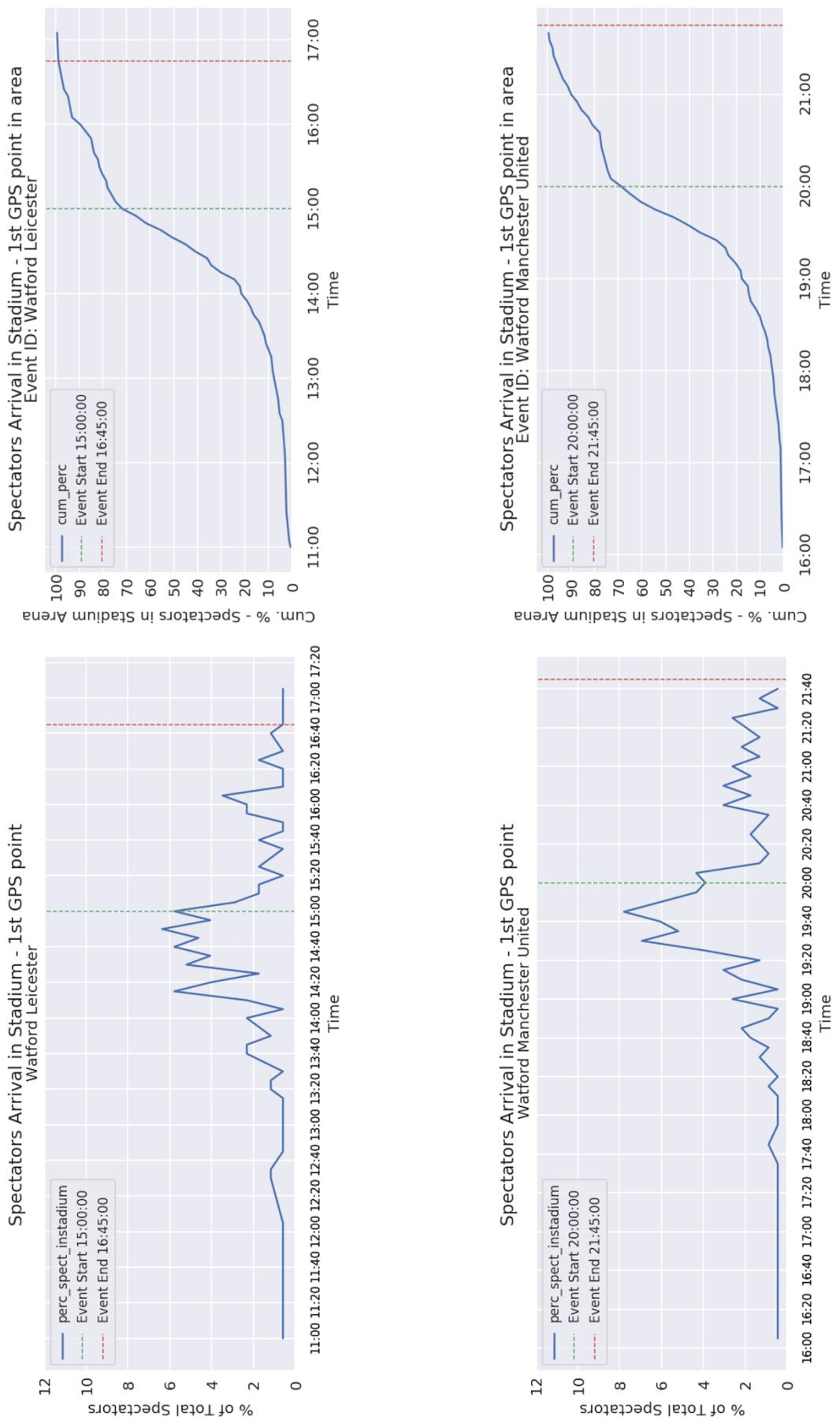


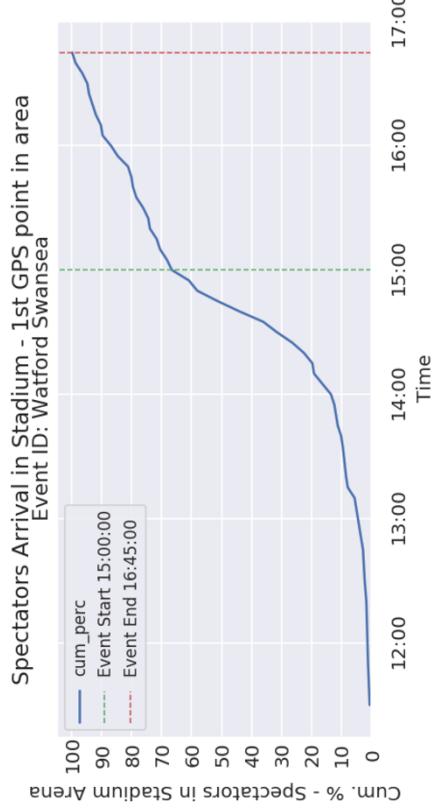
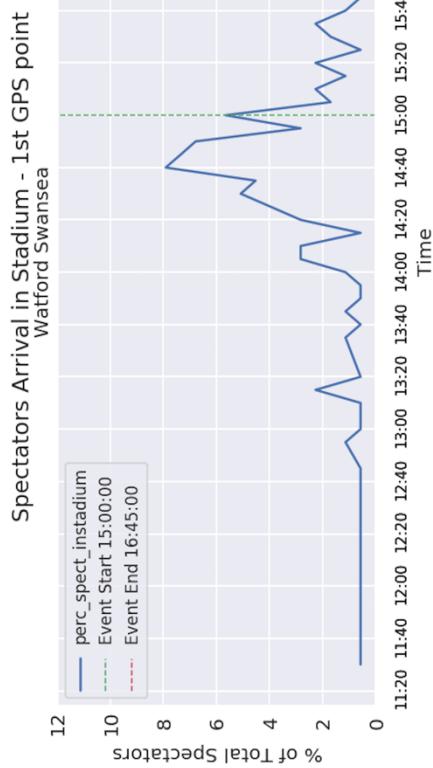
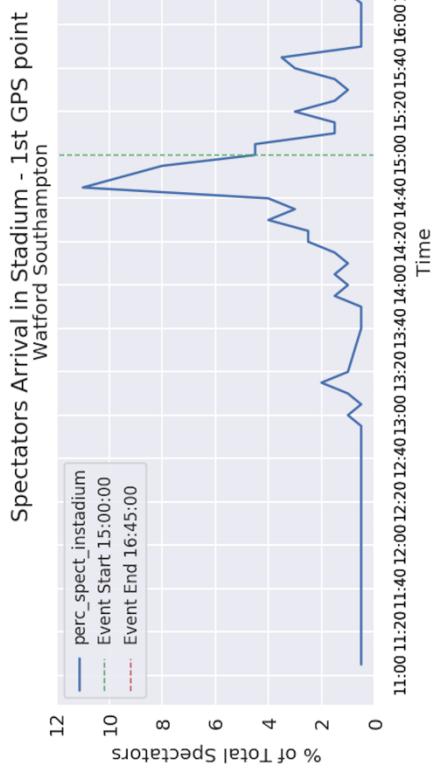


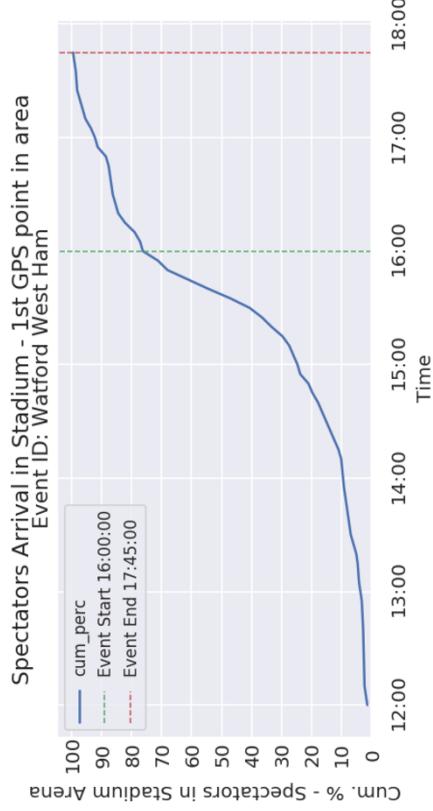
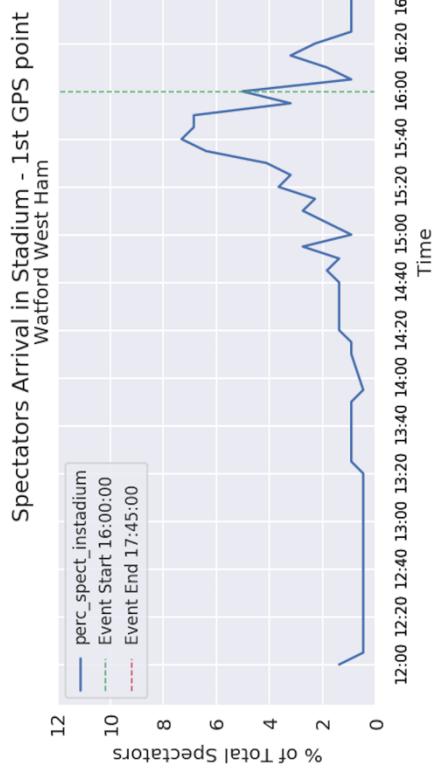
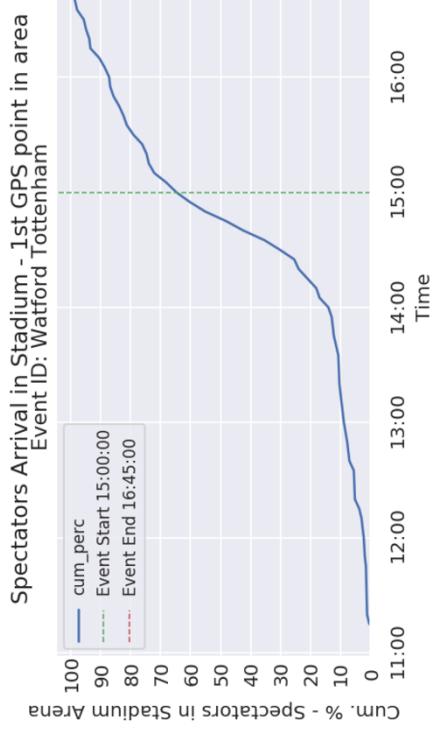
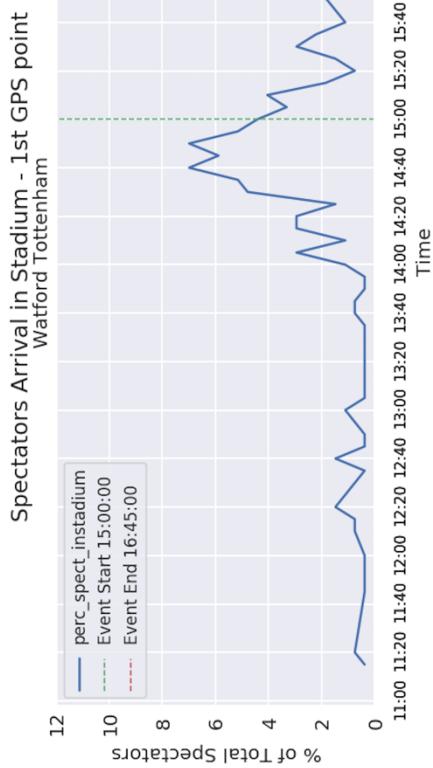


## 6. Premier League –Vicarage Road Stadium (Watford)

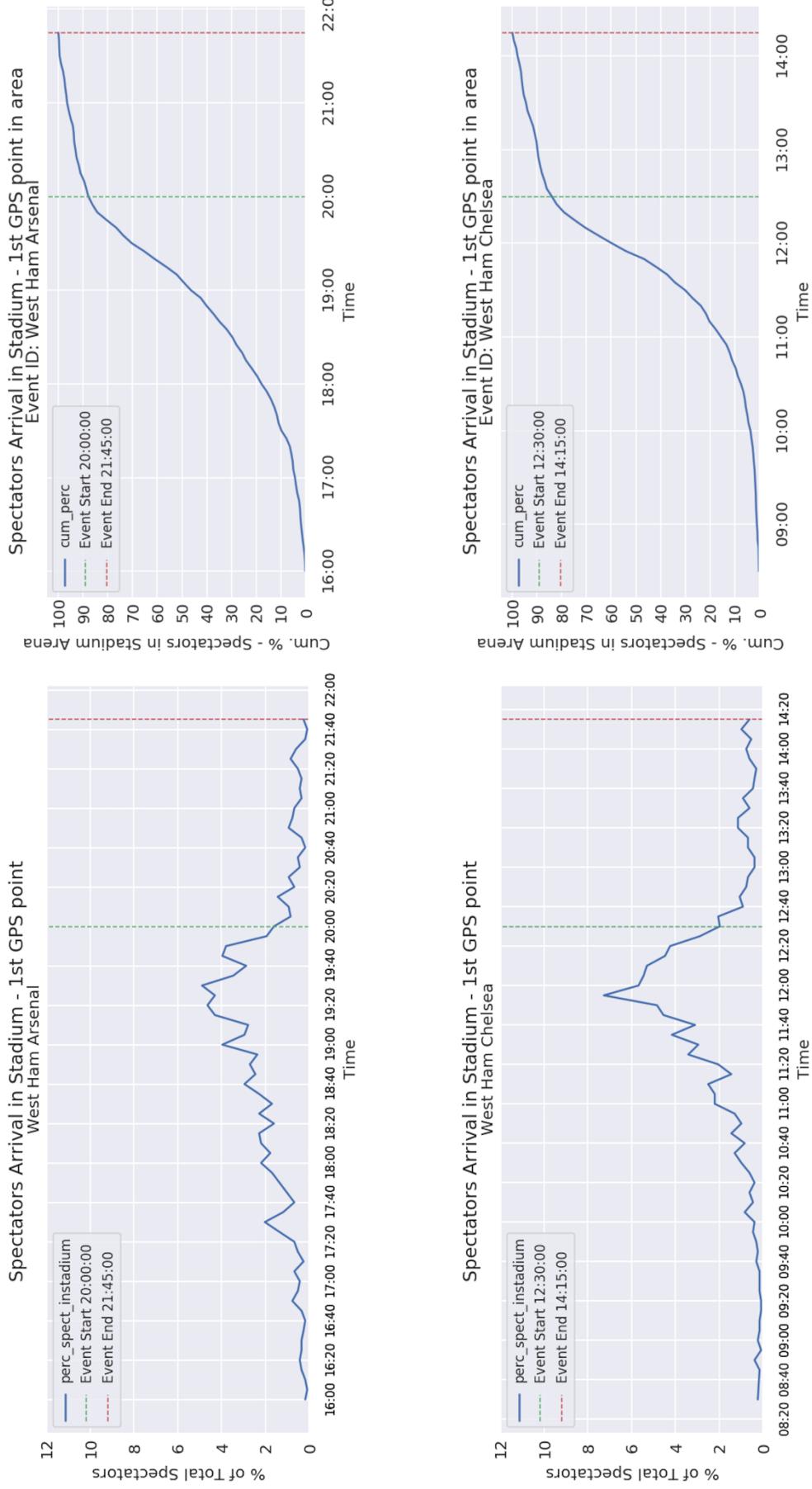


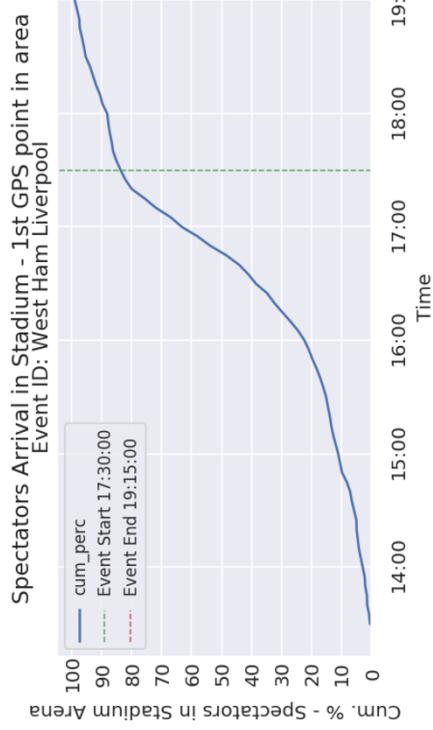
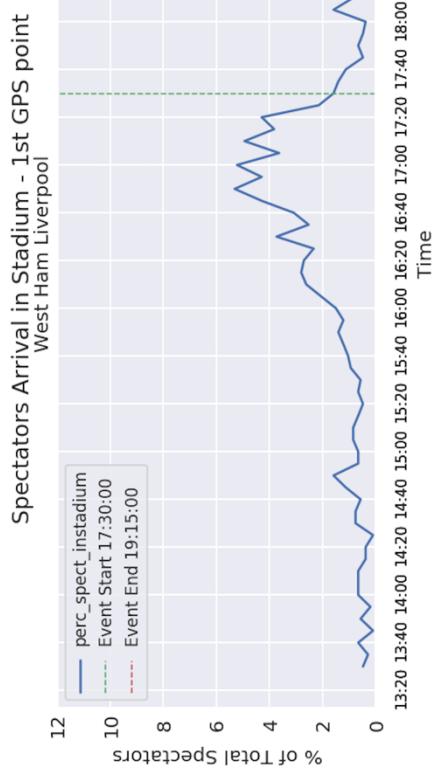
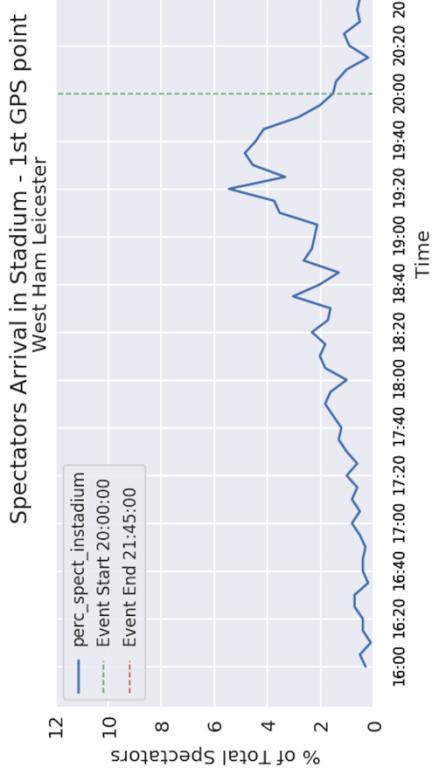


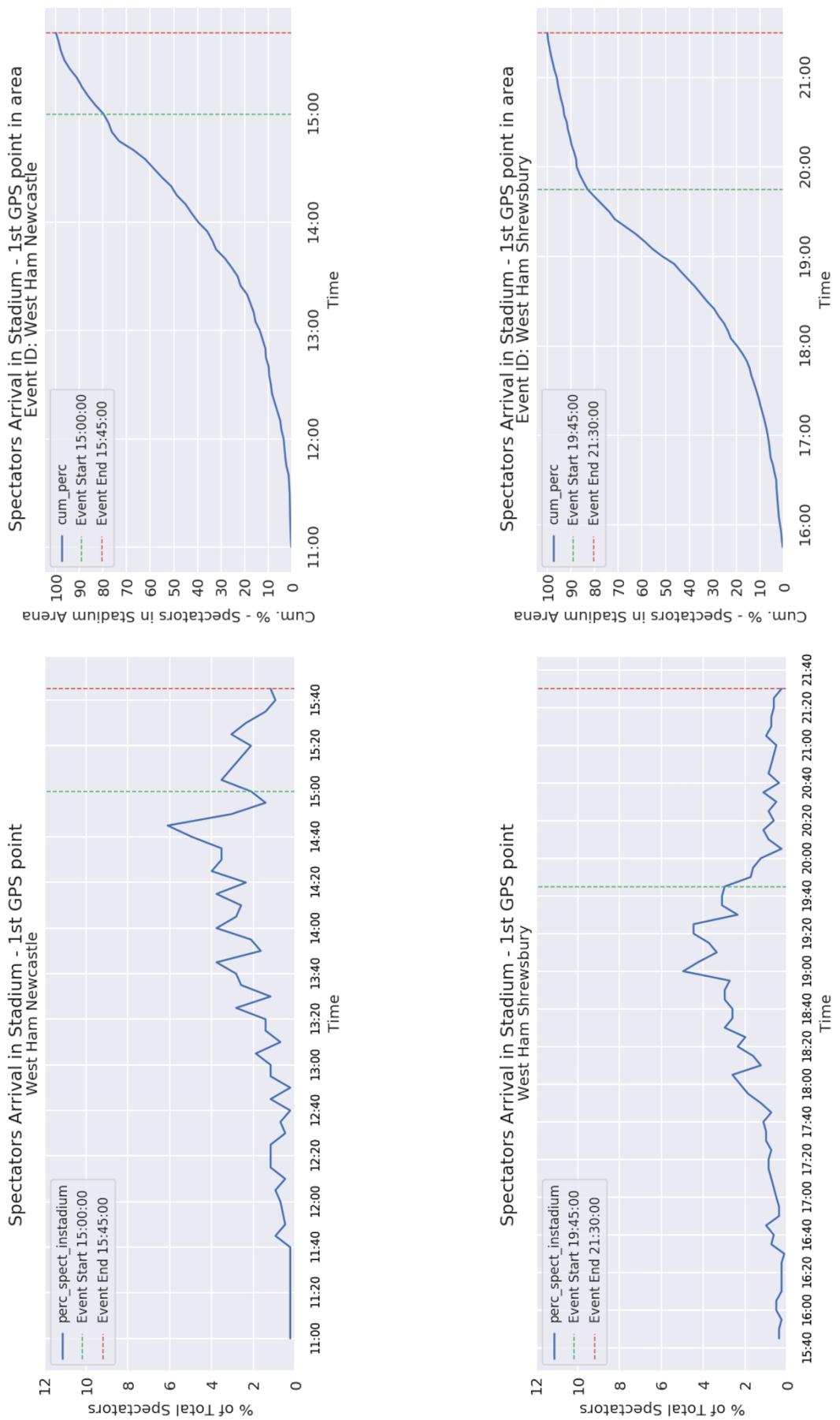


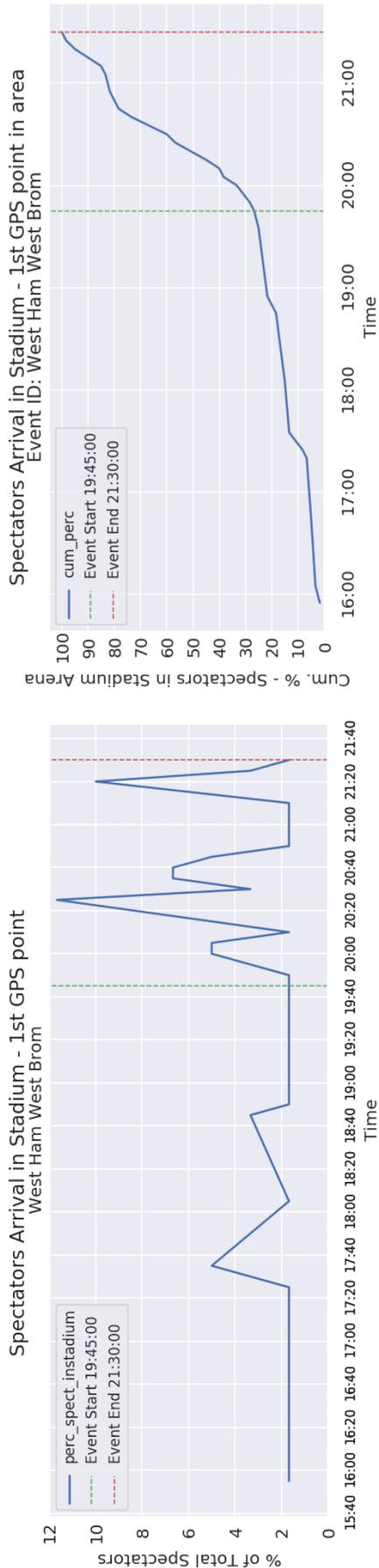


## 6. Premier League – London Stadium

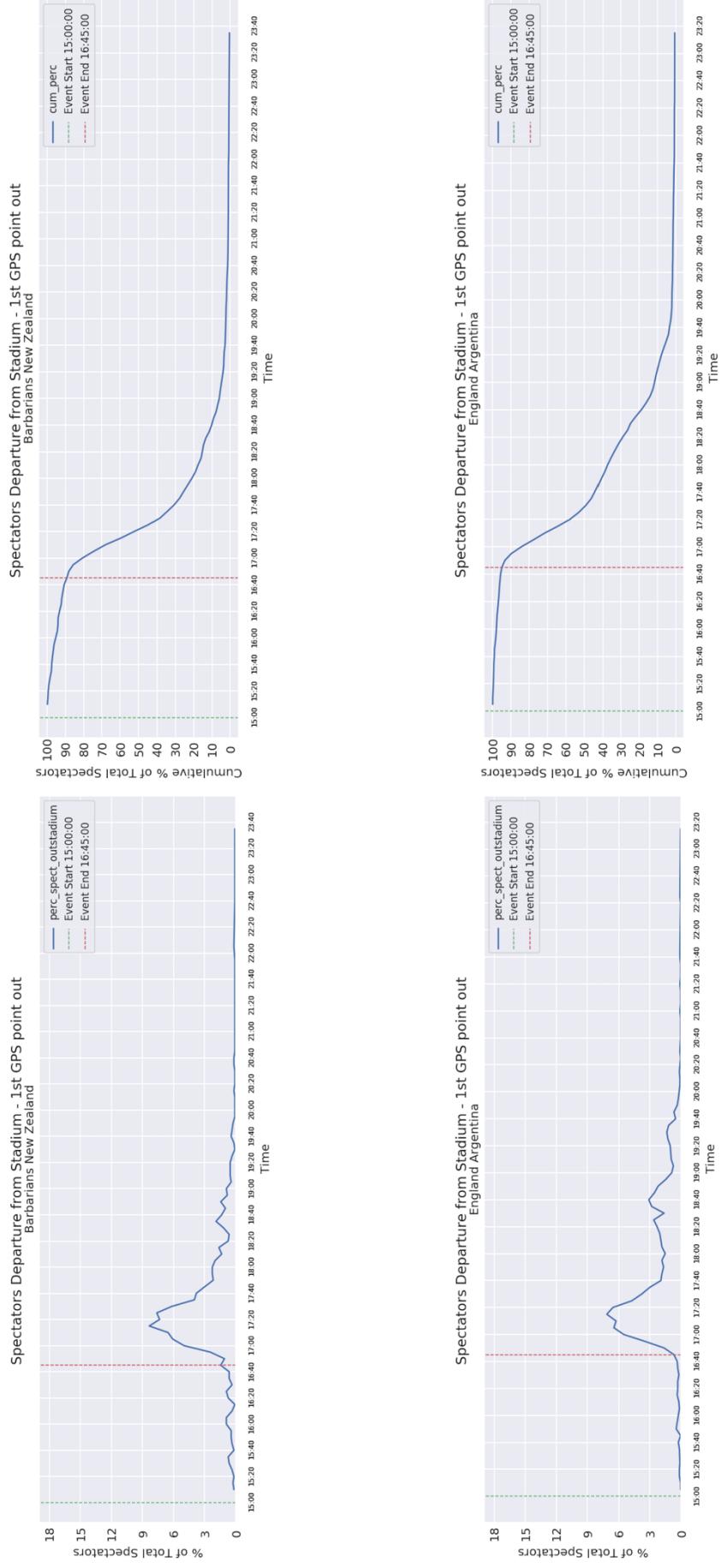


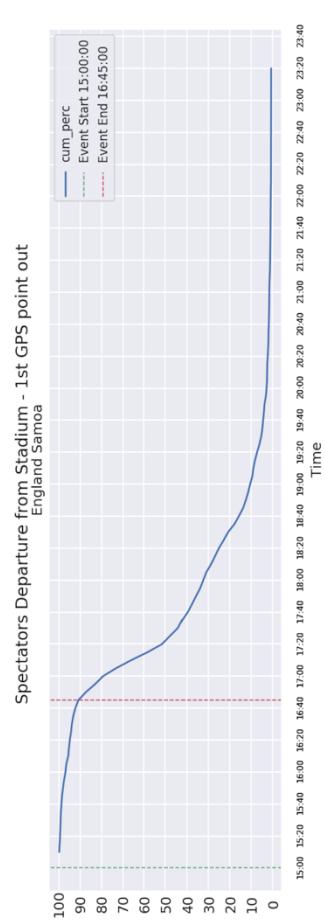
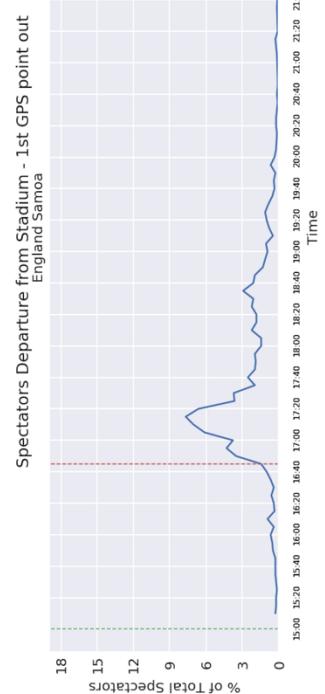
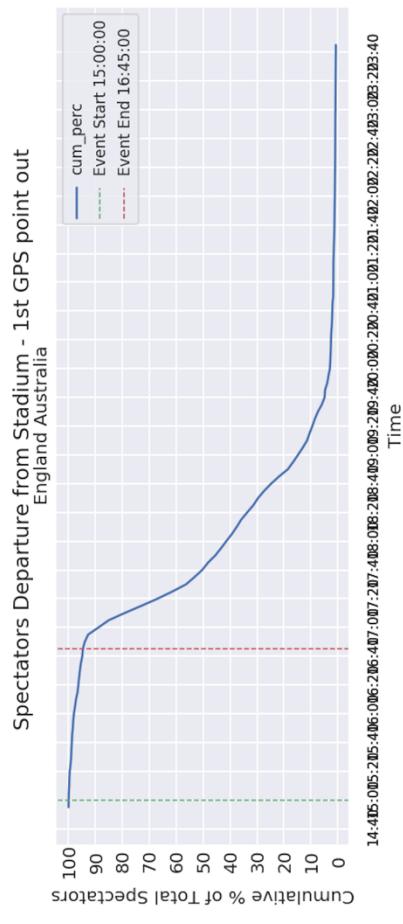
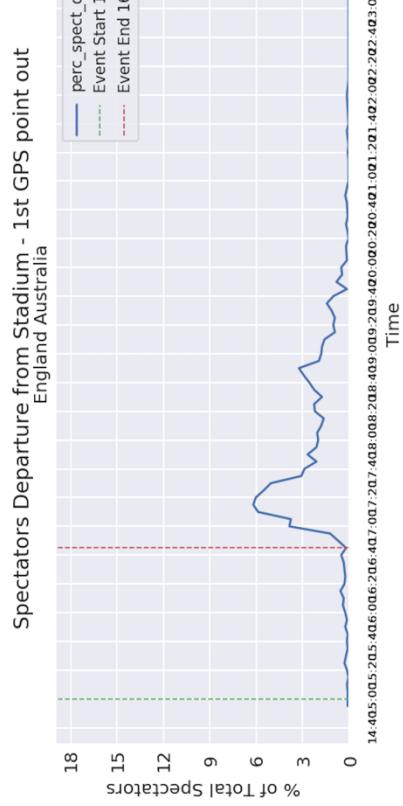




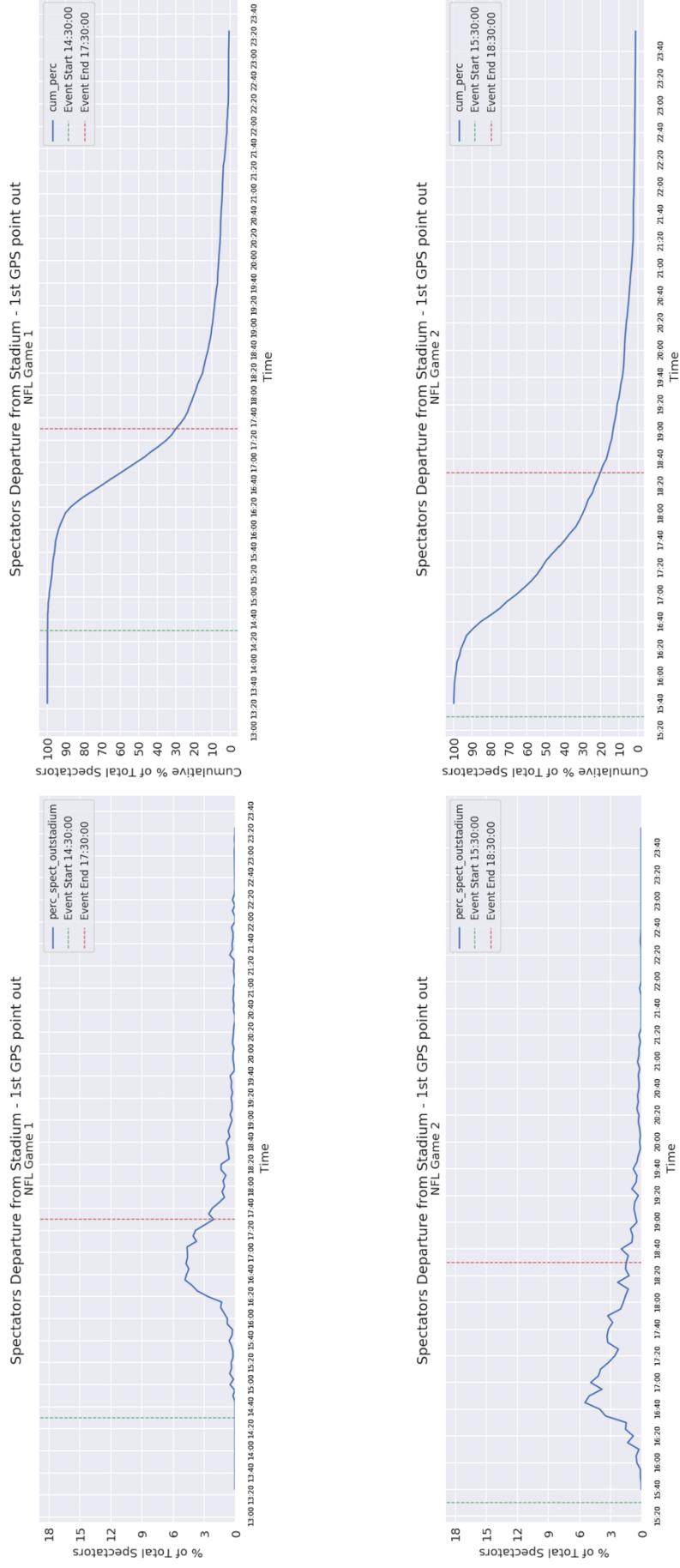


## 1. Rugby World Cup – Twickenham Stadium

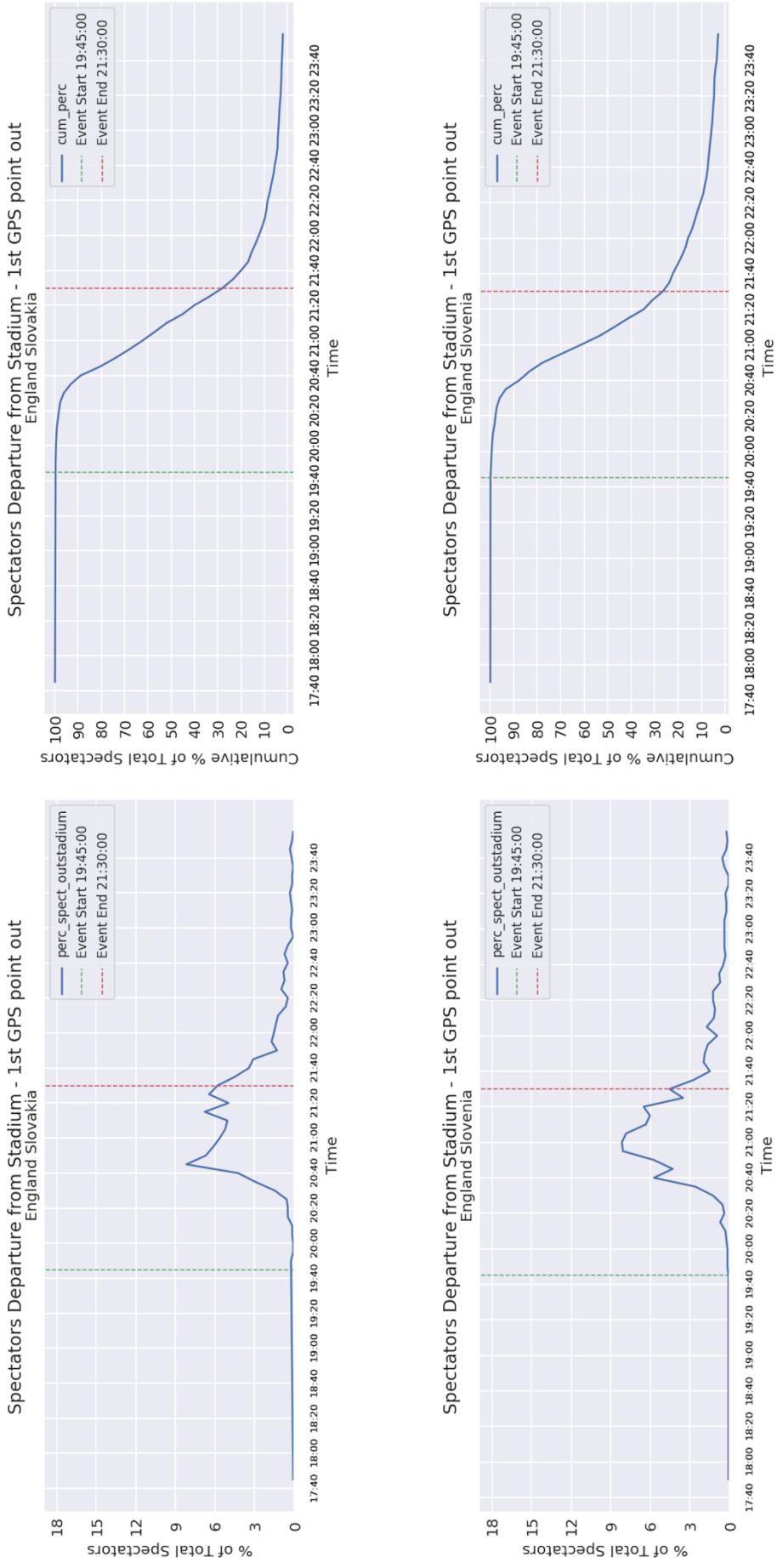


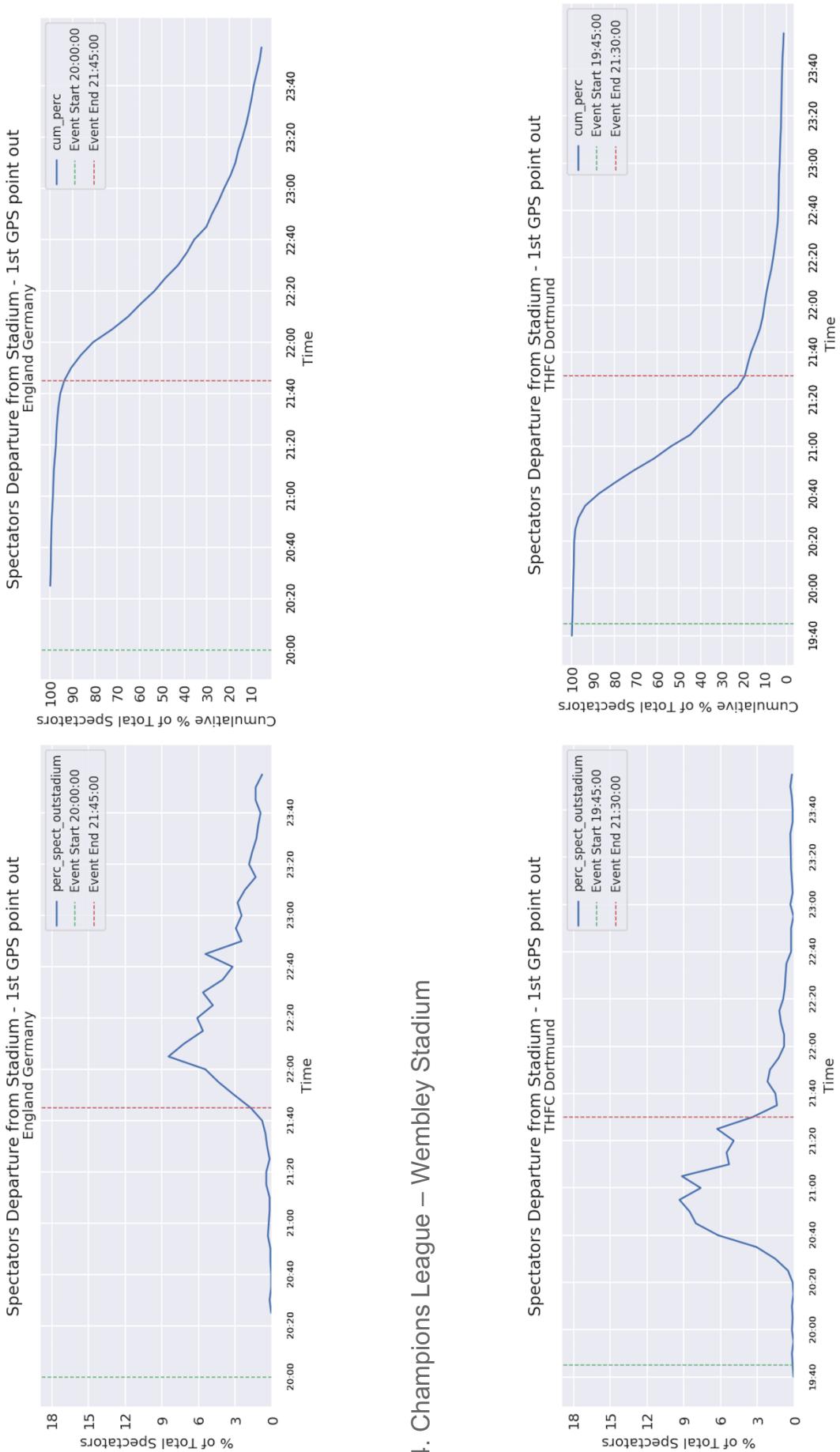


## 2. NFL – Wembley Stadium

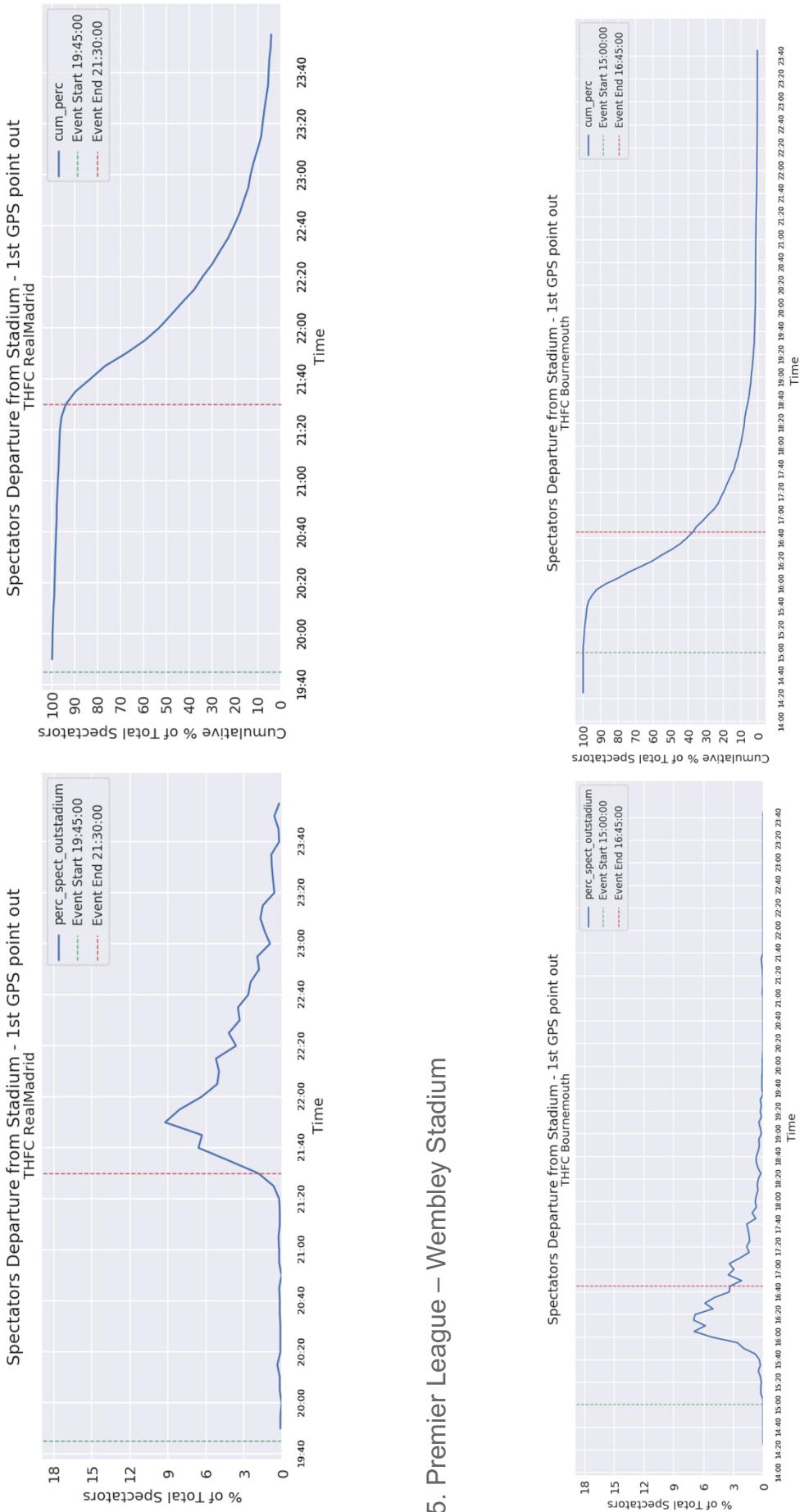


### 3. International Football World Cup Qualification 18 – Wembley Stadium

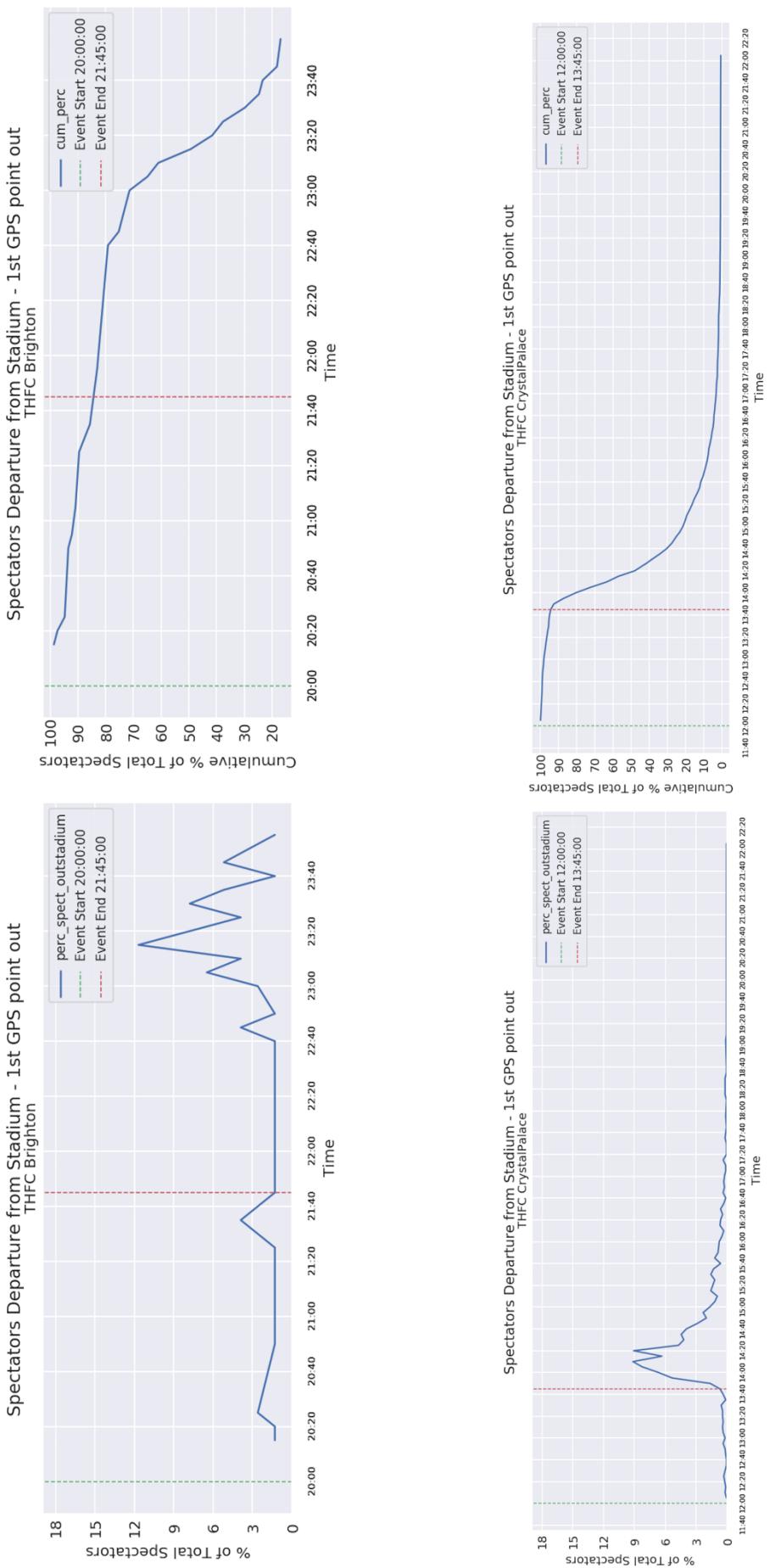


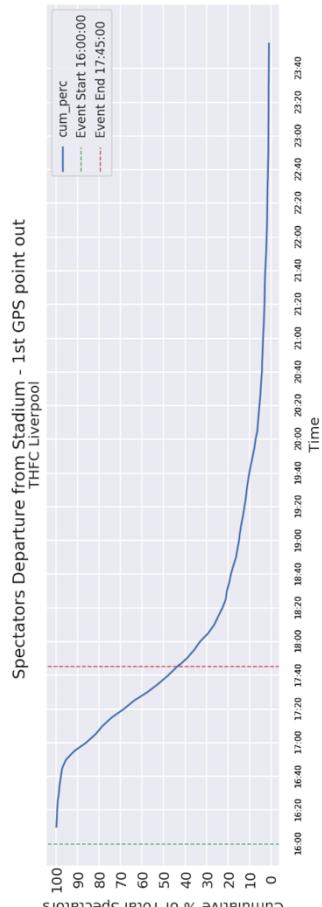
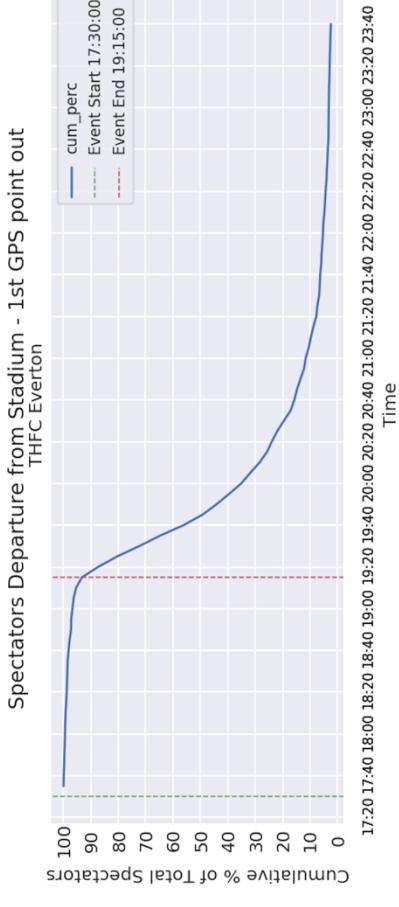
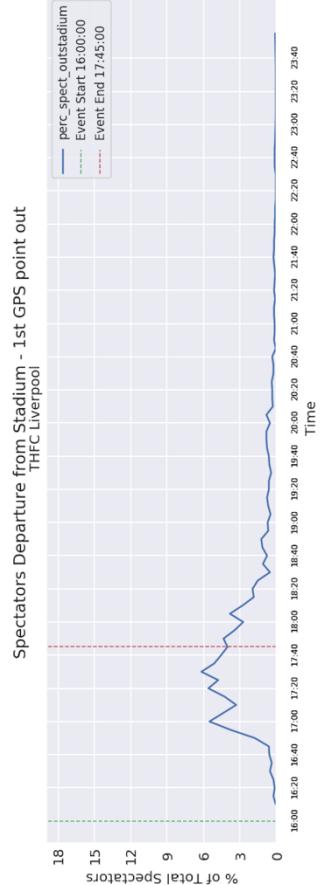
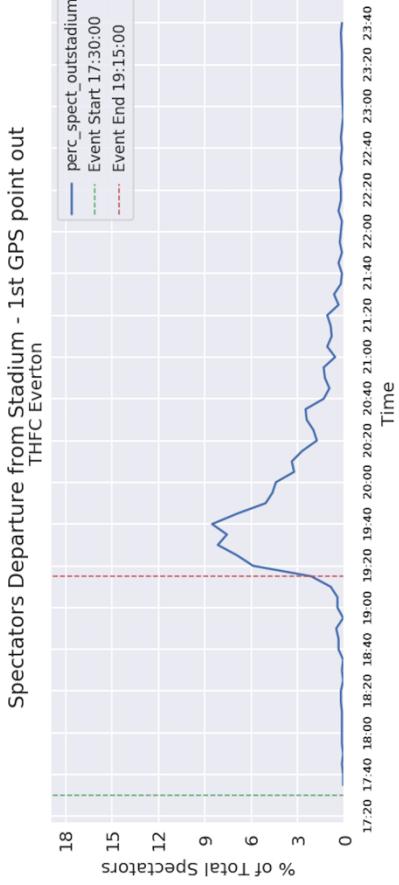


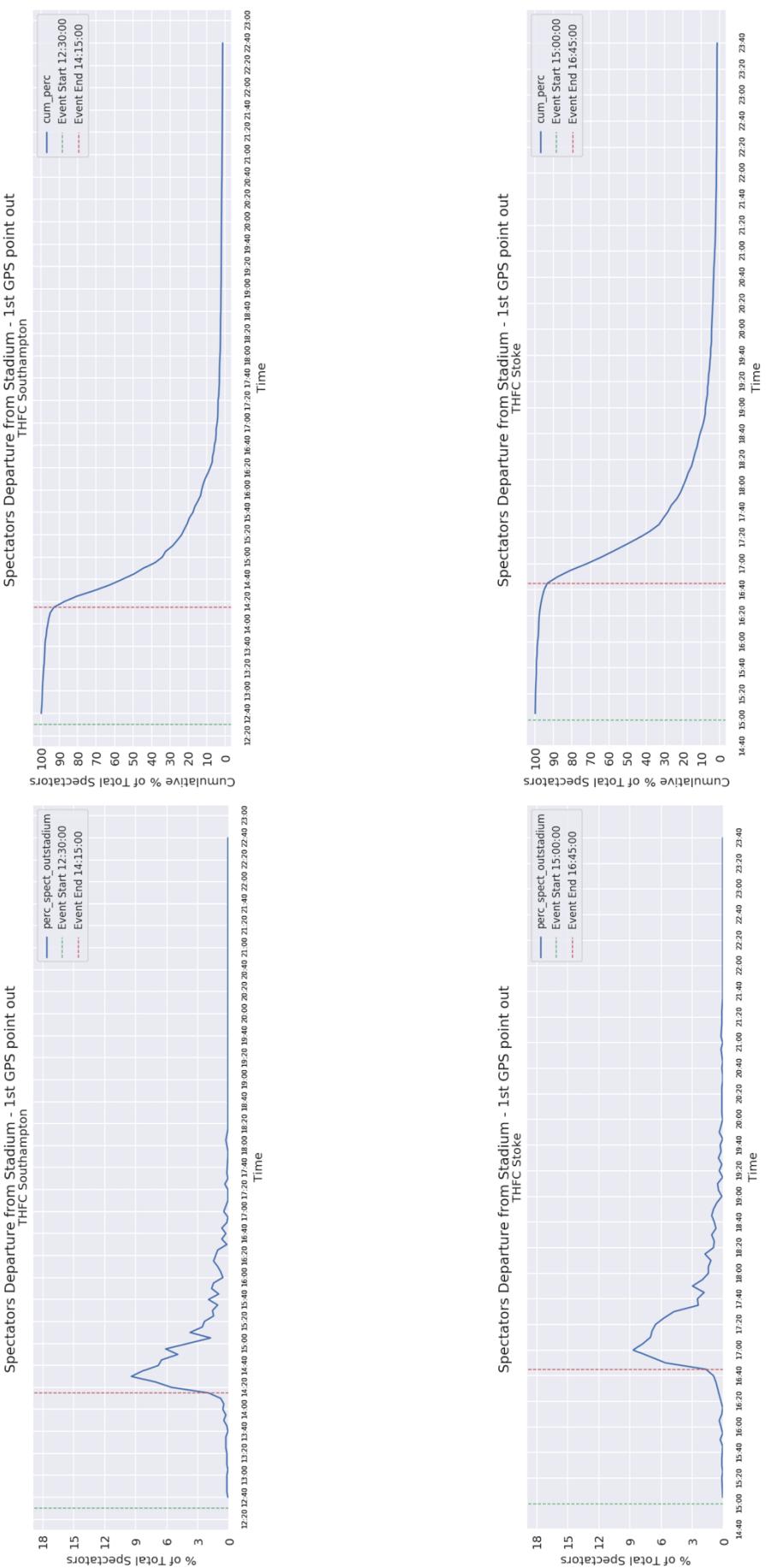
#### 4. Champions League – Wembley Stadium

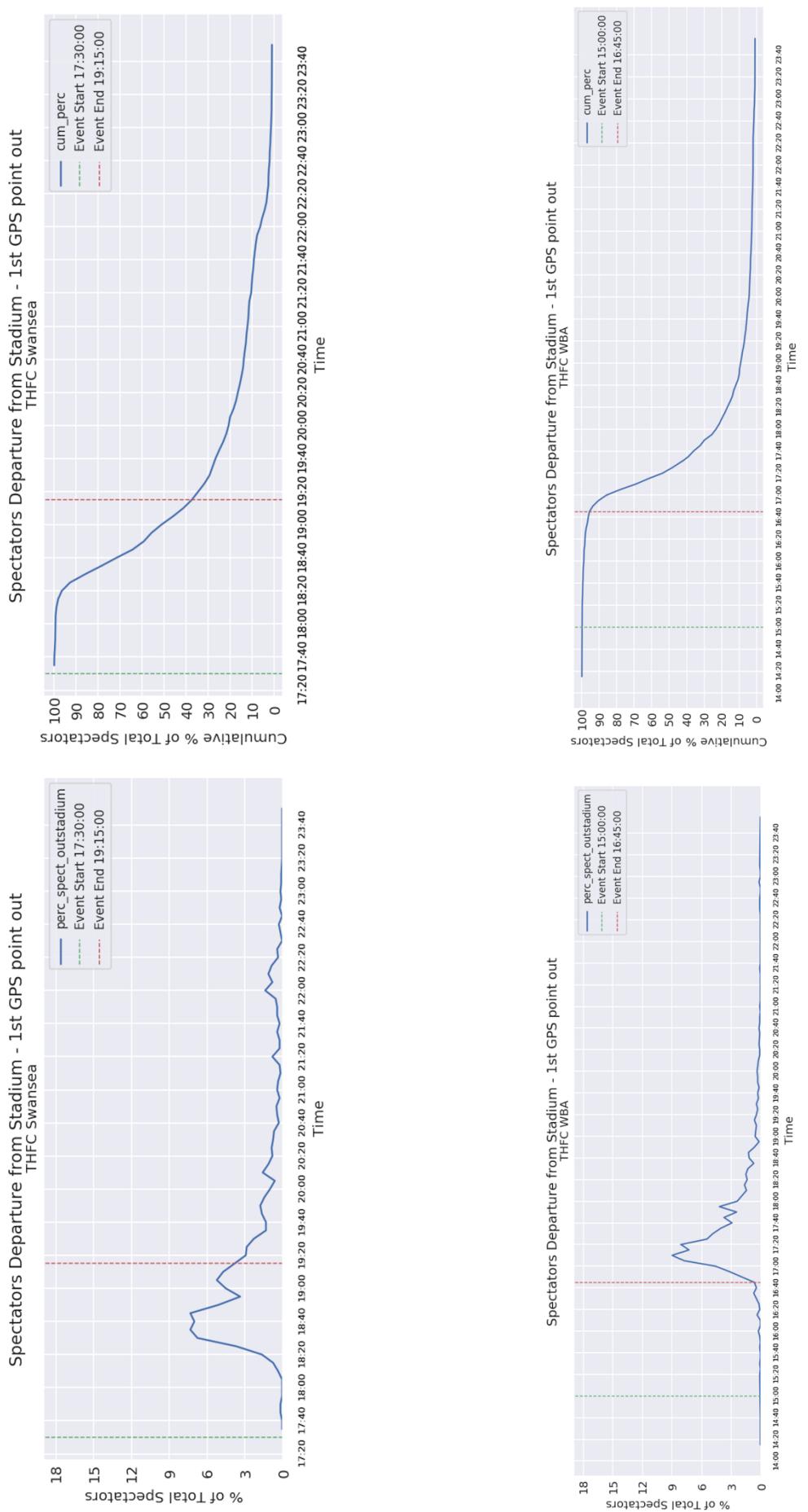


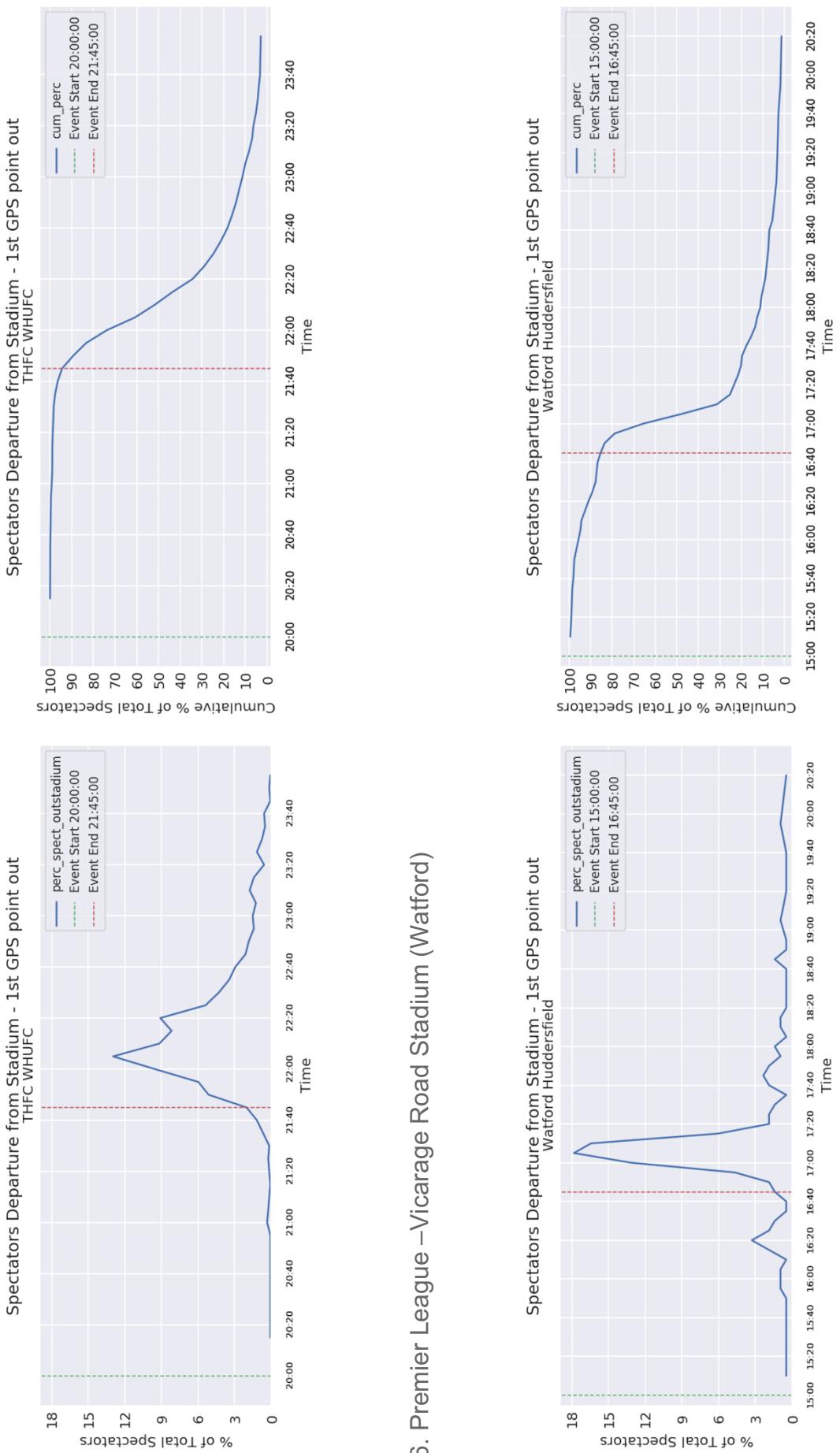
## 5. Premier League – Wembley Stadium



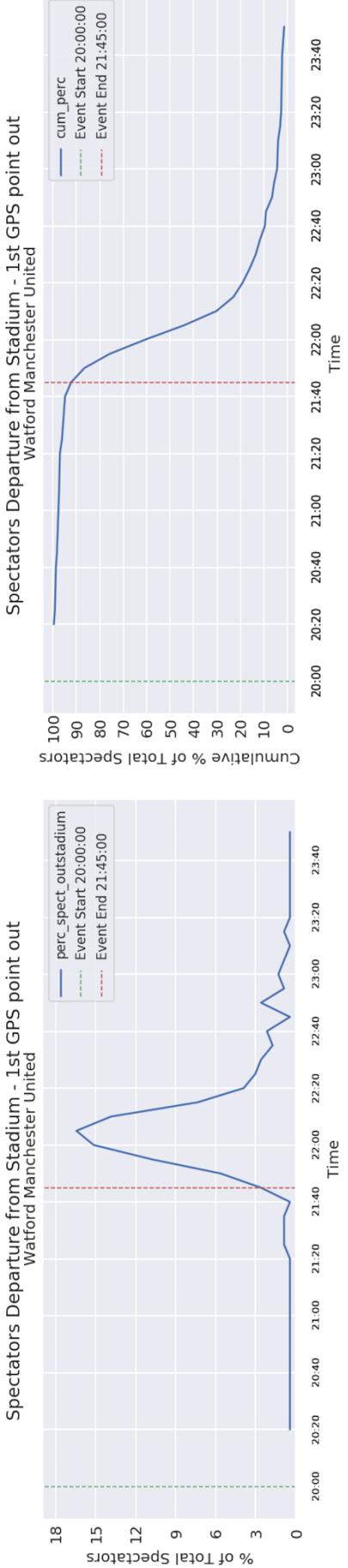
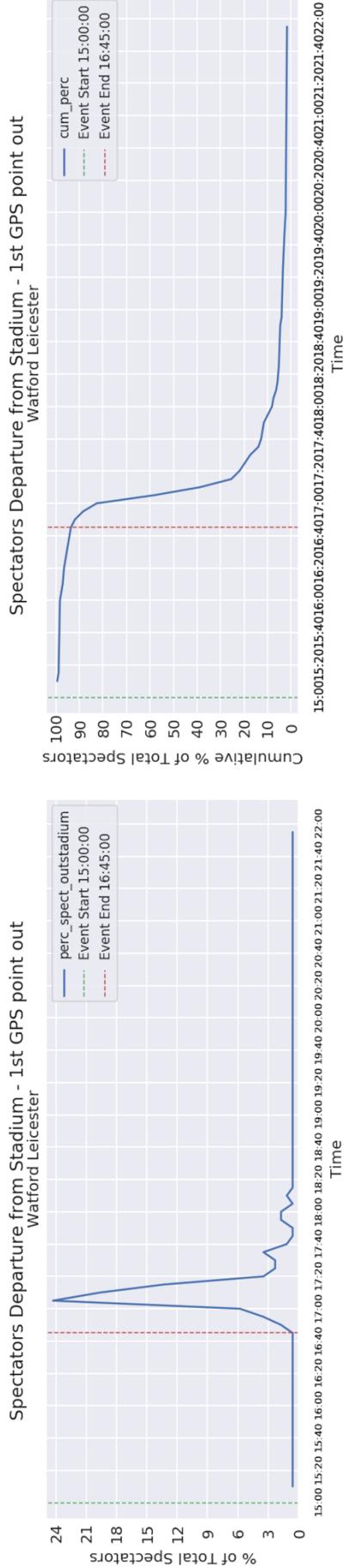


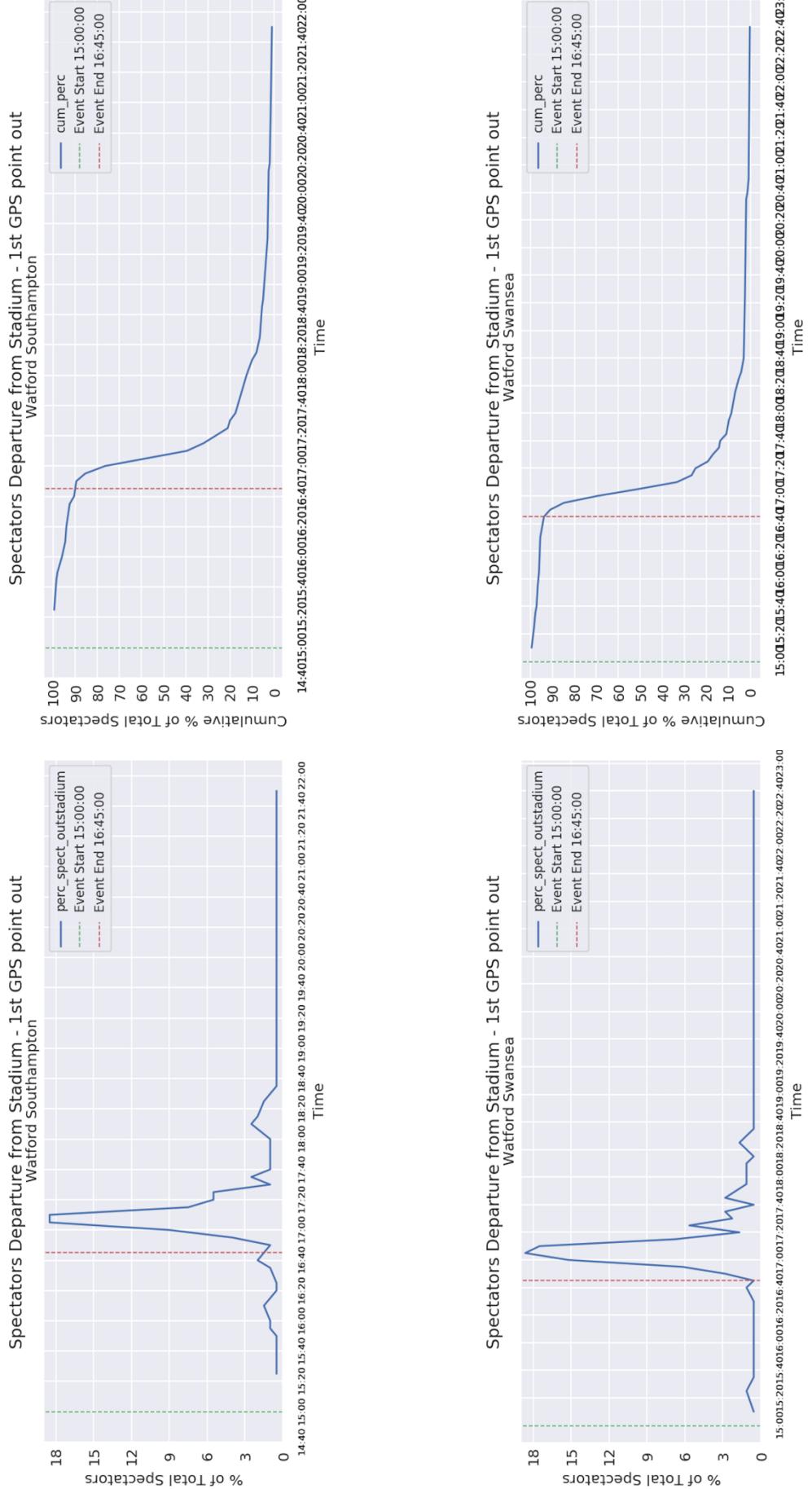


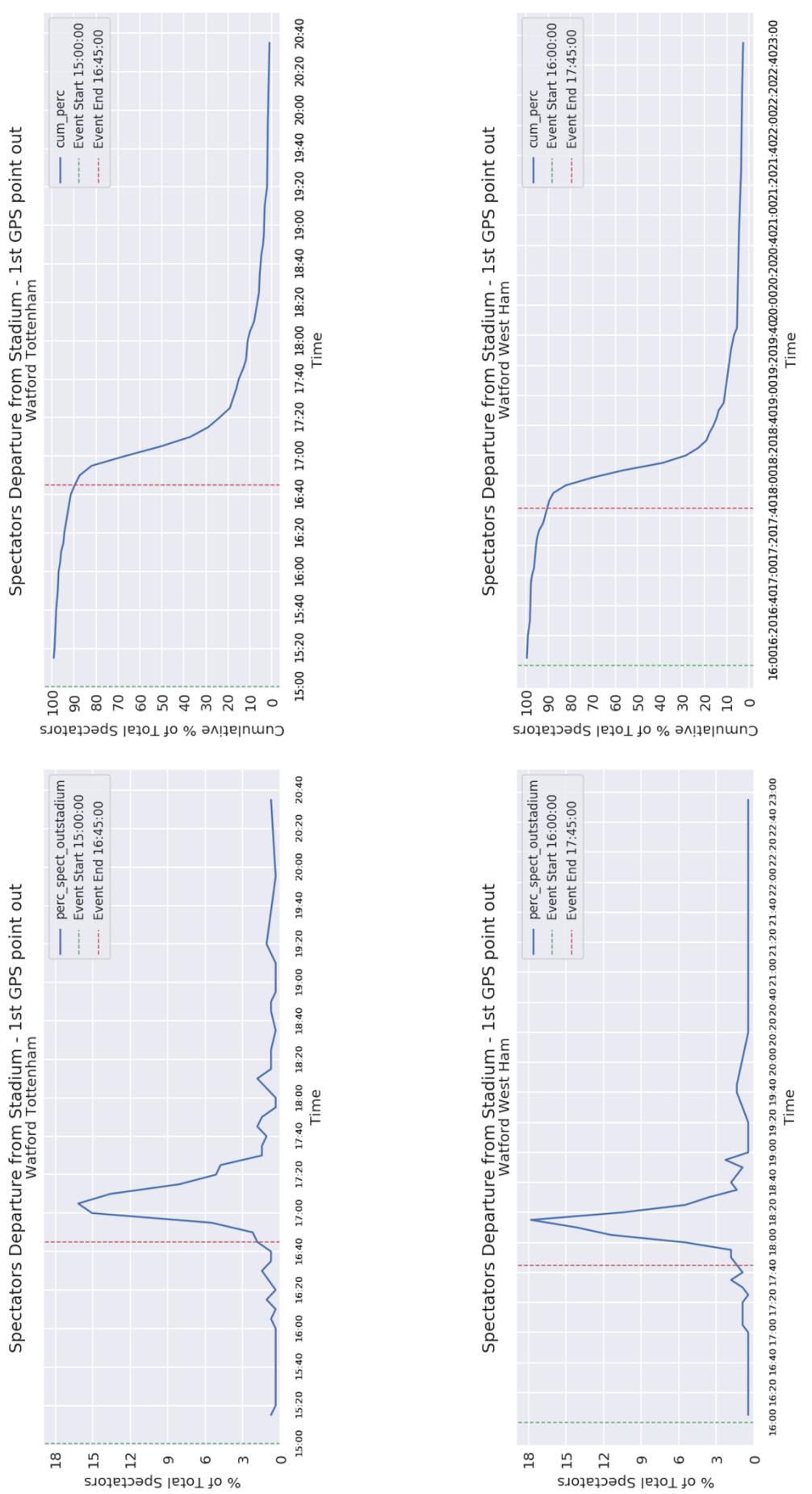




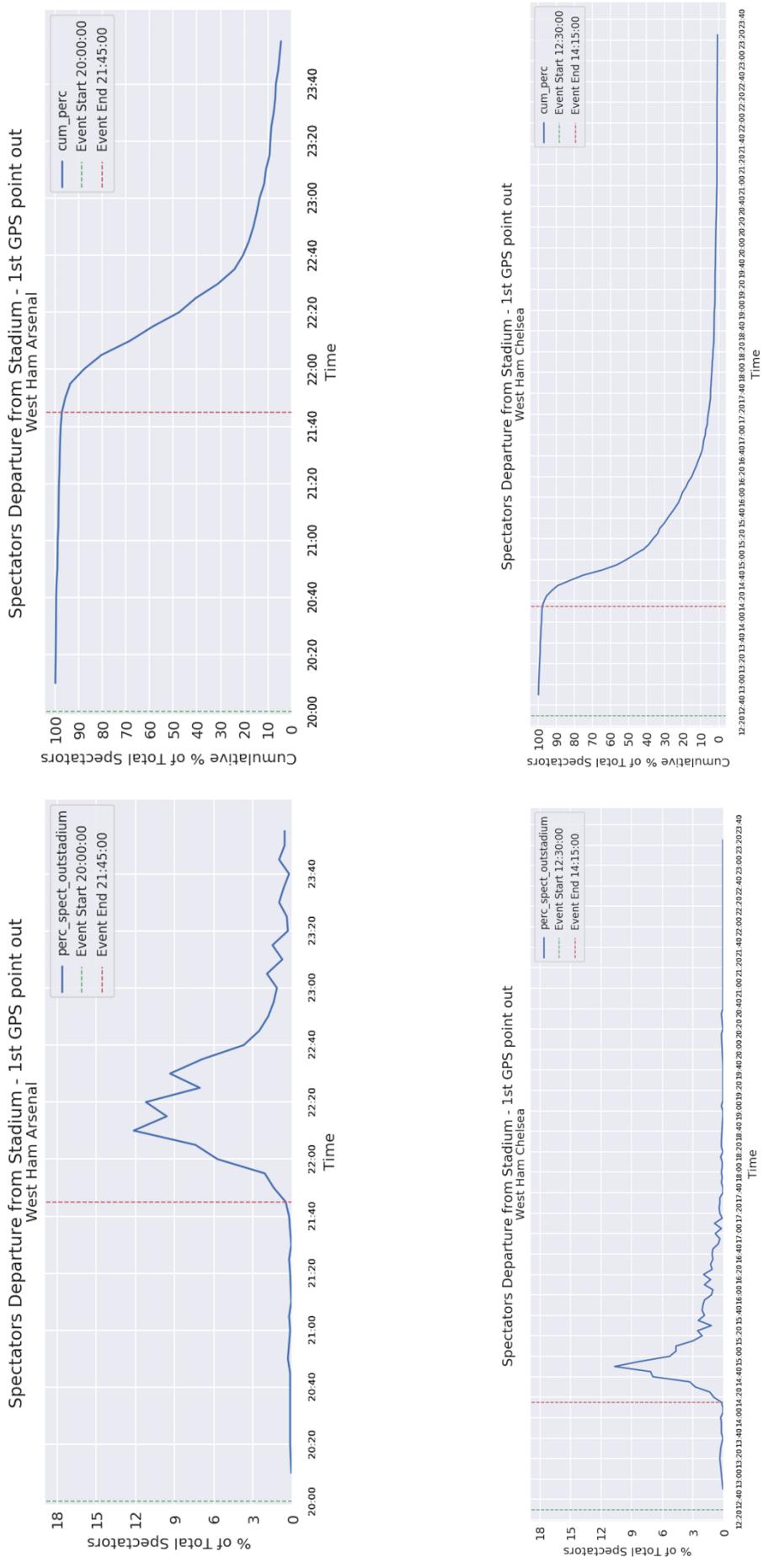
## 6. Premier League – Vicarage Road Stadium (Watford)

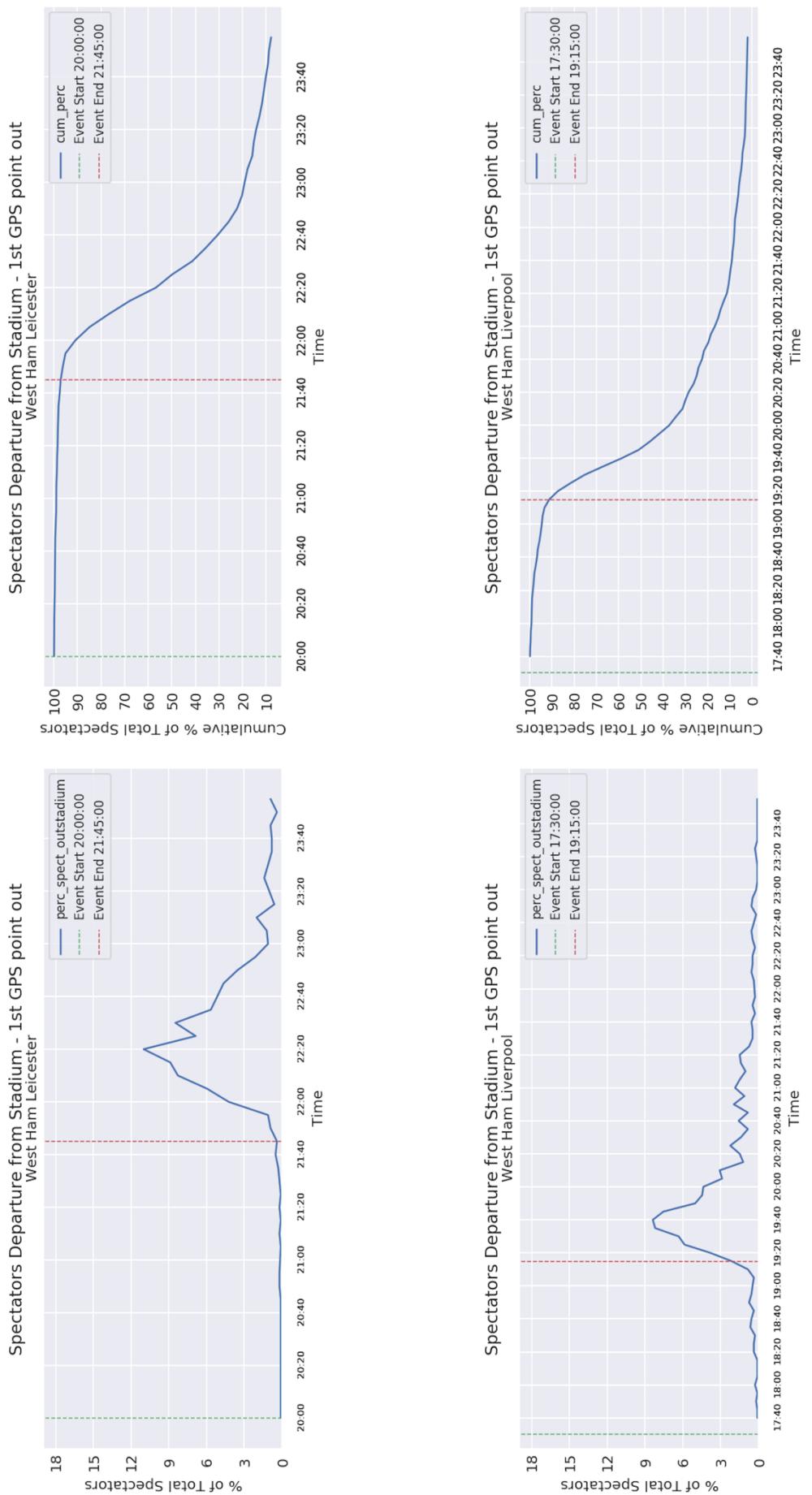


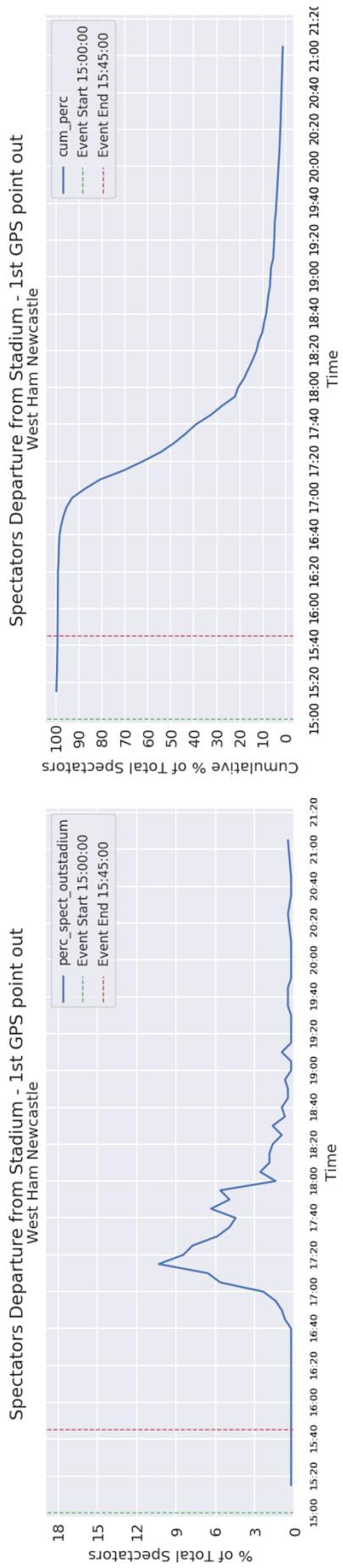


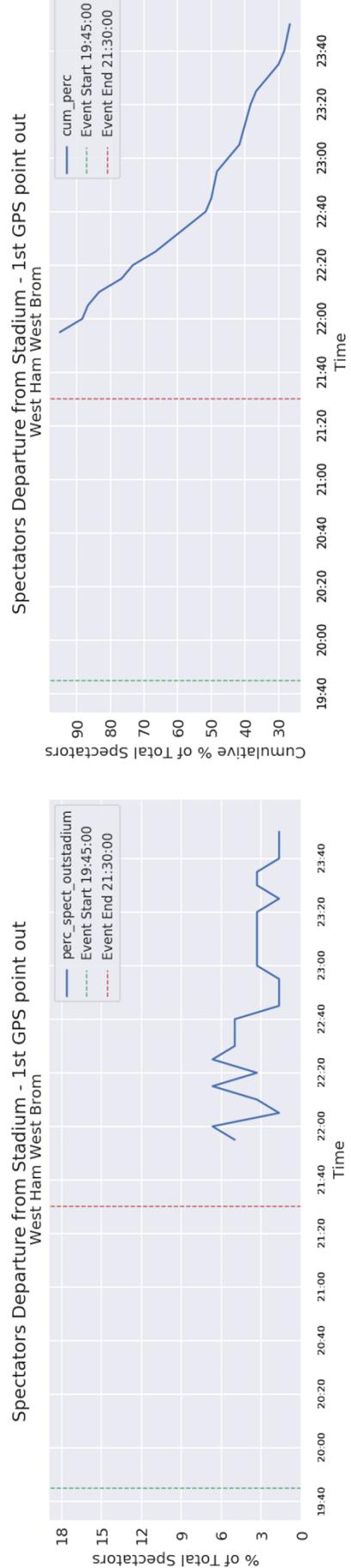


## 6. Premier League – London Stadium

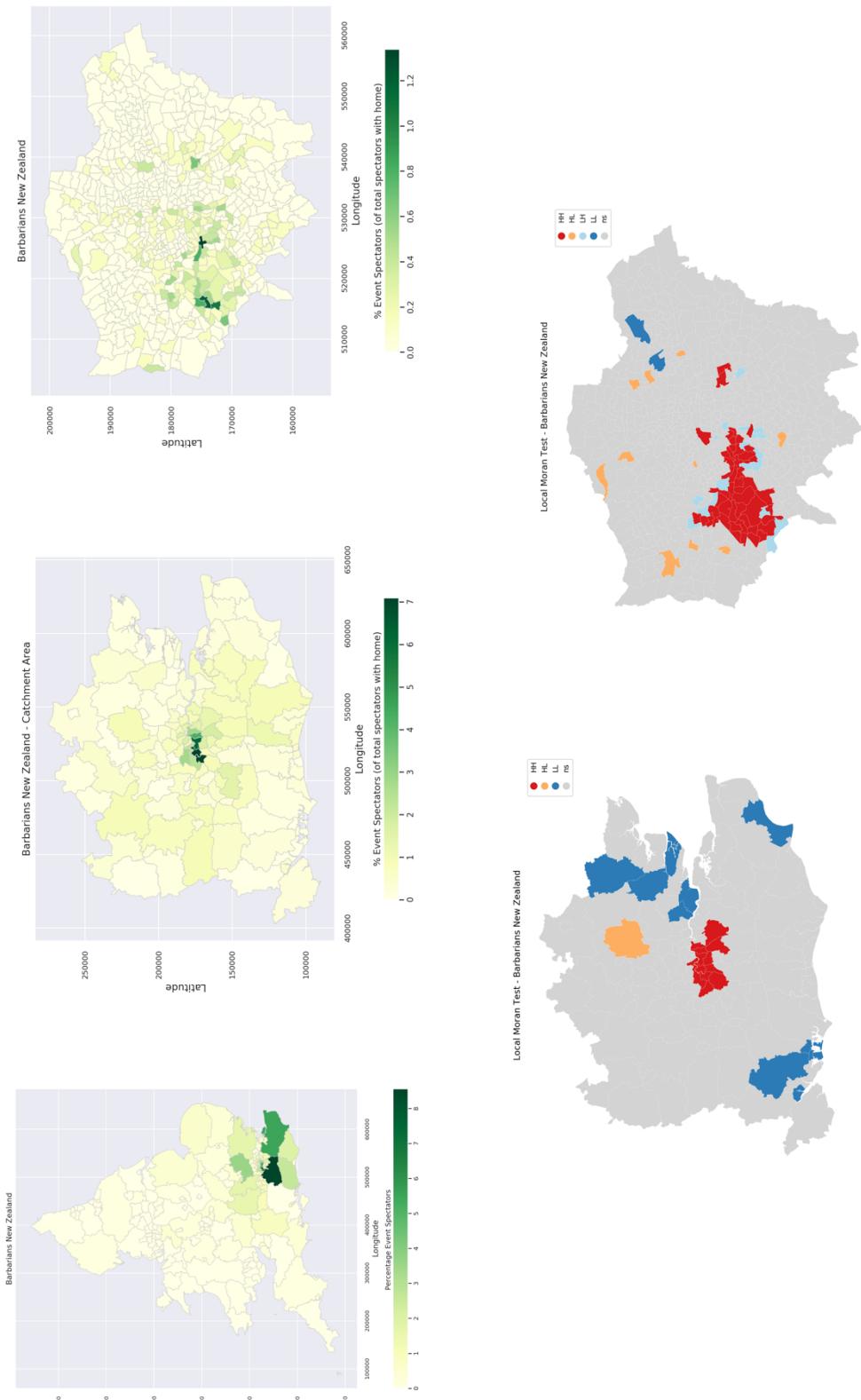


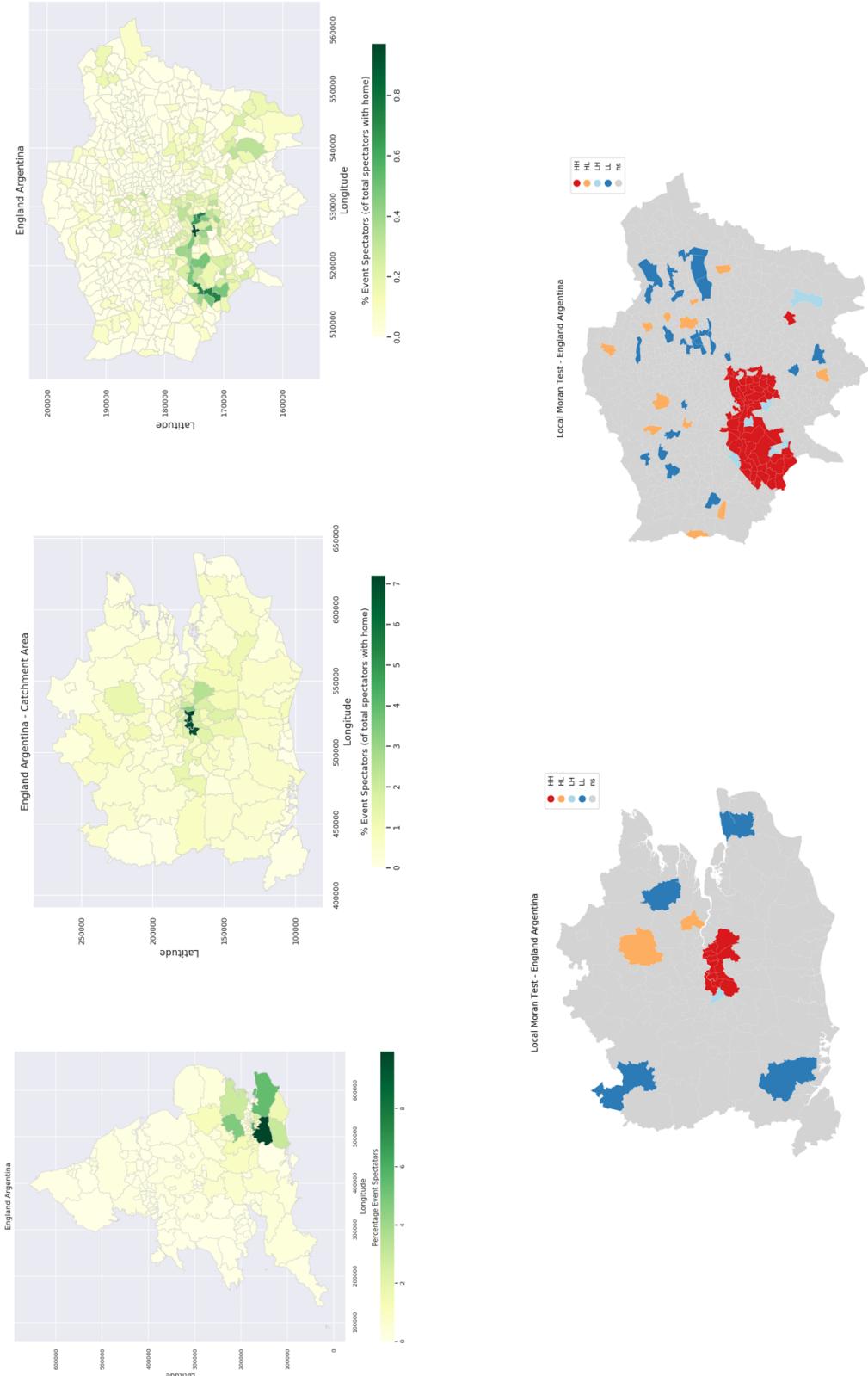


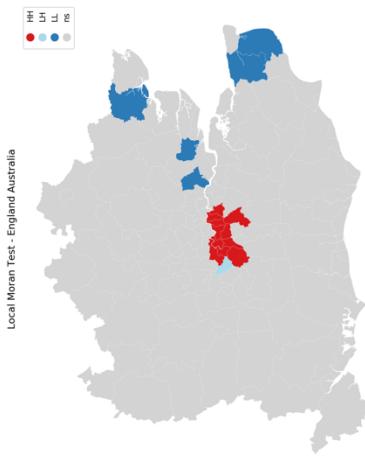
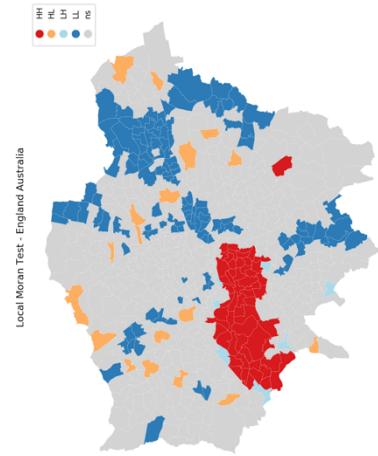
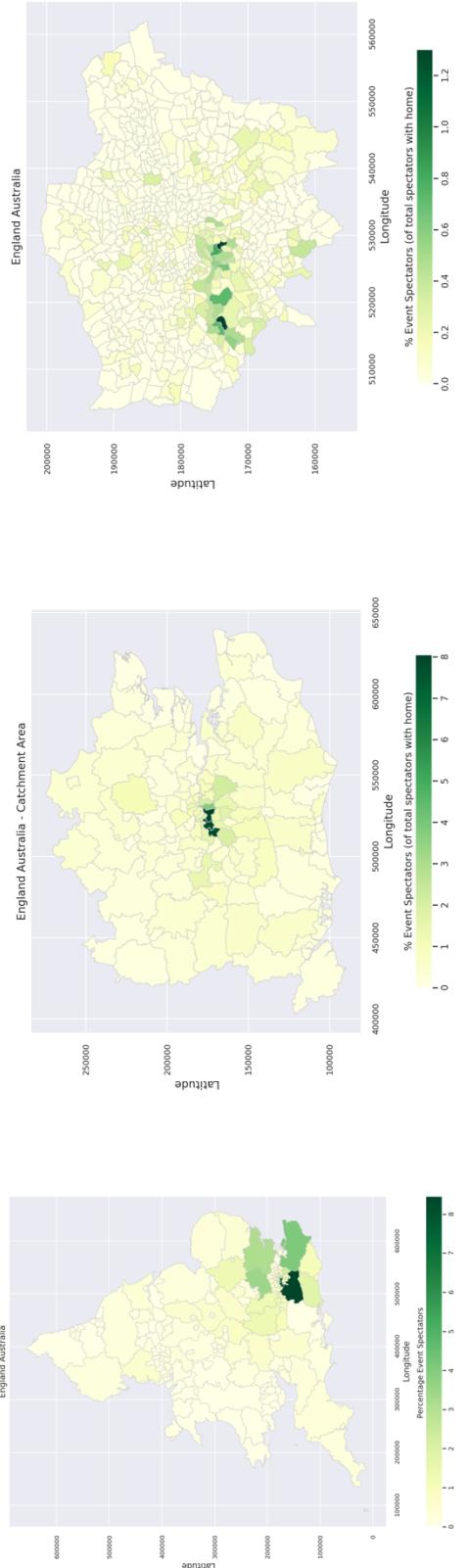


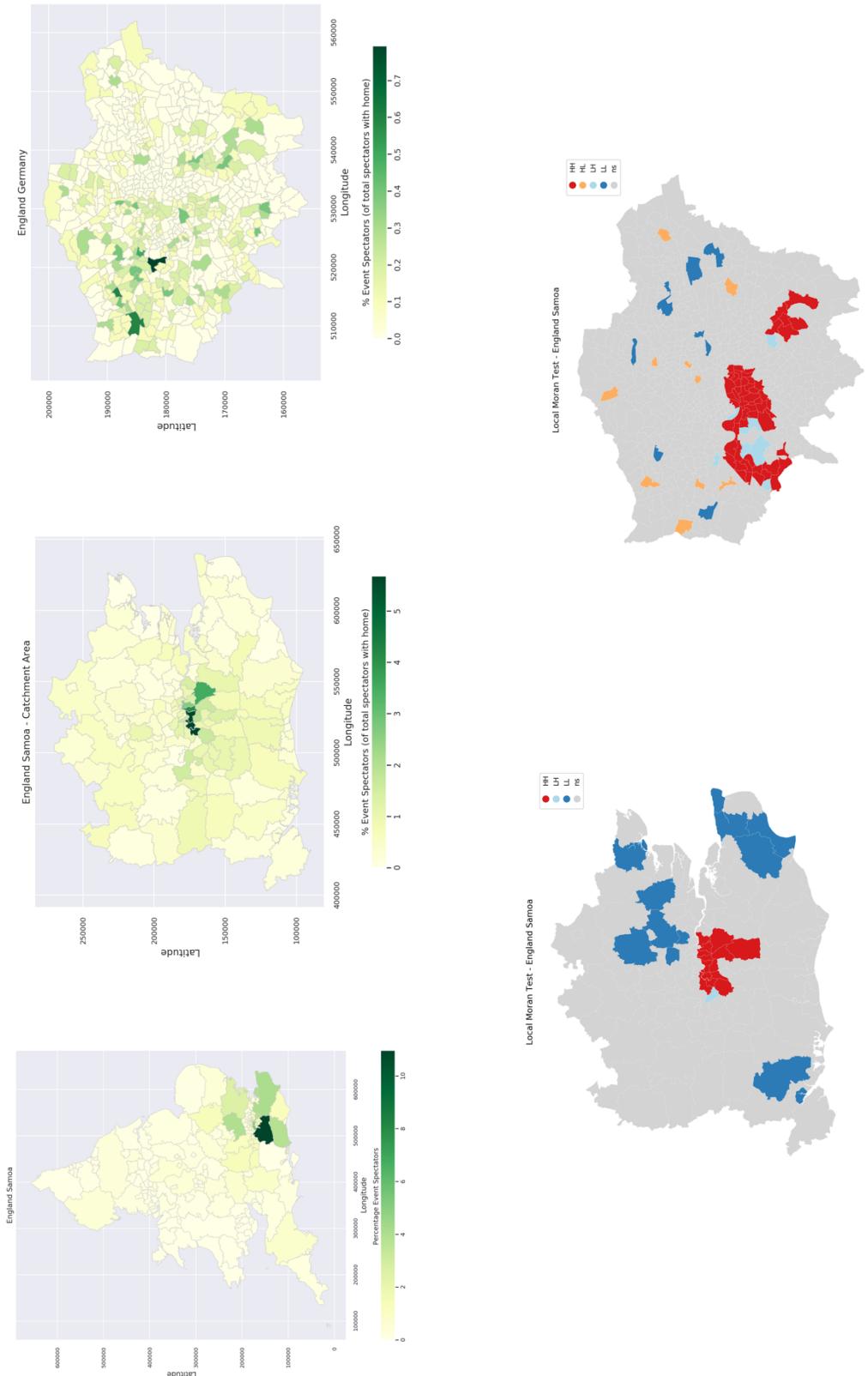


## 1. Rugby World Cup – Twickenham Stadium

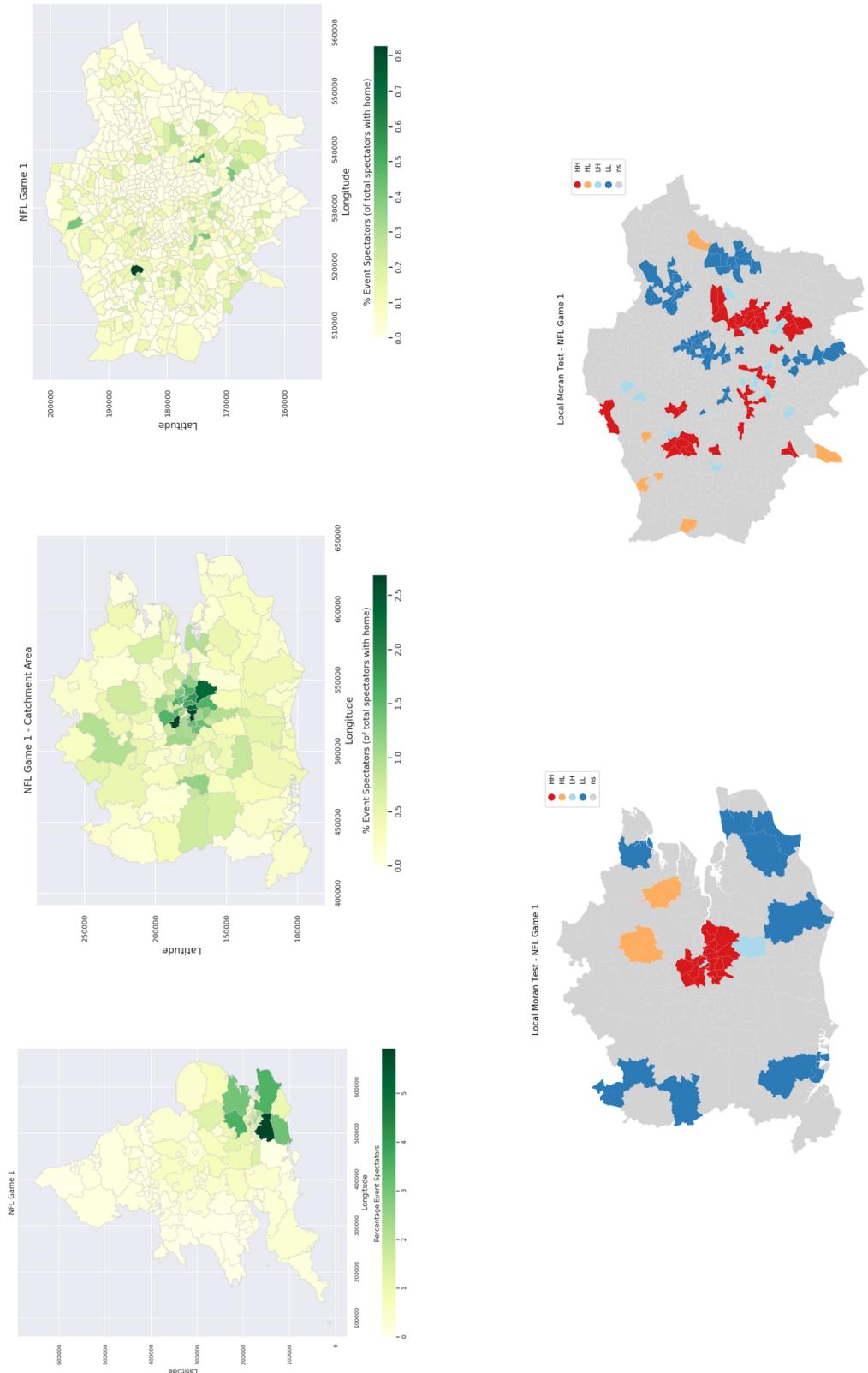


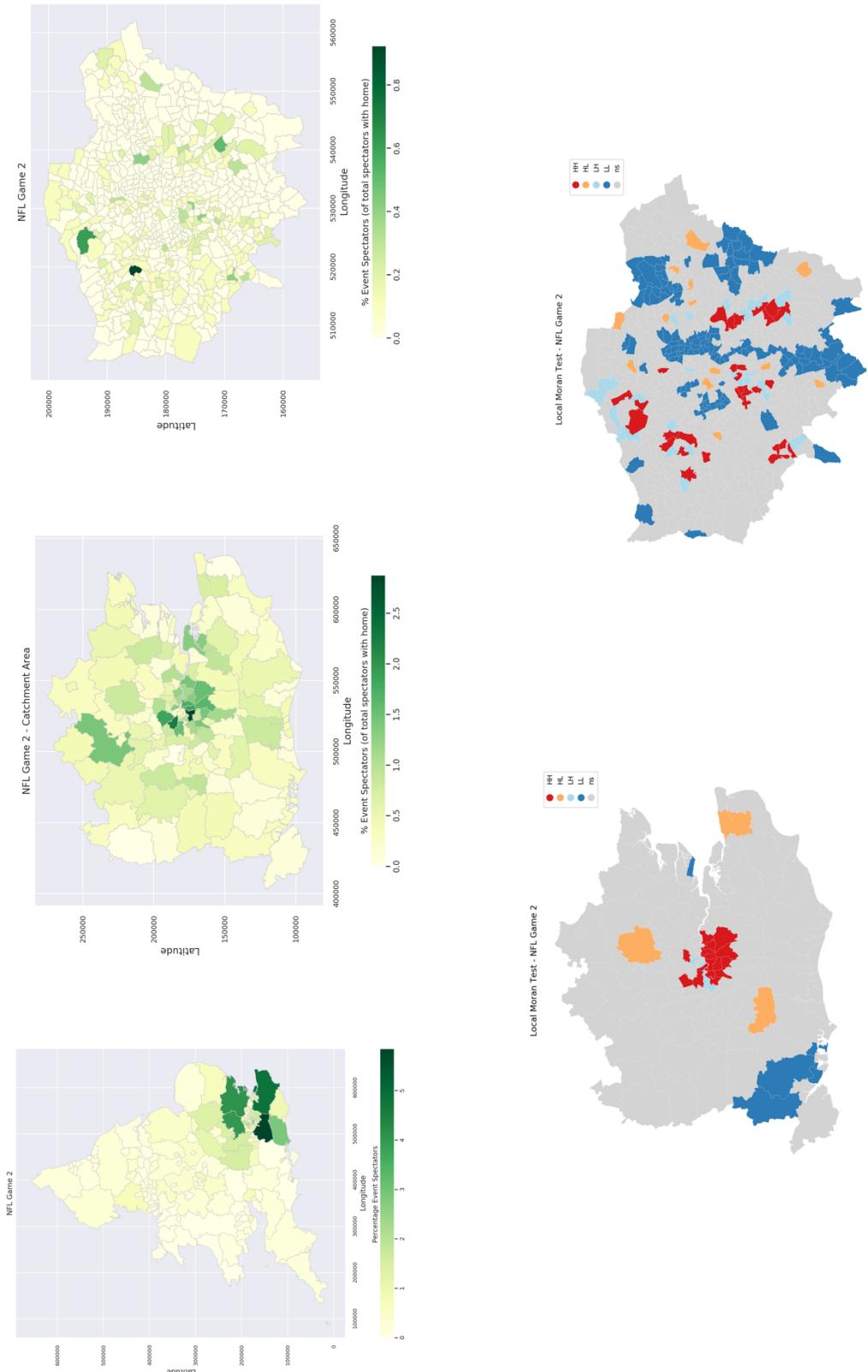




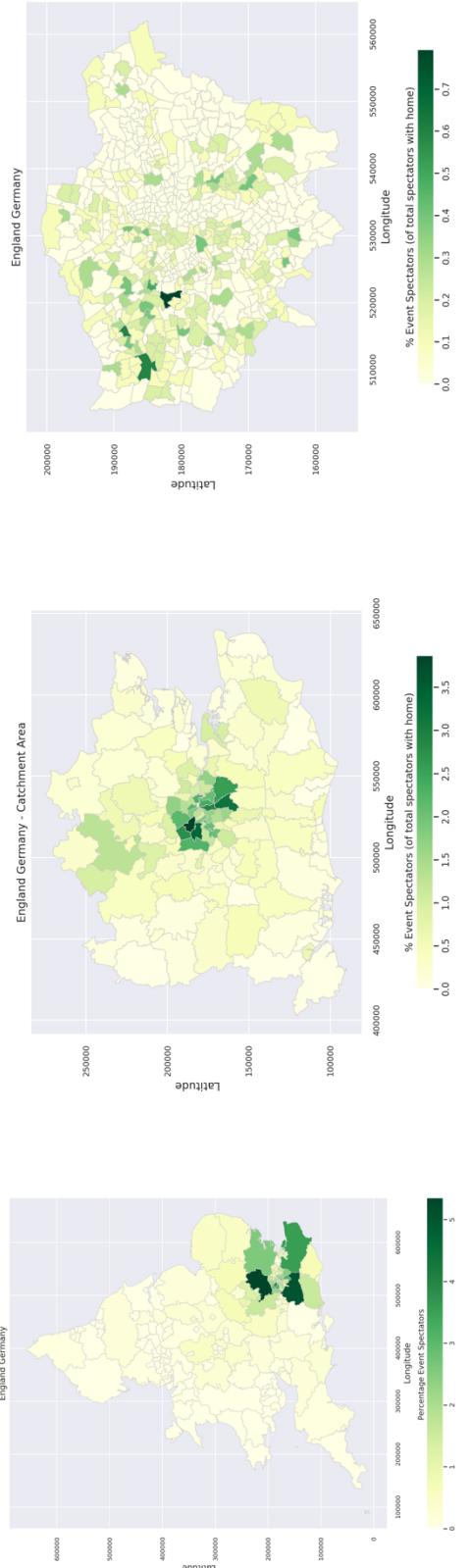


2. NFL – Wembley Stadium

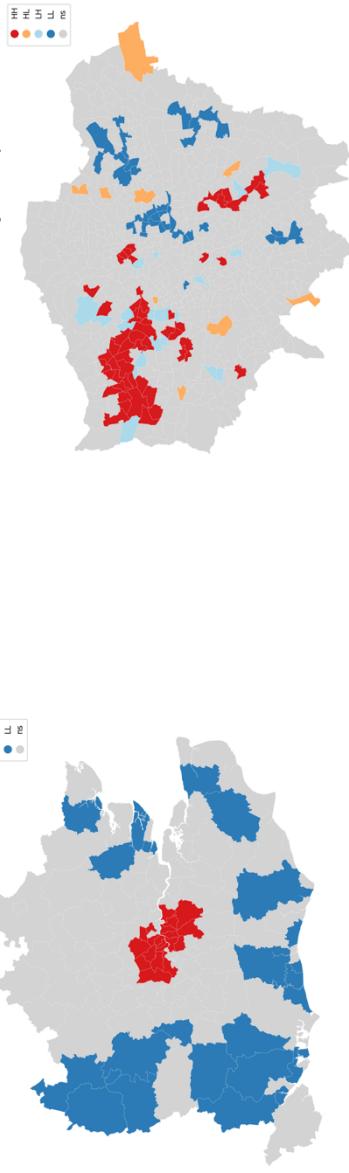


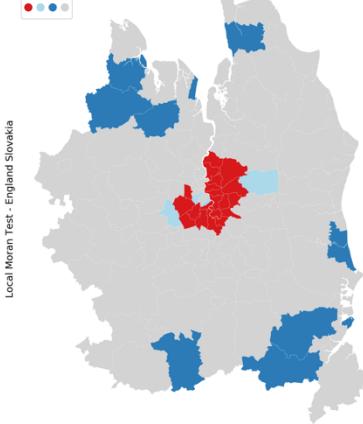
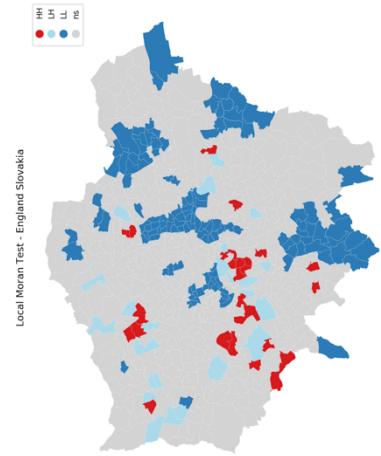
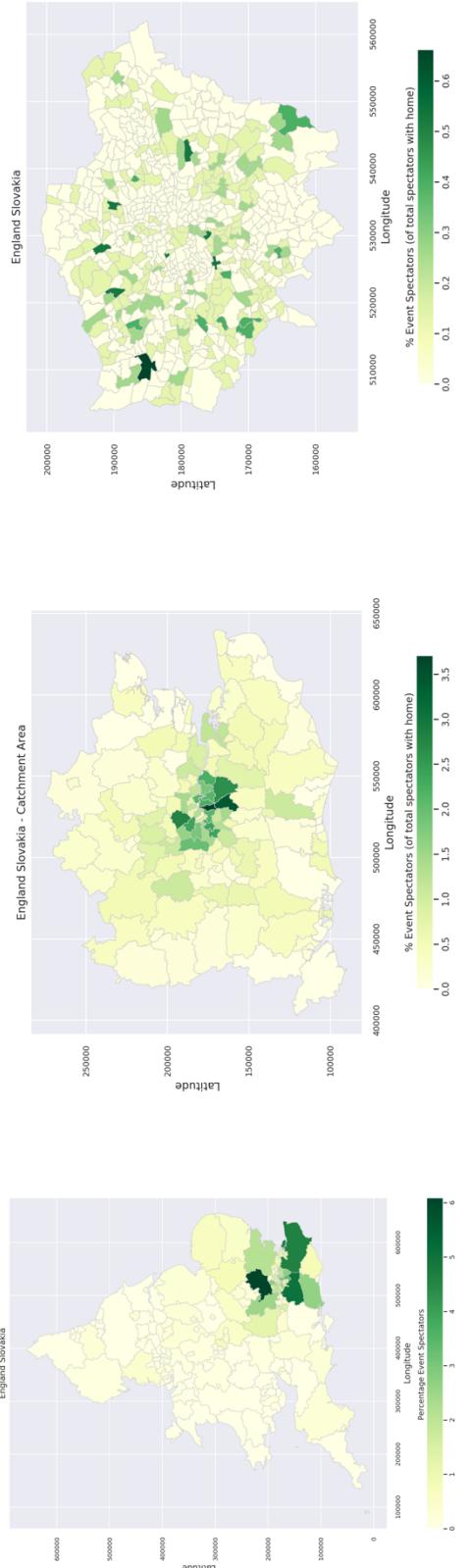


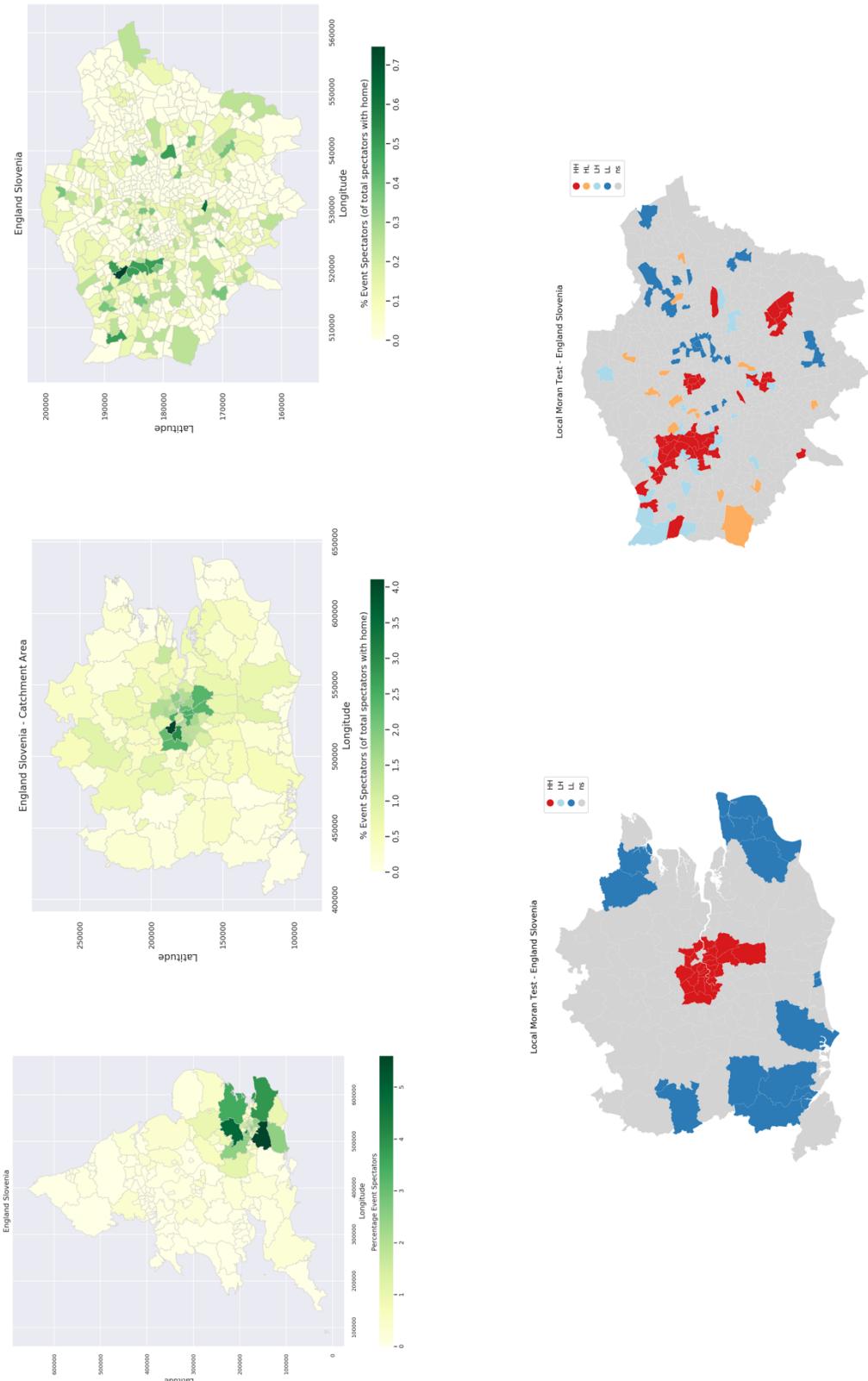
3. International Football World Cup Qualification 18 – Wembley Stadium



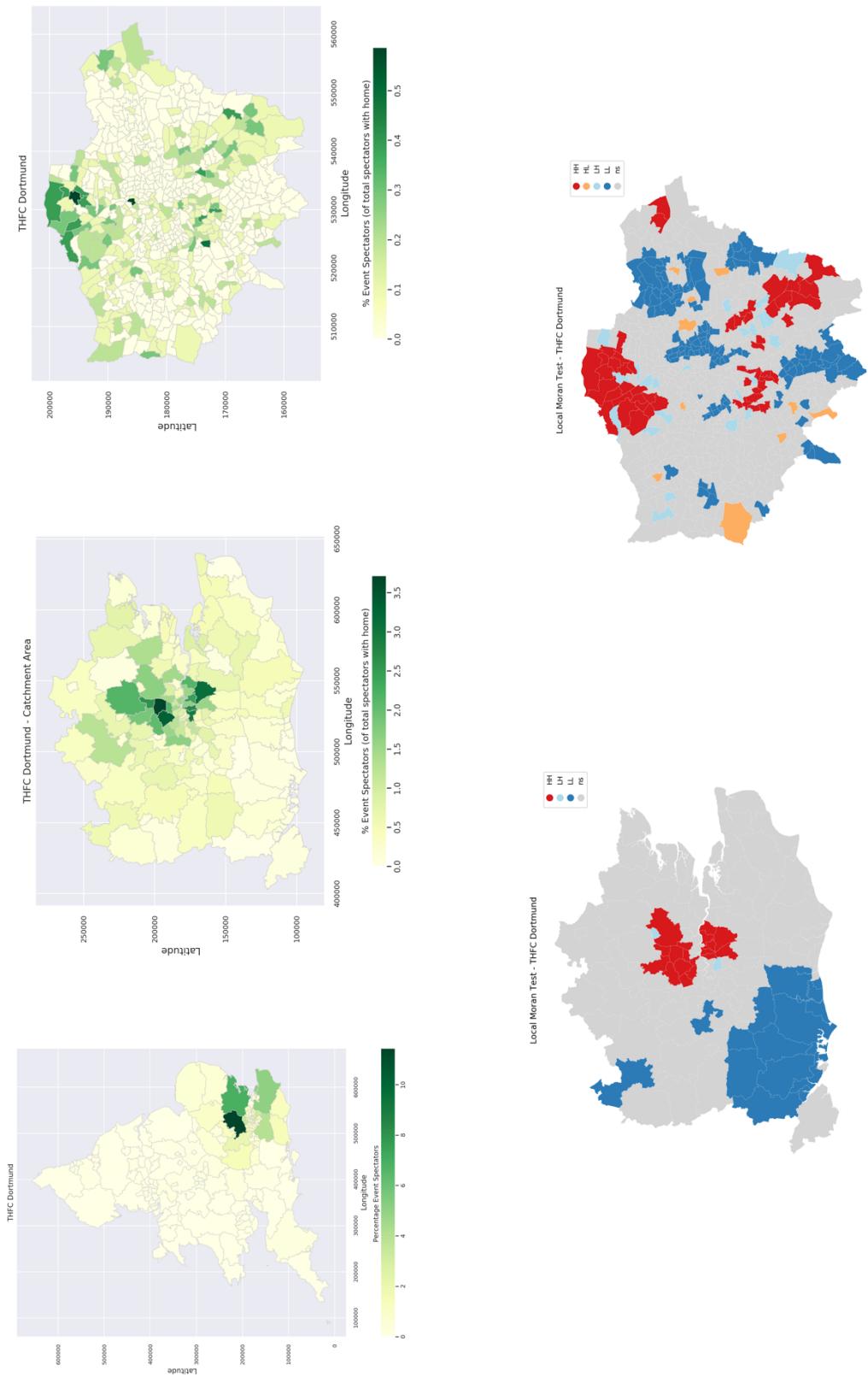
Local Moran Test - England Germany

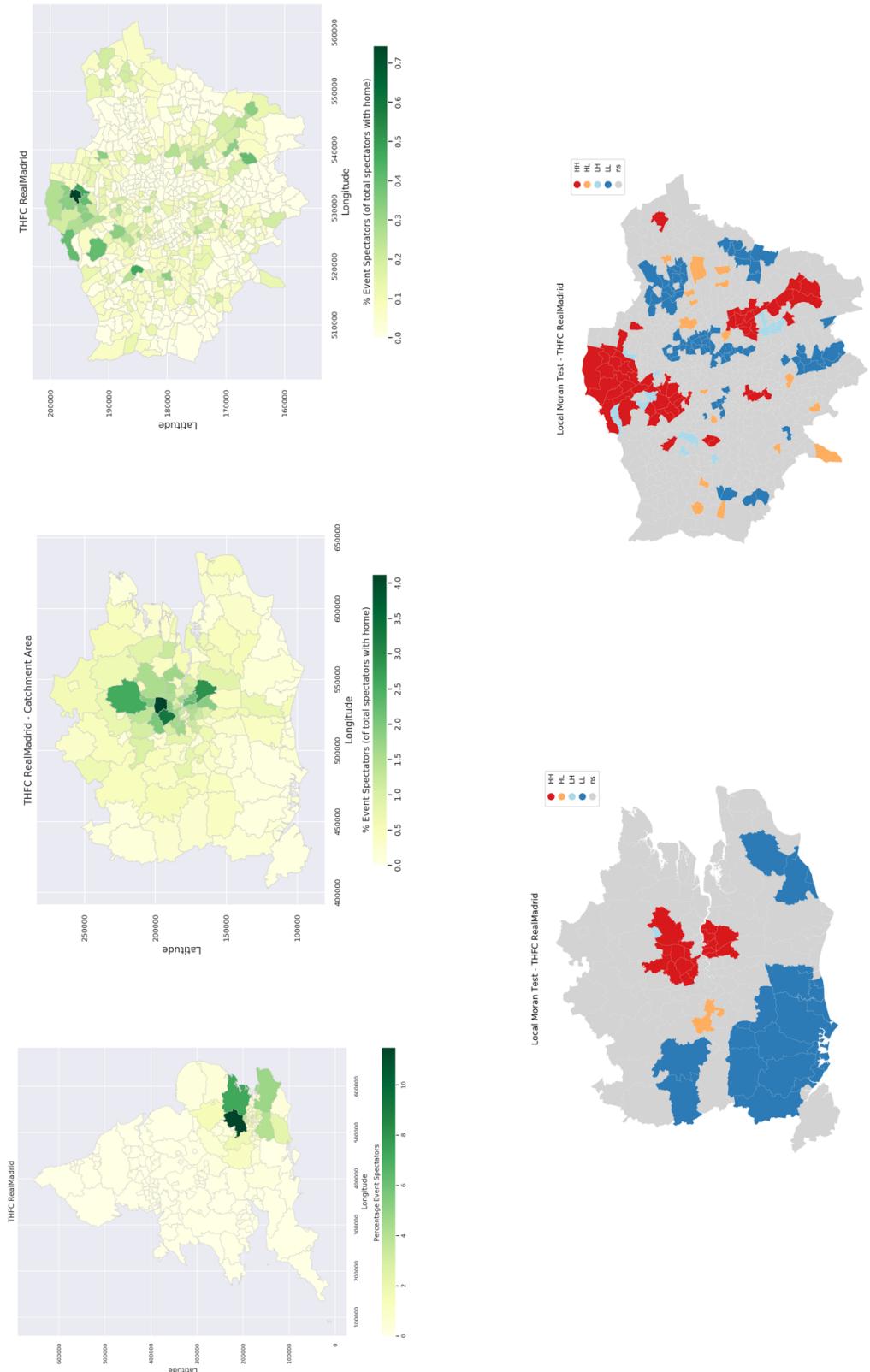




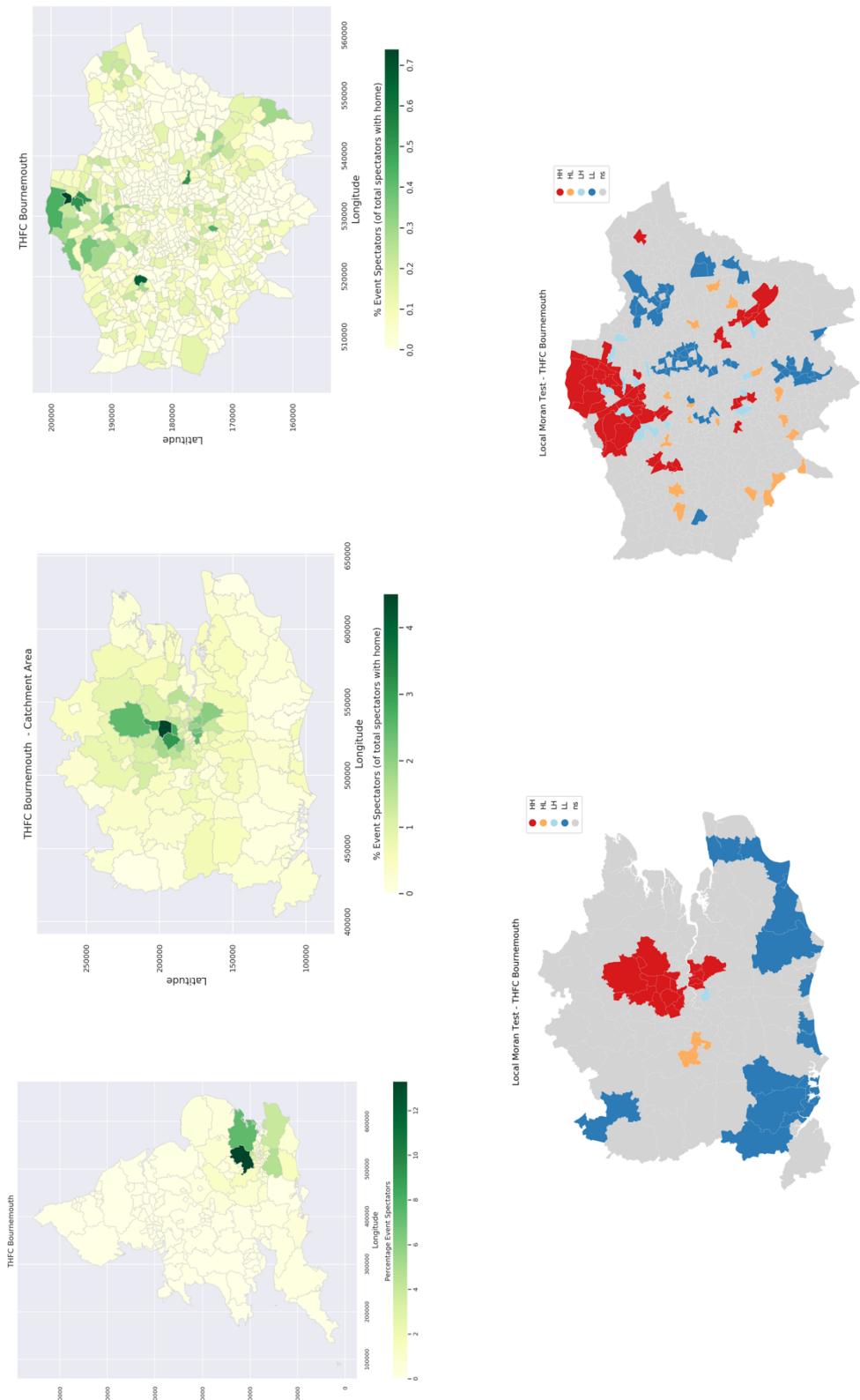


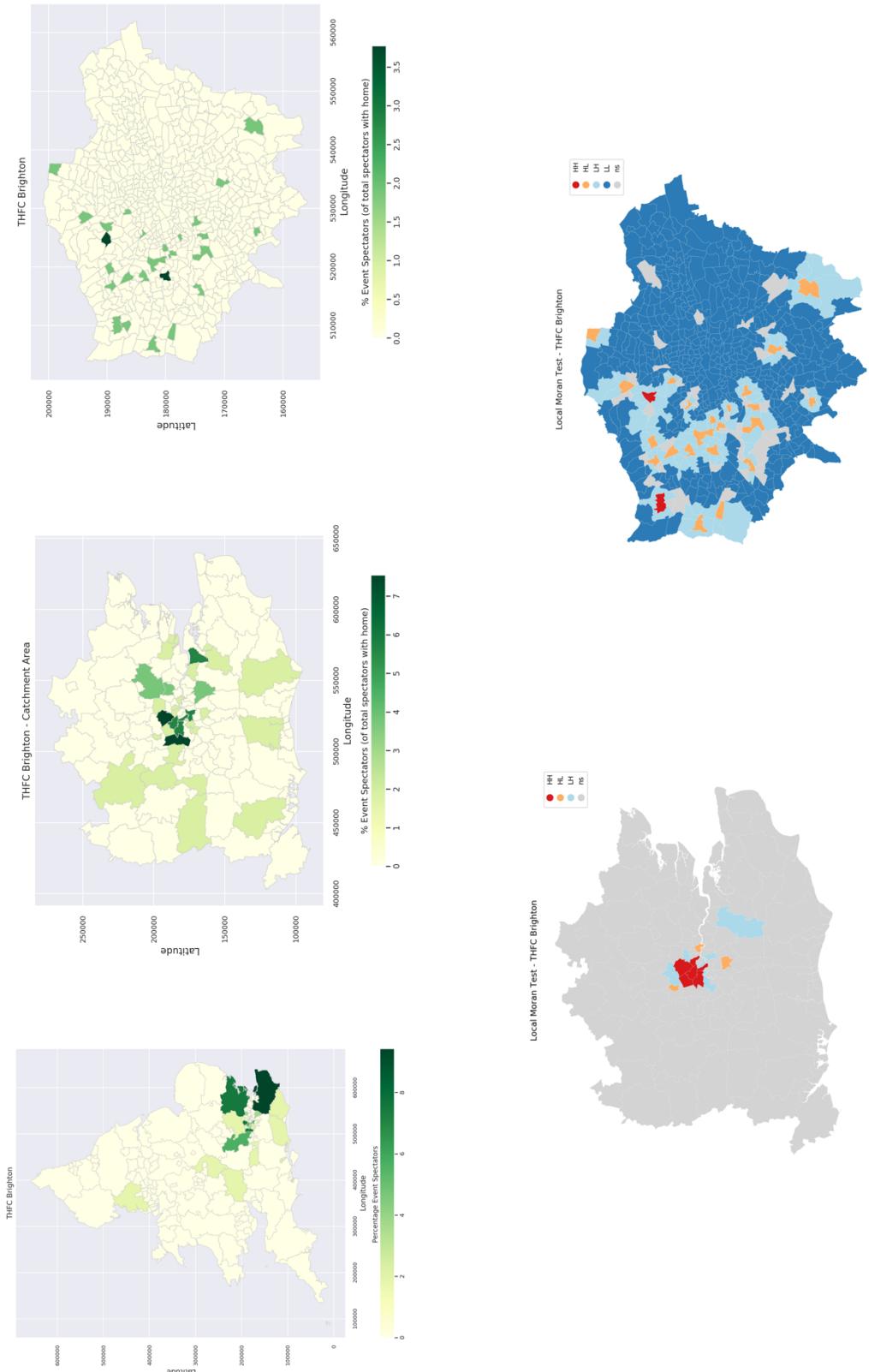
#### 4. Champions League – Wembley Stadium

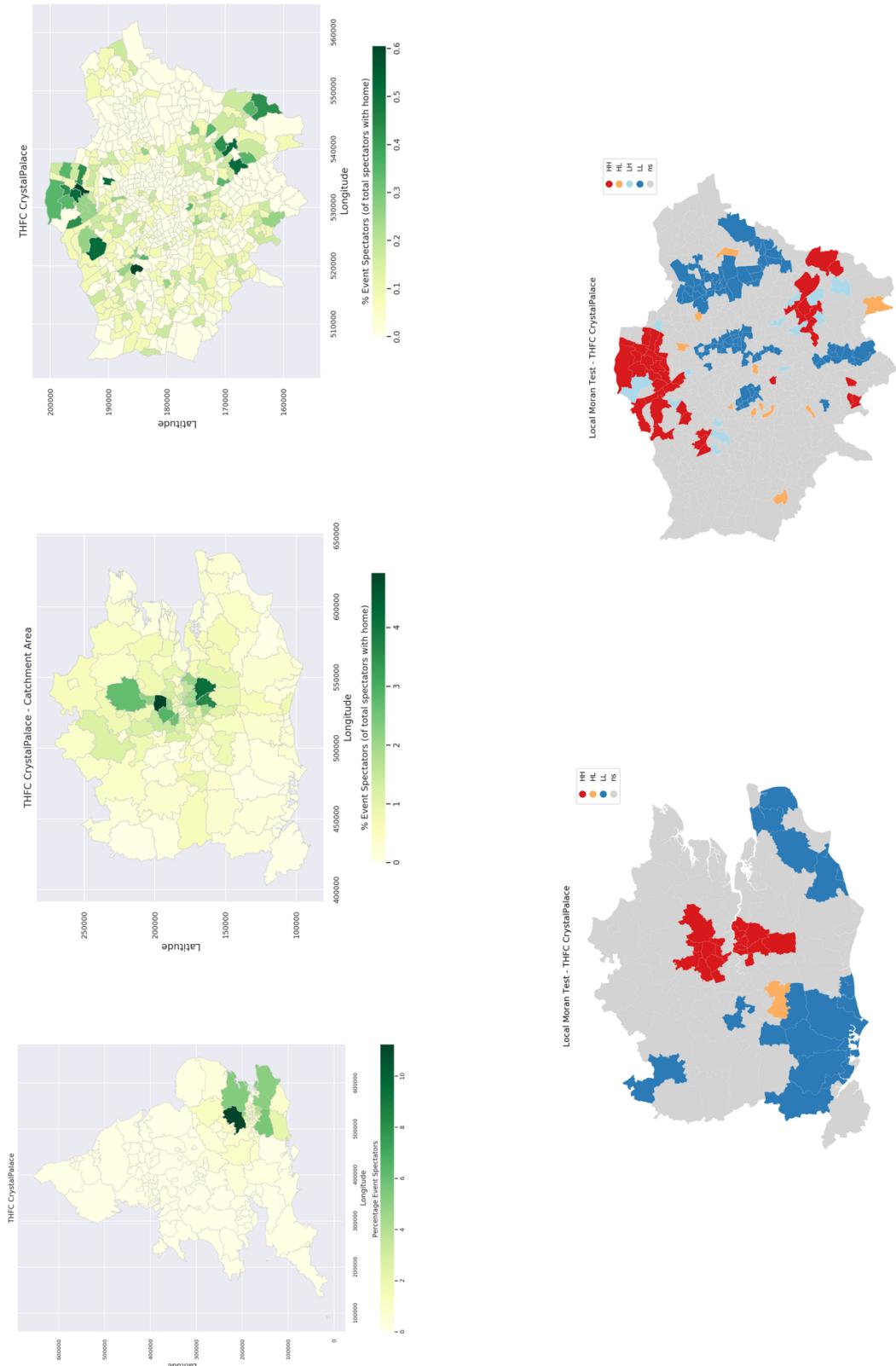


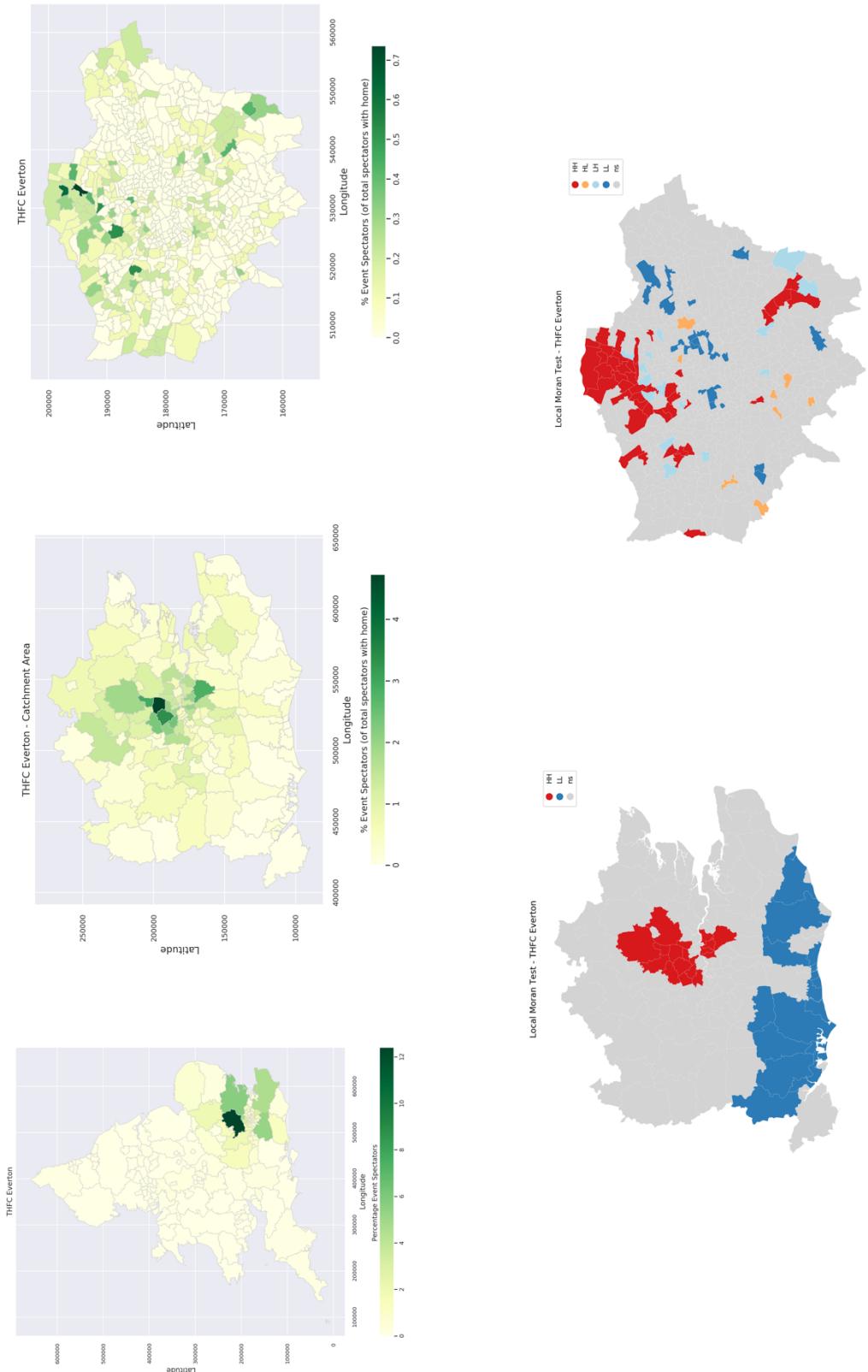


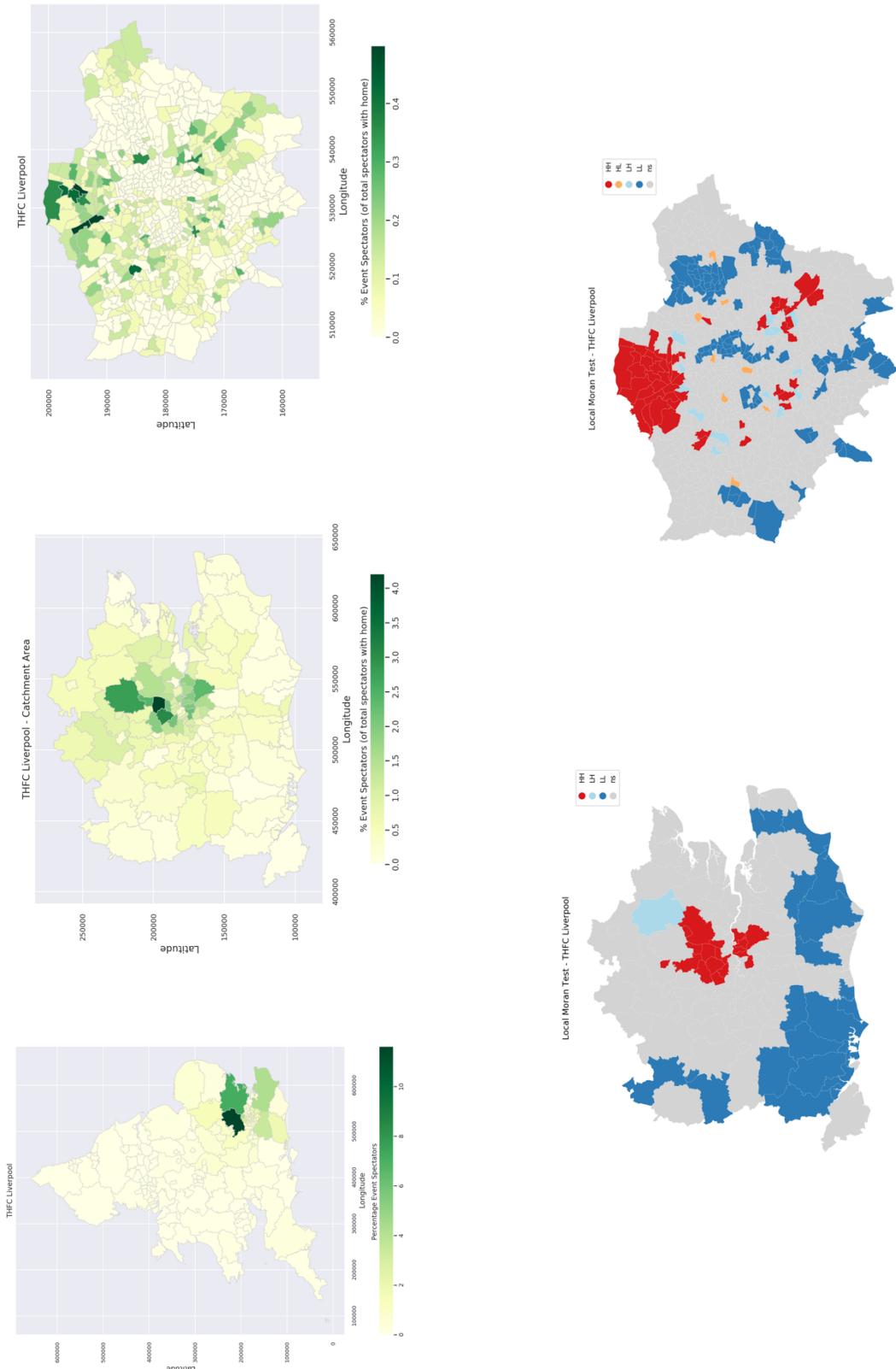
## 5. Premier League – Wembley Stadium

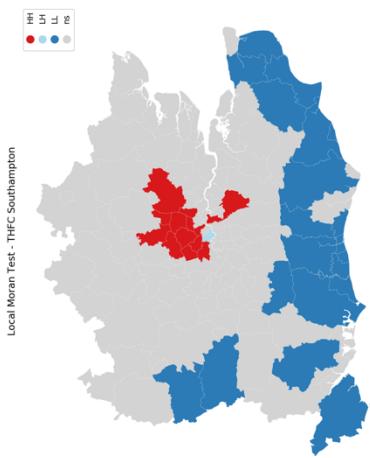
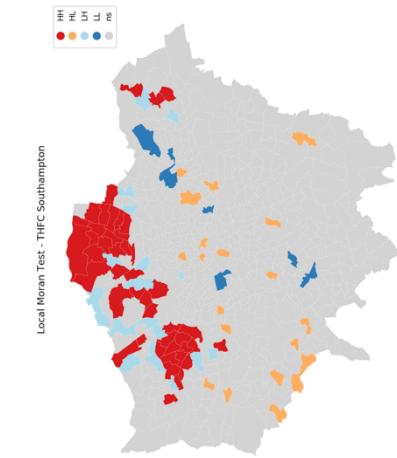
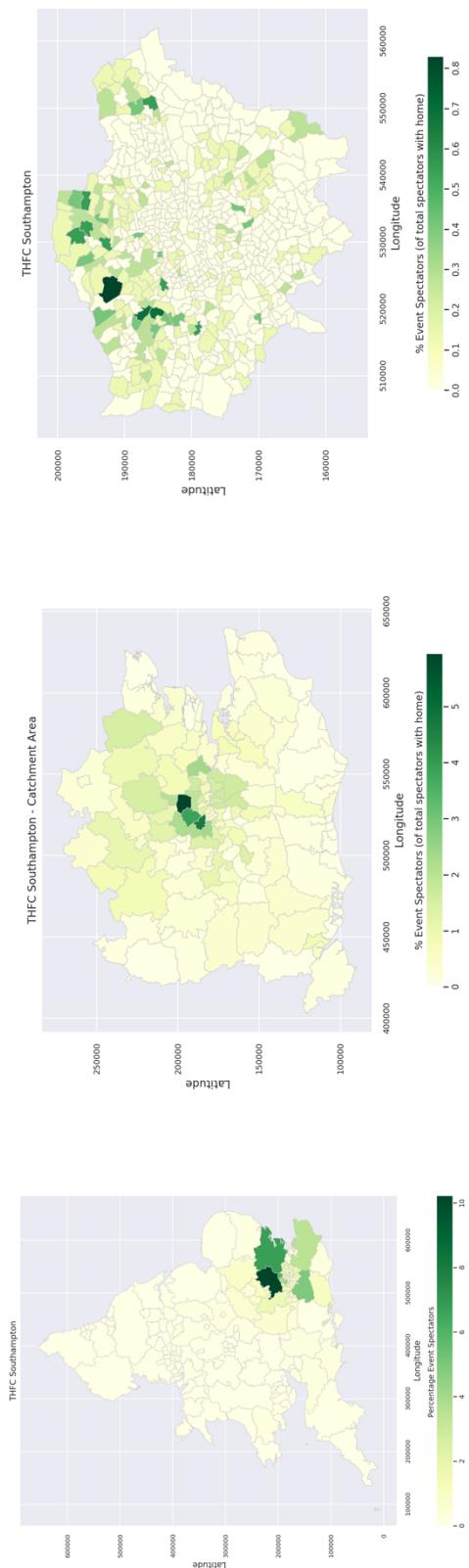


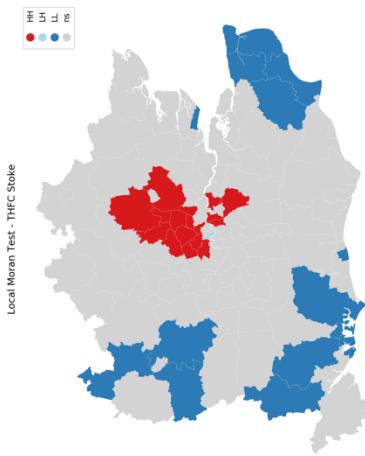
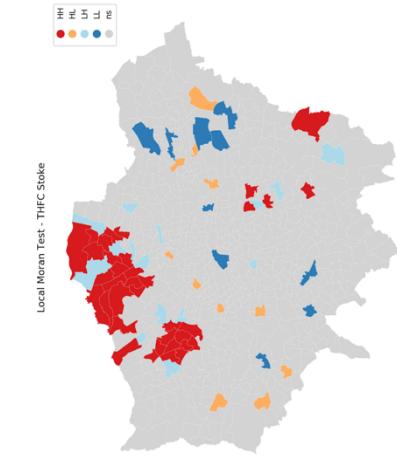
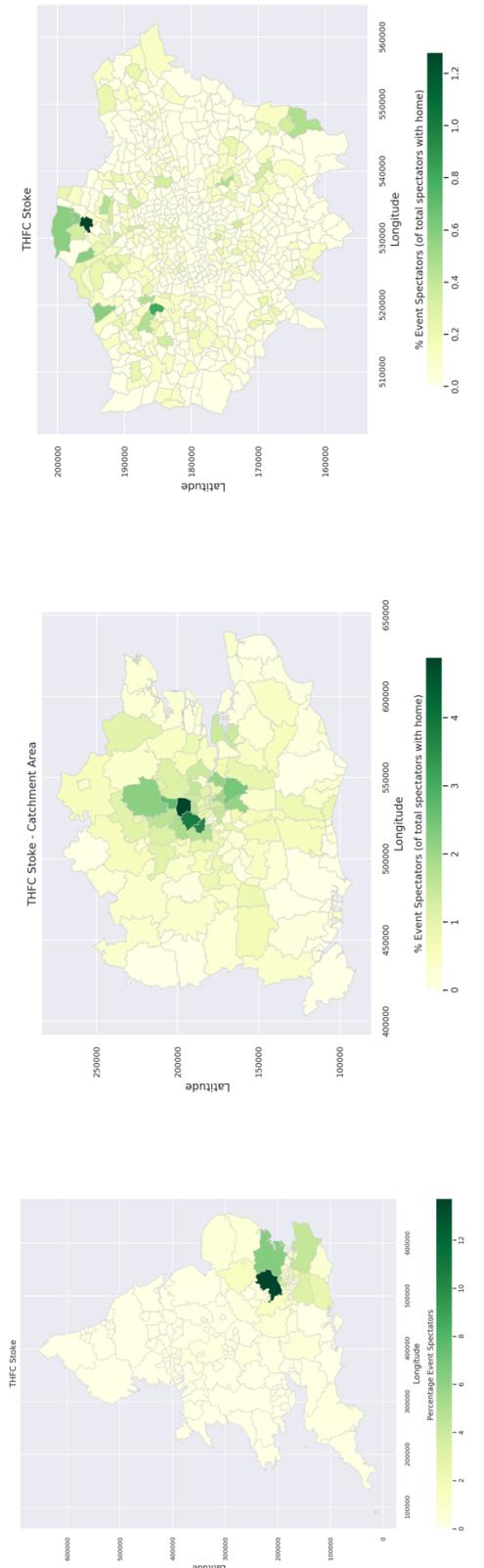


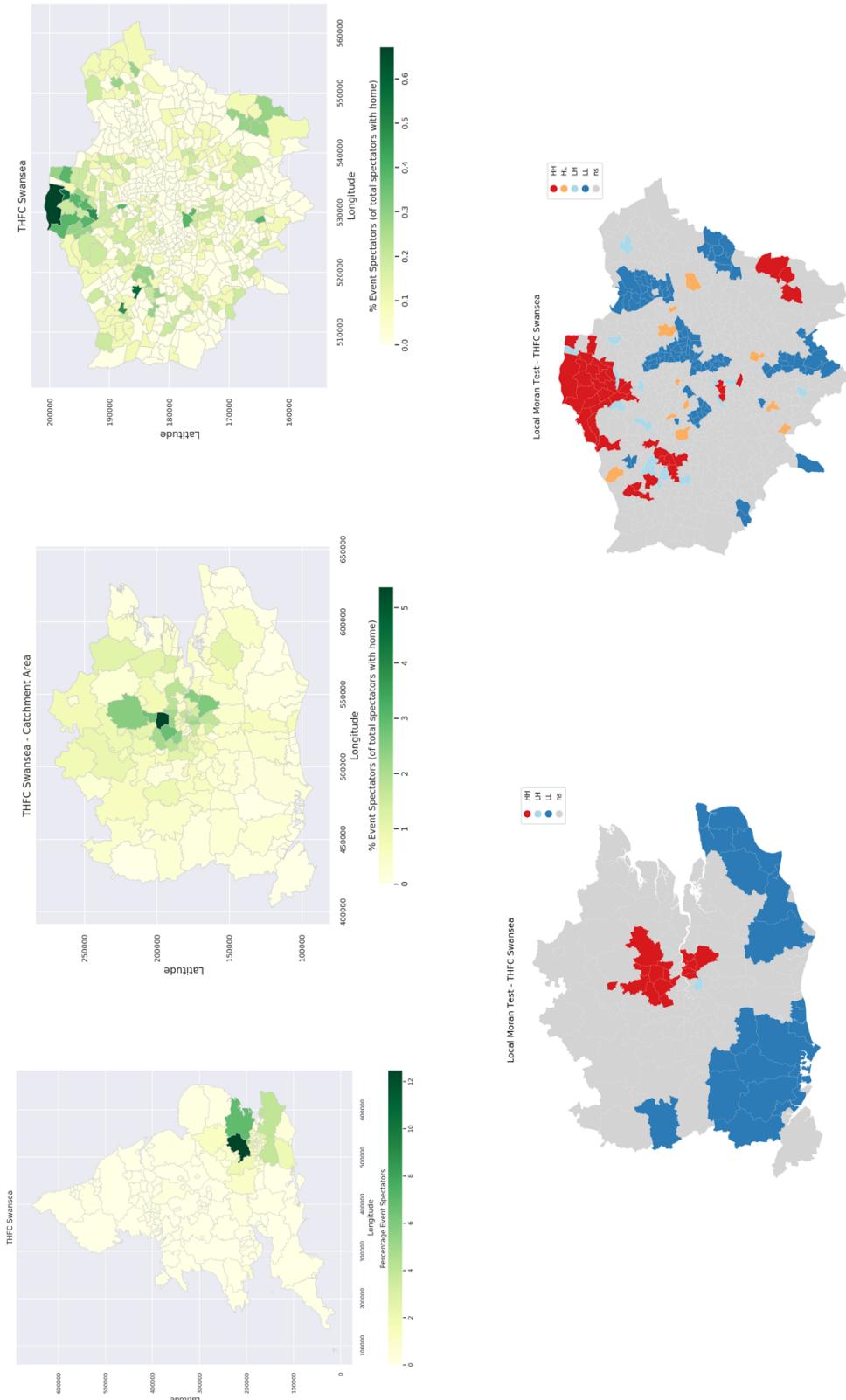


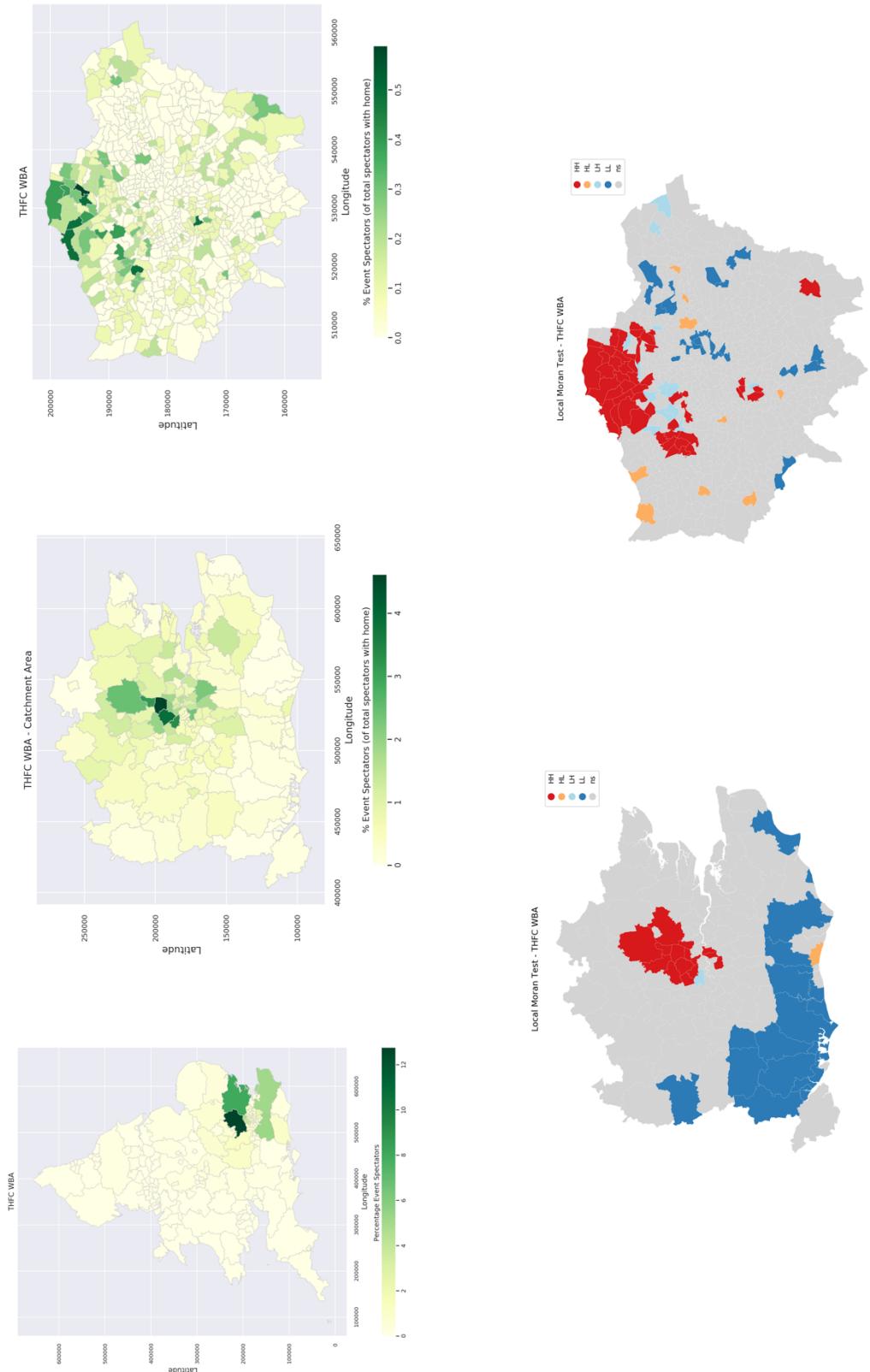


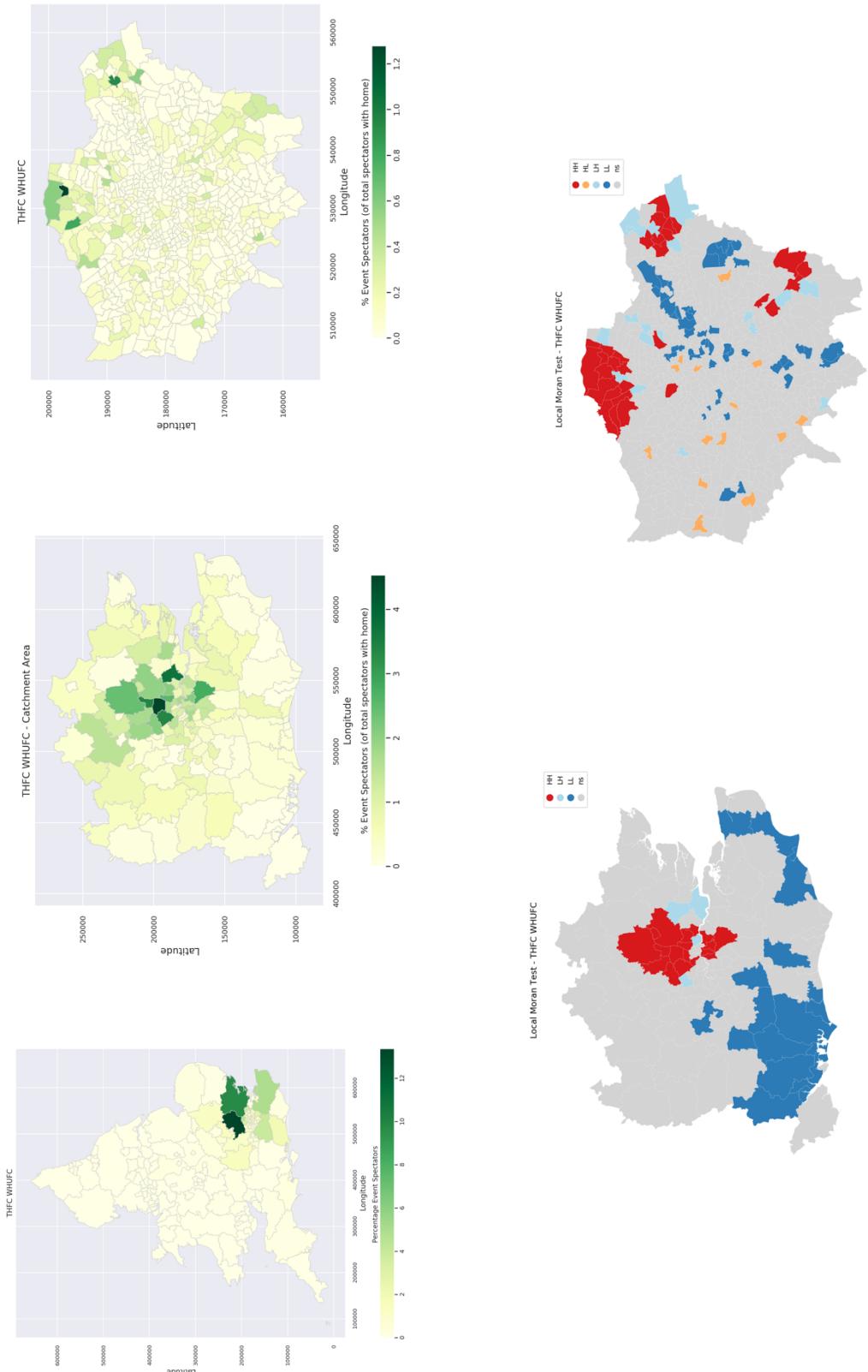




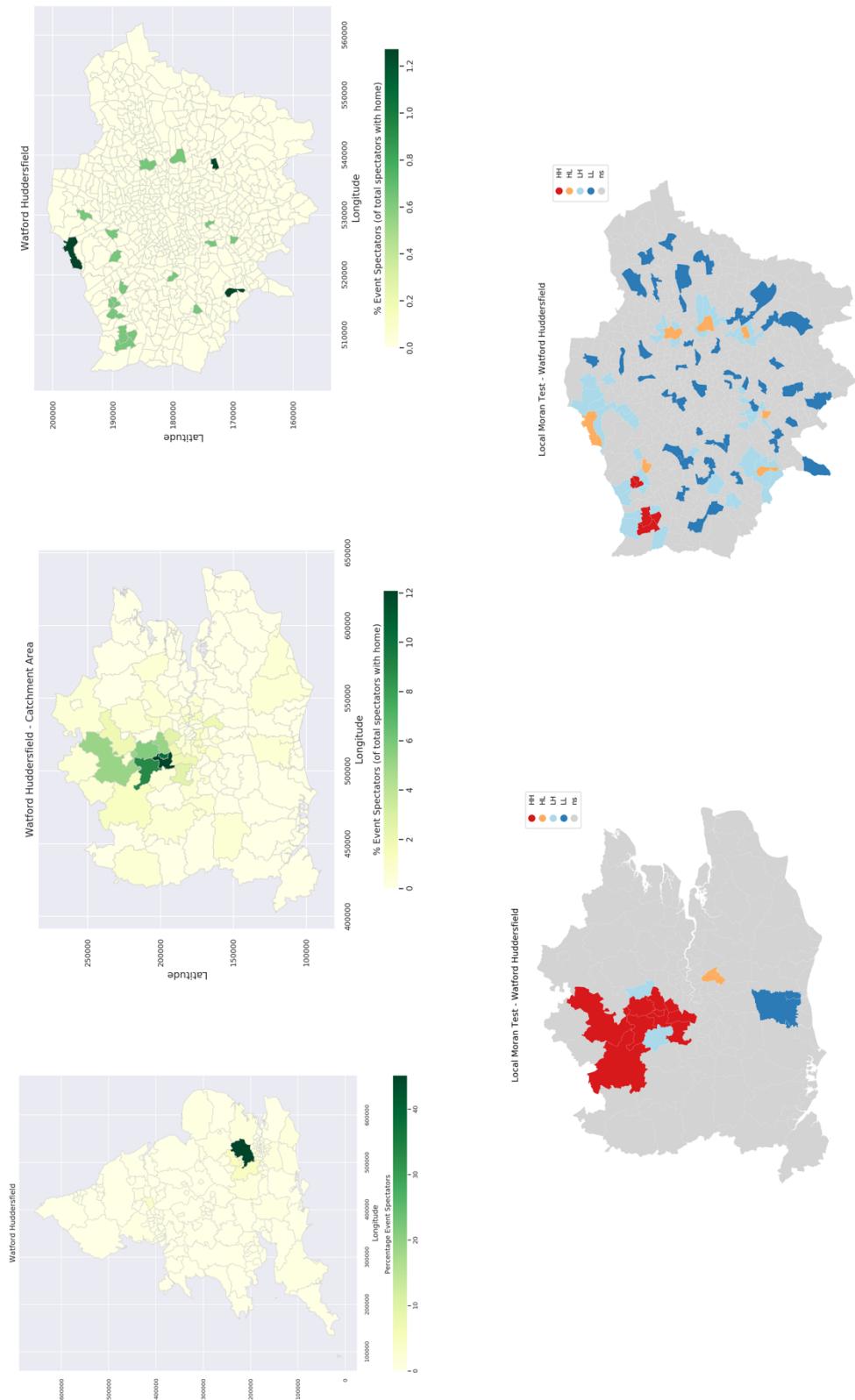


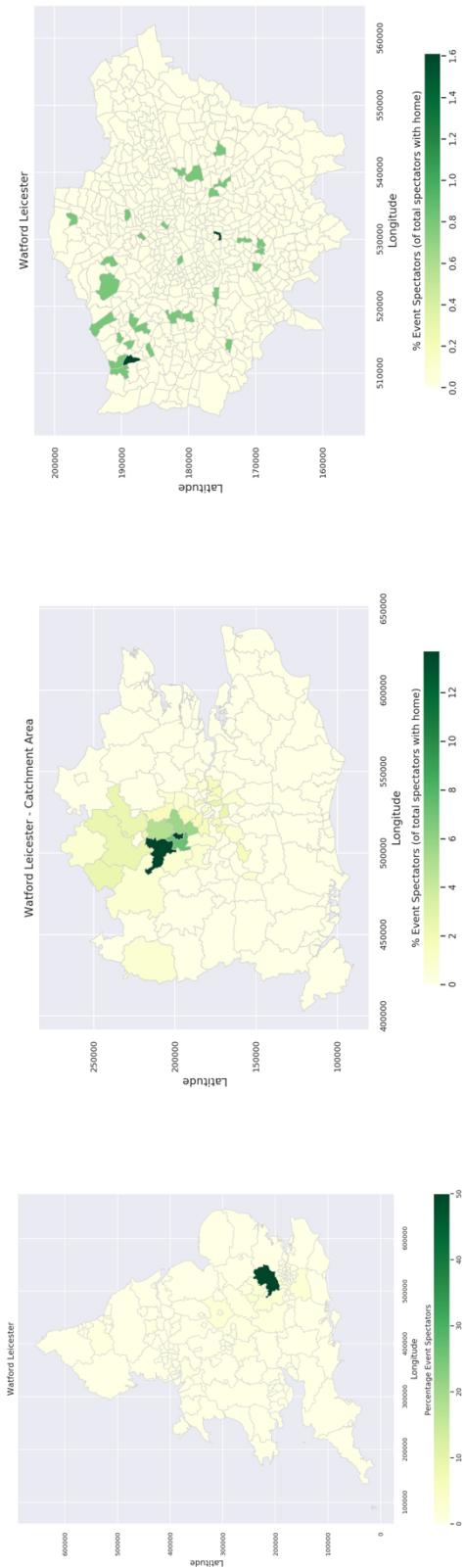




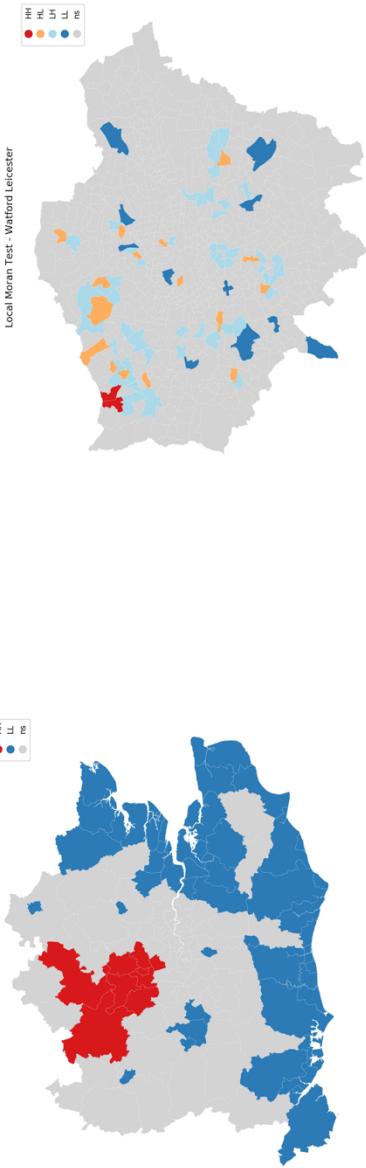


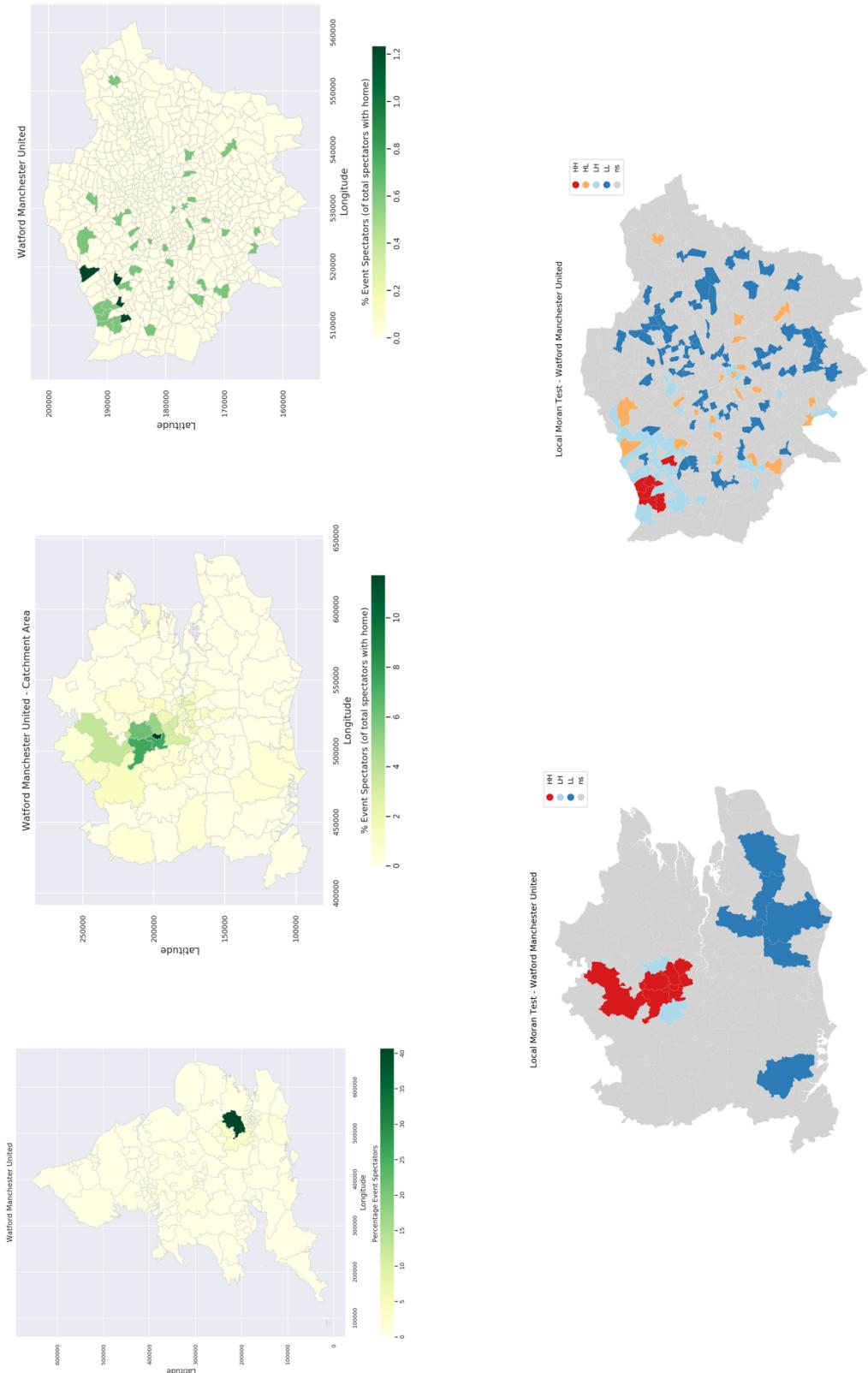
## 6. Premier League – Vicarage Road Stadium (Watford)

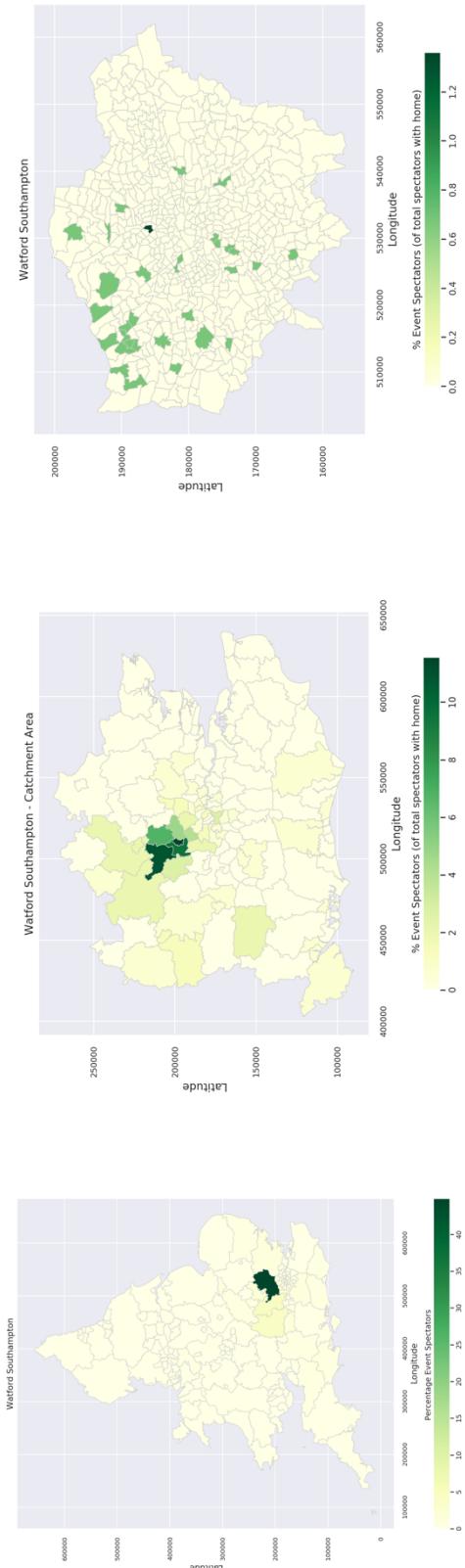




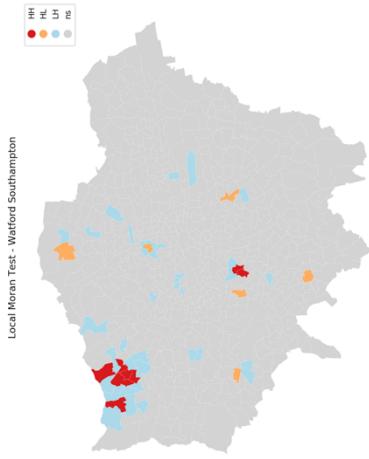
**Local Moran Test - Watford Leicester**



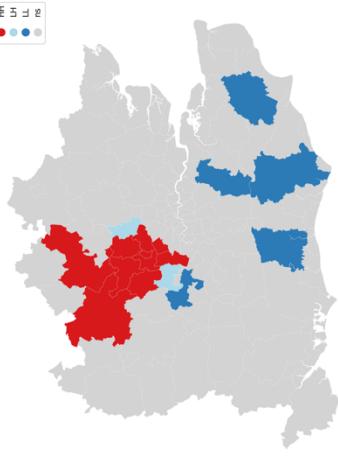


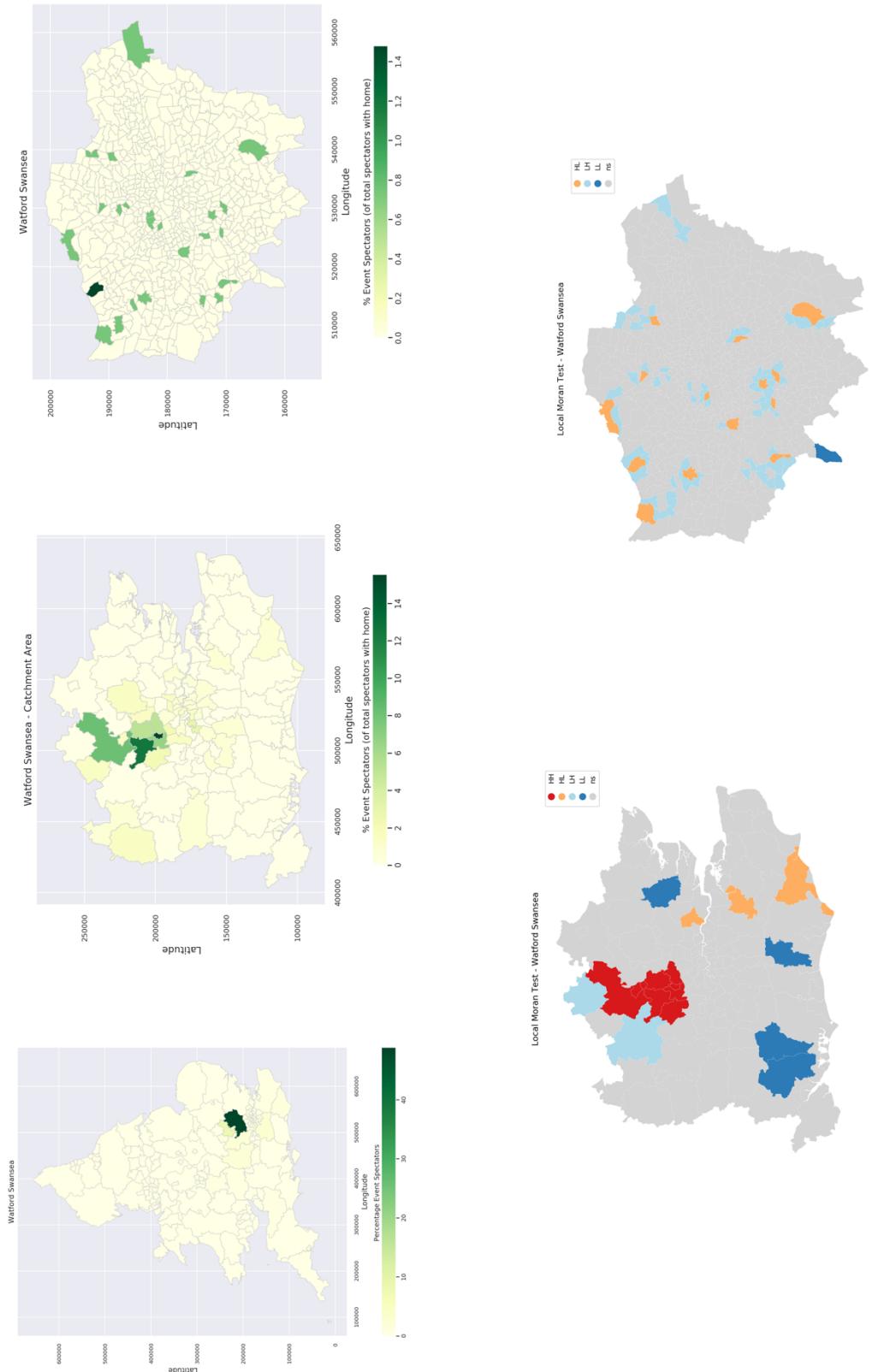


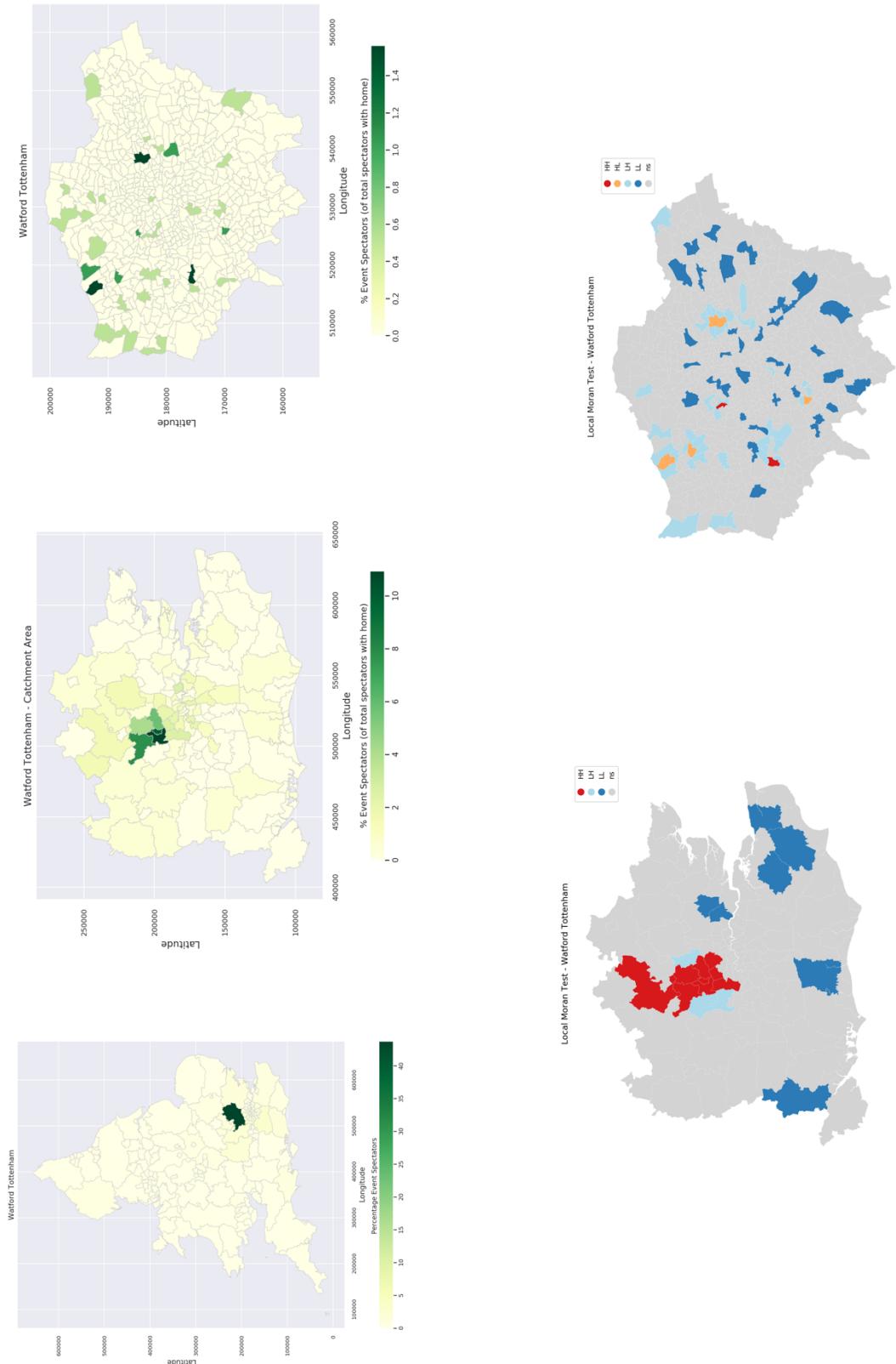
Local Moran Test - Watford Southampton

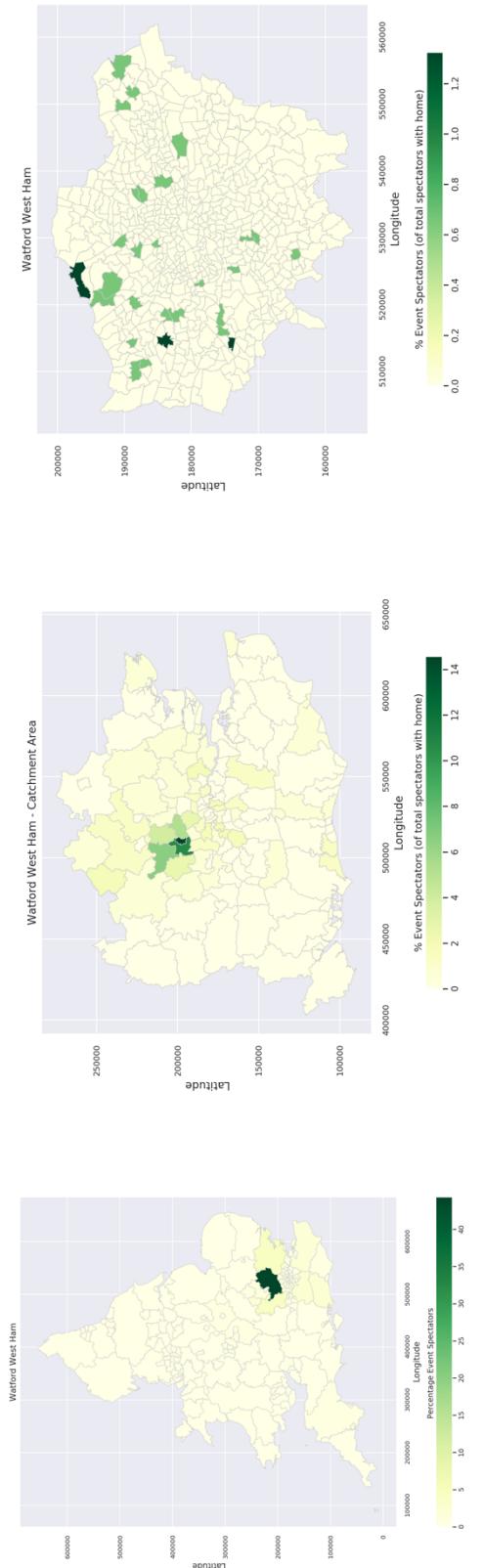


Local Moran Test - Watford Southampton

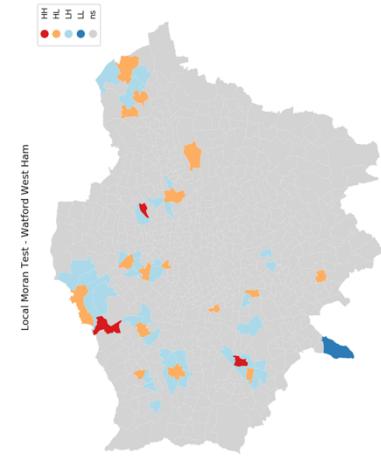




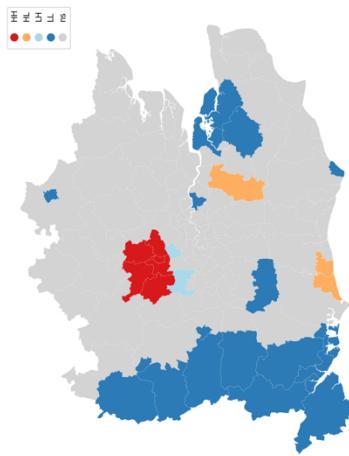




Local Moran Test - Watford West Ham



Local Moran Test - Watford West Ham



## 6. Premier League – London Stadium

